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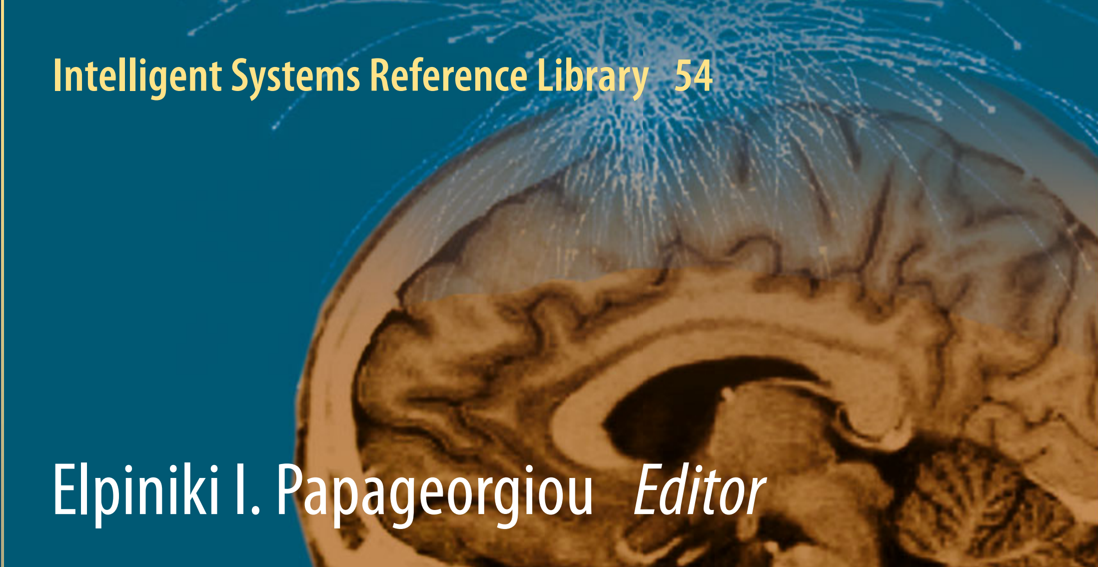

Elpiniki I. Papageorgiou *Editor*

Fuzzy Cognitive Maps for Applied Sciences and Engineering

From Fundamentals to Extensions and Learning Algorithms

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Editor

Fuzzy Cognitive Maps for Applied Sciences and Engineering

From Fundamentals to Extensions and Learning Algorithms

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Editor
Elpiniki I. Papageorgiou
Department of Computer Engineering
Technological Educational Institute of Central Greece
Lamia
Greece

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To my husband Nikos for his patience all these years

and

To Yiannis and Alexandros, the two suns of my life

Foreword

Prof. Elipiniki I. Papageorgiou has organized and edited an important new contribution to the rapidly growing field of fuzzy cognitive maps (FCMs). This new volume further extends the practical and theoretical boundaries of this international FCM research effort. It includes several predictive FCM models that range from rulebased systems to adaptive dynamical systems with their own learning laws.

These diverse models suggest that FCMs will play important roles in the future of both computing and machine intelligence. This includes applications to so-called "big data" and what we can here call "big knowledge."

FCMs are natural tools to process big data. Their graphical structure of a cyclic signed directed graph allows the user to specify coarse or fine levels of causal granularity through the choice of concept nodes and causal edges. Controlling the causal granularity can combat the systemic problem of exponential rule explosion or the curse of dimensionality that infests large rule-based systems and semantic networks. Controlled FCM granularity results in a coarse or fine rule-based compression of the streaming data because the directed causal links define fuzzy if–then rules. Granularized FCMs can use statistical learning laws that scale with the data stream itself. Such adaptive FCMs can gradually update the causal links and can form or split or delete concept nodes as the data streams into the system (although the FCM field still needs a good data-based theory of concept-node formation). This learning process can go on indefinitely. Users can also add or delete FCM elements at any time in the learning process. A user or higher level adaptive system can adjust the learning-rate parameters to match the flow of the data. The resulting FCM at any given time always gives high-level causal and predictive insight into the data flux.

FCMs also offer a natural representational framework for what we can call *big knowledge*—the world's vast and growing body of expert analysis and advice.

This structured knowledge often takes the traditional form of books or technical articles or essays. But it can also take the form of Internet blogs or media interviews or expert-witness court transcripts. Big knowledge includes the whole panoply of fixed or oral knowledge that the law calls documentary or testimonial evidence. Today that knowledge exists largely in disconnected sources or chunks around the world. FCMs have the ability to connect and combine these knowledge chunks into a unified framework for policy and engineering analysis and for further computer and knowledge processing.

FCMs can synthesize this disparate knowledge through a simple transform technique involving connection or adjacency matrices. The technique resembles how a Fourier transform converts a time signal into the frequency domain where the user can filter or modify the signal and then inverse-transform the result back to the time domain. An FCM can represent each knowledge chunk or expert contribution. Then we can translate each such FCM knowledge chunk into an augmented square connection matrix conformable for addition. That in turn allows the formation of a massive knowledge base by appropriately weighting and combining the matrices into a large sparse matrix. Then translating the matrix back into an FCM causal digraph gives the final knowledge base as a massive FCM.

This fusion of all structured knowledge amounts to a worldwide FCM knowledge-representation project. This long-term effort will be the direct beneficiary of Google Books and the Gutenberg Project and Wikisource and related large-scale efforts to digitize and make available the world's text-based documentary evidence. Every book chapter or essay should have its own FCM instantiation. So far there have been a few manual efforts at such FCM knowledge translation and synthesis. That includes some of the FCMs developed in this volume. But a fully automated FCM synthesizer remains a research goal for the future.

FCMs can advance big knowledge in yet another way: they can naturally represent *deep* knowledge in stacked or multilayered FCMs. These multilayer structures are far more complex and expressive than stacked or deep neural networks. Almost all such multilayered neural networks have only a feedforward architecture and thus they have only trivial dynamics. They have no connections at all among the neurons in a given visible layer or hidden layer. Nor do the synaptic edges or most neurons have any meaningful interpretation. So these minimal multilayer structures allow little more than blind statistical training of the contiguous layers and of the overall network itself. But an FCM's representation power and rich feedback dynamics stem directly from the cyclic causal edge connections among the concept nodes in a layer—cycles that undermine most traditional expert systems and Bayesian networks. Stacked FCMs can represent knowledge on different timescales both within FCM layers and especially between FCM layers. These stacked FCMs also do not need to function only in feedforward mode. They can allow feedback from higher layers to lower layers and do so again on different timescales. Thus the entire stacked or multilayer FCM can reverberate as it passes through successive dynamical equilibria. Concept nodes in a given

FCM layer can also branch laterally to other FCMs or even to other stacked FCMs. Hence they too can fuse or combine with other FCMs to produce ever larger connected knowledge bases.

These are near-term and long-term goals for FCM research. The present volume does an excellent job of moving in those and other directions as well as demonstrating the analytic and predictive power of FCM-based knowledge engineering.

Bart Kosko
Professor of Electrical Engineering and Law
University of Southern California
Los Angeles
USA

Contents

Contributors

M. C. Adamescu Department of Systems Ecology and Sustainability, University of Bucharest, Bucharest, Romania

L. V. R. Arruda Federal University of Technology–Paraná, Av Sete de Setembro, Curitiba, Brazil

M. Bachhofer FCMappers.net, Tokyo, Japan

Nick Bassiliades Department of Informatics, Aristotle University of Thessaloniki, Thessaloniki, Greece

Dimitri De Franciscis Megadix, Freelance Java/CMS/Database Consultant, Milan, Italy

Anday Demirsoy Control Engineering Department, Faculty of Electrical and Electronics Engineering, Istanbul Technical University, Maslak, Istanbul, Turkey

Wojciech Froelich Institute of Computer Science, University of Silesia, ul.Bedzinska, Sosnowiec, Poland

R. Ganguli Department of Aerospace Engineering, Indian Institute of Science, Bangalore, India

M. Glykas Department of Financial and Management Engineering, University of the Aegean, Chios, Greece; Greece Aegean Technopolis, The Technology Park of the Aegean Region, Chios, Greece

Steven A. Gray Department of Natural Resources and Environmental Management, University of Hawaii, Honolulu, HI, USA

Stefan R. J. Gray Coastal and Marine Research Center, University College Cork, Cork, Ireland

K. G. Q. Isak NIRAS, Aarhus, Denmark

N. Ismail Department of Mechanical and Manufacturing, Faculty of Engineering, University Putra Malaysia, Selangor, Malaysia

W. Khaksar Department of Mechanical and Manufacturing, Faculty of Engineering, University Putra Malaysia, Selangor, Malaysia

Anjali Mago School of Population and Public Health, University of British Columbia, Vancouver, BC, Canada

Vijay Kumar Mago Department of Computer Science, University of Memphis, Memphis, TN, USA

Márcio Mendonça Federal University of Technology–Paraná, Avenue Alberto Carazzai, Cornélio Procópio, Brazil

Omid Motlagh Department of Robotics and Automation, Faculty of Manufacturing Engineering, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia

F. Neves Federal University of Technology–Paraná, Av Sete de Setembro, Curitiba, Brazil

Elpiniki I. Papageorgiou Department of Computer Engineering TE, Technological Educational Institute of Technical University of Central Greece, Lamia, Greece

Witold Pedrycz Department of ECE, University of Alberta, Edmonton, Canada; Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland

A. Peña-Ayala WOLNM, ESIME-Z IPN, 31 Julio 1859 Leyes Reforma, Mexico, Iztapalapa, Mexico

Katarzyna Piotrowska Department of Computer Science Applications, Kielce University of Technology, Kielce, Poland

Edy Portmann Department of Electrical Engineering and Computer Science, University of California, Berkeley, CA, USA

Napoleon H. Reyes Institute of Information and Mathematical Sciences, Massey University, Auckland, New Zealand

Jose L. Salmeron Computational Intelligence Lab, University Pablo de Olavide, Seville, Spain

F. Skov Department of Wildlife Ecology and Biodiversity, National Environmental Research Institute, Aarhus University, Aarhus, Denmark

Grzegorz Słón Kielce University of Technology, al. Tysiaclecia P. P., Kielce, Poland

J. H. Sossa-Azuela CIC IPN, Mexico, DF, Mexico

S. H. Tang Department of Mechanical and Manufacturing, Faculty of Engineering, University Putra Malaysia, Selangor, Malaysia

Tolga Tezcan Scientific and Technological Research Council of Turkey, Kocaeli, Turkey

Athanasios Tsadiras Department of Economics, Aristotle University of Thessaloniki, Thessaloniki, Greece

Leon Urbas Chair of Distributed Control Systems Engineering, Institute of Automation, Dresden University of Technology, Dresden, Germany

M. N. Văidianu CICADIT, University of Bucharest, Regina Elisabeta Blv, Bucharest, Romania

Ján Vaščák Center for Intelligent Technologies, Technical University of Košice, Košice, Slovakia

Martin Wildenberg GLOBAL 2000, Umweltforschungsinstitut, Neustiftgasse, Vienna, Austria

Alexander Yastrebov Department of Computer Science Applications, Kielce University of Technology, Kielce, Poland

Engin Yesil Faculty of Electrical and Electronics Engineering, ControlEngineering Department, Istanbul Technical University, Maslak, Istanbul, Turkey

E. Zanre Department of Natural Resources and Environmental Management, University of Hawaii, Honolulu, HI, USA

Introduction

This book is dedicated to providing readers with deep insights into fundamentals, modeling methodologies, extensions, and learning algorithms for fuzzy cognitive maps (FCMs), supplemented with codes, software tools, and applications of FCMs in applied sciences and engineering. This will help the academics, new generation researchers, applied researchers to use the FCM methodology, the several extensions of FCMs, the FCM learning algorithms, and the new and most available software tools for modeling, decision making, and support.

The primary goal of this book is to fill the existing gap in the literature and comprehensively cover the state-of-the-art modeling and learning methods as well as software tools of FCMs, and provide a set of applications that demonstrate the various usages of FCM-based methods and algorithms in the real world.

Description

Fuzzy cognitive maps are fuzzy feedback dynamical systems for modeling causal knowledge. They were introduced by Bart Kosko in 1986 as an extension of cognitive maps. Cognitive maps are a set of nodes linked by directed and signed edges. The nodes represent concepts relevant to a given domain. The causal links between these concepts are represented by the edges which are oriented to show the direction of the influence and are signed to show a promoting or inhibitory effect.

FCM describes a cognitive map model with two significant characteristics. The first one is the type of the causal relationships between concepts which have different intensities represented by fuzzy numbers. A fuzzy number is a quantity whose value is uncertain, rather than exact. The second one is the system dynamicity, that is, it evolves with time. It involves feedback, where the effect of change in a concept node may affect other concept nodes, which in turn can affect the node initiating the change. These two characteristics were proposed by Prof. Kosko who is considered the "father" of FCMs.

FCMs have emerged as tools for representing and studying the behavior of systems and people. By combining the main aspects of fuzzy logic, neural networks, expert systems, semantic networks, they have gained considerable research interest and are widely used to analyze causal complex systems. From an Artificial Intelligence perspective, FCMs are dynamic networks with learning capabilities, where in more and more data are available to model the problem, the system becomes better at adapting itself and reaching a solution. They gained momentum due to their dynamic characteristics and learning capabilities. These capabilities make them essential for modeling, analysis, and decision-making tasks as they improve the performance of these tasks. In addition, several FCM extensions have been proposed during the last decade. Each one of them improves the conventional FCM in different ways.

During the past decade, FCMs played a vital role in the applications of diverse scientific areas, such as social and political sciences, engineering, information technology, robotics, expert systems, medicine, education, prediction, environment, etc. The number of published papers (in the last 10 years) was extremely high and in the last 2 years was exceptionally high showing that there is a strong interest in FCMs by contemporary researchers. The research in the theory of FCMs was concentrated on providing major improvements and enhancements/extensions in its theoretical underprinning. Thus, it seems that there is a need for a new book in the area of FCMs for applied sciences and engineering focusing on fundamentals, extensions, and learning algorithms.

Objective of the Book

This book tries to present emerging trends and advances in FCMs in a concrete and integrated manner focusing on FCM fundamental methodologies for FCM modeling, extensions, and learning algorithms for applied sciences and engineering. Also, this book is accompanied with a CD including some main algorithms for modeling and learning algorithms for FCMs, as well as tools and some useful demos of developed softwares.

New features of this book:

- Presents systematically and comprehensively the fundamentals of FCM methodology, the extensions of FCMs with their theories and learning algorithms, and innovative applications of them as a whole;
- Provides readers with deep insights into dynamical modeling and learning algorithms, codes, software tools, and applications of FCMs in applied sciences and engineering;
- Presents different case studies of learning algorithms successfully applied to real-world problems;
- Provides basic codes and algorithms for FCM-based modeling and learning approaches, as well as tools and interesting demos.

Target Audience

The audience of this book is both the academic and applied research community that has an interest in using FCMs, either as a theoretical framework or as a methodology and tool for applied research, engineering, industrial applications, environmental management, medical decision support, etc. Also, students and new generation researchers could be helped and addressed through mathematical and computational modeling, as well as learning algorithms for FCMs.

Book Chapters

This volume is the result of 1 year of effort, where more than 30 chapters were rigorously peer-reviewed by a set of 18 reviewers. (*All contributions have undergone a rigorous review process, involving two independent experts in two to three rounds of reviews*.) After several cycles of chapter submission, revision and tuning based on the Springer international quality principles, 20 works were approved, edited as chapters, and organized according to three kinds of topics: Modeling, Learning algorithms and Tools, and Applications. So the first part corresponds to *Modeling* and includes Chaps. 1–6 the second part represents *Learning Algorithms and Tools* and embraces Chaps. 7–13 the third part is related to *Applications*, and contains Chaps. 14–20. A profile/description of the chapters is given next:

Chapter 1, written by Elpiniki Papageorgiou and Jose Salmeron, presents the challenging problem of complex systems modeling, with efficient learning algorithms, using methods that utilize existent knowledge and human experience. Special focus is devoted on two issues, methods and learning algorithms for FCMs applied to modeling and decision-making tasks. A comprehensive survey of the current modeling methodologies and learning algorithms of FCMs is provided. Leading methods and algorithms, concentrated on modeling, are described analytically and analyzed presenting experimental results of a known case study concerning process control. The main features of computational methodologies are compared, highlighting their advantages and limitations, and future research directions are outlined.

Chapter 2, written by Steven Gray, E. Zanre and S. R. J. Gray, presents the theoretical foundations of concept mapping, cognitive mapping, mental models, and the notion of "expertise" in the elicitation of a subject's knowledge as they are of particular interest on FCM construction and interpretation. It discusses issues related to analyzing FCMs collected from non-traditional experts, which is a growing area of research that seeks to characterize group knowledge structure to inform community decision-making. To sum up, this chapter addresses how FCM can be used to understand shared knowledge and what trade-offs should be considered in the selection of FCM data collection techniques.

Chapter 3, written by Omid Motlagh, S. H. Tang, W. Khaksar and N. Ismail, discusses FCM application in relationship modeling context using some agile inference mechanisms. A sigmoid-based activation function for FCM-based relationship model is discussed with application in modeling hexapod locomotion gait. The activation algorithm is then added with a Hebbian weight training technique to enable automatic construction of FCMs. A numerical example case is included to show the performance of the developed model. The model is examined with perceptron learning rule as well. Finally, a real-life example case is tested to evaluate the final model in terms of FCM relationship modeling.

Chapter 4, written by Athanasios Tsadiras and Nick Bassiliades, proposes a new representation scheme of FCMs based on RuleML representation, accompanied by the implementation of a system that assists decision makers to simulate their own developed Fuzzy Cognitive Maps. The system is designed and implemented in Prolog programming language to assist experts to simulate their own FCMs. This system returns results in valid RuleML syntax, making them readily available to other cooperative systems. The design choices of the implemented system are discussed and the capabilities of the RuleML representation of FCM are presented. The use of the system is exhibited by a number of examples concerning an e-business company.

Chapter 5, written by Edy Portmann and Witold Pedrycz, presents Fuzzy Cognitive Maps as a vehicle for Web knowledge aggregation, representation, and reasoning. The authors introduce a conceptual framework for Web knowledge aggregation, representation, and reasoning, along with a use case, in which the importance of investigative searching for online privacy and reputation is highlighted. The framework is practicable and robust as solution to seize the presented requirements of online privacy and reputation management using Fuzzy Cognitive Maps.

In Chap. 6, Alejandro Peña-Ayala and Humberto Sossa apply an extension of the traditional Fuzzy Cognitive Maps called Rules-based Fuzzy Cognitive Maps (RBFCM). This version depicts the qualitative flavor of the object to be modeled and is grounded on the well-sounded fuzzy logic. A case study in the educational field was selected to show the RBFCM usefulness. Their decision-making approach offers decision-making services to the sequencing module of an intelligent and adaptive web-based educational system (IAWBES). According to the student-centered education paradigm, an IAWBES elicits learners' traits to adapt lectures to enhance their apprenticeship. This RBFCM-based decision-making approach models the teaching scenery, simulates the bias exerted by authored lectures on the student's learning, and picks the lecture option that offers the highest achievement.

In Chap. 7, Wojciech Froelich and Elpiniki Papageorgiou tackle with the issue of FCM learning using evolutionary algorithms for multivariate time-series prediction. Since FCM is a parametric model, it can be trained using historical data. Previous studies have shown that the genetic algorithm can be also used not only for optimizing the weights of FCM but also for optimization of FCM transformation functions. The main idea of this work is to further extend the FCM evolutionary learning process, giving a special attention on fuzzyfication and transformation function optimization, applied in each concept separately, in order to improve the efficacy of time-series prediction. The proposed extended evolutionary optimization process was evaluated in a number of real medical data gathered from the Internal Care Unit (ICU). Comparing this approach with other known genetic-based learning algorithms, less prediction errors were observed for this dataset.

Chapter 8, written by Alexander Yastrebov and Katarzyna Piotrowska, is devoted to the analysis of multistep learning algorithms for fuzzy cognitive maps, which are some kind of generalization of known one-step methods of FCM learning. This type of multi-step learning consists of supervised learning based on gradient method and unsupervised learning type of differential Hebbian learning (DHL) algorithm. These methods were compared with one-step algorithms, from the point of view of the influence on the work of the medical prediction system (average percentage prediction error). The analyzed map was initialized and learned based on historical data, and then used to predict the clinician's Parkinson's disease symptom. Simulation research together with the analysis results was done on prepared software tool ISEMK (Intelligent Expert System based on Cognitive Maps).

Chapter 9, written by Grzegorz Słon and Alexander Yastrebov, deals with certain aspects of the design of fuzzy cognitive maps, whose operations are based not on a set of causal rules but on mathematically defined relationships between the model key concepts. In such a model, which can be called a relational FCM, the key concepts are described by fuzzy numbers, and the relationships between concepts take the form of specially shaped fuzzy relations. As a result, the operation of the model is described mathematically by the system of special equations operating on fuzzy numbers and relations. It presents formal and technical difficulties; however, it allows applying certain automation of the process of creating and modifying the relational model of an FCM. It also enables detachment from the rigidly defined linguistic values in relation to their abstract equivalents, which number can easily be changed depending on the current needs of the modeling process.

Chapter 10, written by Marcio Mendoza, Lúcia Valéria Ramos de Arruda, and Flávio Neves-Jr, presents an architecture for cooperative autonomous agents based on dynamic fuzzy cognitive maps (DFCM) that are an evolution of FCMs. This architecture is used to build an autonomous navigation system for mobile robotics that presents learning capacity, online tuning, self-adaptation abilities, and behaviors management. The navigation system must support the development of swarm robotics applications. For this, bio-inspired algorithms were used allowing agents to realize tasks. Subsumption architecture was also proposed to manage agent behaviors. Finally, the several DFCMs that correspond to behavioral modules of an agent were organized in a layered hierarchy of subsumption. The DFCMs placed in the lower layer present only purely causal relationships and/or fuzzy type relationships. In the higher layer, the functionalities to adaptation, communication with other agents and model evolution are inserted. A multi-agent scheme to share experiences among robots was also implemented at the last hierarchy level based on pheromone exchange by ant colony algorithm. The proposed architecture was validated on a simple example of swarm robotics.

The need of developing novel approaches for an automated generation of FCMs using historical data is the focus of Chap. 11. Engin Yesil, Leon Urbas and Anday Demirsoy, present a software development focusing on a learning method for FCMs. A new optimization algorithm, which is called Big Bang-Big Crunch (BB-BC), is proposed for an automated generation of FCMs from data. Moreover, a graphical user interface (GUI) is designed and an FCM-GUI is developed using Matlab. In this study, two real-world examples; namely a process control system and a synthetic model generated by the proposed FCM-GUI are used to emphasize the effectiveness and usefulness of the proposed methodology. The results of the studied examples show the efficiency of the developed FCM-GUI for design, simulation, and learning of FCMs.

Chapter 12 presents Java Fuzzy Cognitive Maps (JFCM) developed by Dimitri De Franciscis. JFCM is an open source library that implements fuzzy cognitive maps using the JavaTM programming language. Dimitri De Franciscis introduces the library and its main features, along with many code examples and experiments that show how to effectively use it in projects. The proposed library is a simple, standalone library written in Java, so it can run on many operating systems, has very few dependencies on other libraries, and is released under LGPL license, which permits inclusion in commercial projects. Due to these advantages, the library can be used to build a wide range of cognitive maps.

In Chap. 13, Martin Wildenberg, Michael Bachhofer, Kirsten G. Q. Isak, and Flemming Skov, apply Fuzzy Cognitive Mapping as a tool to support conservation management. As part of ALTER-Net, FCM was applied to five cases and subsequently was evaluated by means of a SWOT framework. This approach examines the strengths and weaknesses of, and the opportunities and threats to FCM when applied in conservation management which is dealing with landscapes as socio-ecological systems. Moreover, the FCMapper (see www.fcmappers.net) software for FCM modeling and analysis, is presented and used. This software is freely available, based on excel and allows to calculate the basic FCM indices, conduct dynamical analysis, and visualize the fuzzy cognitive maps.

Chapter 14, written by Jose Salmeron and Elpiniki Papageorgiou, applies Fuzzy Grey Cognitive Maps (FGCM) for process problems in industry. FGCM, as an extension of Fuzzy Cognitive Maps, mixing fuzzy logic, grey systems theory, and cognitive map theories, is capable of dealing with uncertain problems and human reasoning as well. It is an innovative approach for modeling complex systems and thus it is used to elaborate on industrial process control. The developed FGCM model is composed of grey nodes that represent the main factors involving the control problem linked by directed grey edges that show the cause-effect relationships between them. This FGCM model is improved using the NHL learning algorithm. Some experiments are conducted showing the effectiveness, validity, and especially the advantageous behavior of the proposed grey-based methodology of constructing and learning FCMs.

The use and perspectives of Fuzzy Cognitive Maps in Robotics is the focus of Chap. 15. This chapter, written by Jan Vascak and Napoleon H. Reyes, deals with specification of needs for a robot control system and divides defined tasks into three basic decision levels dependent on their specification of use as well as applied means. Concretely, examples of several FCMs applications from the low and middle decision levels are described, mainly in the area of navigation, movement stabilization, action selection, and path cost evaluation. FCMs are applied in robotics to offer an overview of potential possibilities for this perspective means of artificial intelligence. FCMs can find use not only on higher decision levels, which require a certain measure of intelligence, but also on lower levels of control, where conventional PID controllers are used very often. Actually, a rough survey of the use of FCMs in robotics is given.

In Chap. 16, Ranjan Ganguli applies Fuzzy Cognitive Maps for structural damage detection. Structures such as bridges, buildings, nuclear power plants, aircraft, helicopters, turbines, vehicles etc., constitute a key component of modern engineering and economic infrastructure. However, such structures are susceptible to damage due to the environment and harsh operating conditions. Damage in structures can lead to degradation in performance and potential catastrophic failure. Therefore, there is a need on algorithms for accurate structural damage detection. This chapter applies FCMs with the efficient nonlinear Hebbian learning algorithm for detecting structural damage in a cantilever beam from measured natural frequencies. Numerical simulations from a finite element model are used to create a fuzzy rule base which is used to design the FCM. Hebbian learning allows the FCM to improve itself and the numerical results show that the FCM with Hebbian learning is a robust tool for damage detection with noisy data.

In Chap. 17, Michael Glykas focus on the presentation and use of fuzzy strategic maps. He presents the theoretical framework of FCM and its associated modeling and simulation tool to Strategy Maps (SMs). Strategy maps represent visually relationships among the key components of an organization's strategy. They are powerful tools which show how value is created through cause and effect relationships. Some main limitations of the scenario based SMs are the inherited inability to change scenarios dynamically as well as the missing element of time. FCMs are presented as an alternative to overcome these shortfalls with the introduction of fuzziness in their weights and the robust calculation mechanism. An FCM tool is presented that allows simulation of SMs as well as interconnection of nodes (performance measures) in different SMs which enables the creation of SM hierarchies. An augmented FCM calculation mechanism that allows this type of interlinking is also presented. The resulting methodology and tool are applied to two Banks and the results of these case studies are presented.

In Chap. 18, Tolga Teczan handles the issue of migration at a conceptual level. Migration is generally considered as a demographic event and many studies have tried to investigate how social dynamics and identities play a role in the migration phenomenon in urban areas. However, none of them have analyzed this through a model that allows presenting a perception towards migrants and the phenomenon of migration from the point of view of social groups at a conceptual and relational level. In this study, FCM approach is presented in order to understand historical experiences of migration that have reflections on daily practices and identify the causal characteristics of the migration issue. Through this proposal, it is possible to observe how social inequalities caused by and/or leading to migration become visible and more comprehensive from the perspective of different social categories of migrants.

In Chap. 19, Maria-Nataşa Văidianu, Mihai Cristian Adamescu, Martin Windelberg and Cristian Tetelea, examine the perceptions of local stakeholders in Sfantu Gheorghe, Danube Delta Biosphere Reserve (DDBR), Romania, with the aim of developing key concepts that will be used in future information and communication strategies regarding economic characteristics, sustainable development and biodiversity conservation in the area. FCM approach was applied to help people gain knowledge, values, and the awareness they need to manage efficiently environmental resources and to assume responsibility for maintaining environmental quality. For this, 30 cognitive maps were developed together with stakeholders. Analysis reveals that DDBR Administration, county authorities, and local authorities are substantially worried about the pollution and overfishing, while other social groups care more about touristic activities, accessibility degree, health system, or financial resources.

In Chap. 20, Vijay Mago, Elpiniki Papageorgiou and Anjali Mago, elaborate on the use of FCMs as a decision support mechanism for periodontal disease assessment, and with the development of a software tool for supporting dentists in making decisions. An FCM approach accompanied with an easy to use software system to assess the severity level of periodontal disease in dental patients was proposed. The origin of this work is based on the application of FCM methodology to assess uncertainty inherent in the medical domain thus deciding the severity of periodontal disease and the cause of the disease. Dentist usually relies on his knowledge, expertise, and experiences to design the treatment(s). Therefore, it is found that there is a variation among treatments administered by different dentists. The causal relationships between different sign-symptoms have been defined using easily understandable linguistic terms following the construction process of FCM and then converted to numeric values using Mamdani inference method. Also, a software tool with an easy to use Graphical User Interface (GUI) for dentists was developed. The tool can also benefit the non-specialized dentists in decision making in their daily practice.

This volume covers an important range of FCM modeling methods, extensions, learning algorithms, and software tools in its 20 chapters. Modeling advances include new relationship modeling laws, new designing methods using non-traditional experts and web knowledge, new causal learning laws and the use of dynamic features such as cooperative autonomous agents for concepts, and weighted edges to establish dynamic fuzzy cognitive maps. Learning advances include new and extended evolutionary learning approaches, multi-step learning algorithms for prediction and decision making, multi-agents for navigation tasks. The FCMs with their advanced methodologies found applications on engineering, control, management, environmental modeling, decision making, medical decision support, among many others.

Also, a CDROM is provided with this volume, which contains 14 resources from the respective chapters, devoted to FCM-based modeling and learning algorithms (six codes), software tools that allow the design, simulation, learning, and result reporting of FCM (six software packages), as well as some interesting demos.

Thanks

I would like to sincerely thank from the bottom of my heart, the "Inspirer" of Fuzzy Cognitive Map, Prof. Bart Kosko, who accepted my invitation to contribute to the foreword of this book, providing a new insight and vision to the field. It is a deep honor for me and for all the contributors to this book.

Moreover, I wish to express my gratitude to all the contributors of this book for presenting their research in an easily accessible manner, and for putting such discussion into a historical context. Without them, this work would not be accomplished.

Chapter 1
Methods and Algorithms for Fuzzy Cognitive Map-based Modeling

Elpiniki I. Papageorgiou and Jose L. Salmeron

Abstract The challenging problem of complex systems modeling methods with learning capabilities and characteristics that utilize existence knowledge and human experience is investigated using Fuzzy Cognitive Maps (FCMs). FCMs are ideal causal cognition tools for modeling and simulating dynamic systems. Their usefulness has been proved from their wide applicability in diverse domains. They gained momentum due to their simplicity, flexibility to model design, adaptability to different situations, and ease of use. In general, they model the behavior of a complex system utilizing experts knowledge and/or available knowledge from existing databases. They are mainly used for knowledge representation and decision support where their modeling features and their learning capabilities make them efficient to support these tasks. This chapter gathers the methods and learning algorithms of FCMs applied to modeling and decision making tasks. A comprehensive survey of the current modeling methodologies and learning algorithms of FCMs is presented. The leading methods and learning algorithms, concentrated on modeling, are described analytically and analyzed presenting experimental results of a known case study. The main features of computational methodologies are compared and future research directions are outlined.

Electronic supplementary material The online version of this article (doi: 10.1007/978-3-642-39739-4_1) contains supplementary material, which is available to authorized users.

E. I. Papageorgiou (✉)
Department of Computer Engineering, Technological Educational Institute of Central Greece, 3rd Km Old National Road Lamia-Athens, 35100 Lamia, Greece
e-mail: epapageorgiou@teilam.gr

J. L. Salmeron
Computational Intelligence Lab, University Pablo de Olavide, 1st km. Utrera Road, Seville, Spain
e-mail: salmeron@acm.org

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1 Introduction

Fuzzy Cognitive Map (FCM) is a method for modeling complex systems utilizing existence knowledge and human experience. It has learning capabilities and characteristics which improve its structure and computational behavior [39, 44, 63]. It was introduced by Kosko [31], as an extension to cognitive maps [10], providing a powerful machinery for modeling of dynamical systems. As a knowledge representation and reasoning technique, it depicts a system in a form that corresponds closely to the way humans perceive it. Also, it is able to incorporate experts' knowledge and available knowledge from data in the form of rules [44, 63, 69, 71]. This approach represents knowledge by emphasizing causal connections and map structure.

The resulting fuzzy model is used to analyze, simulate, and test the influence of parameters and predict system behavior. The FCM model is easily understandable, even by a non-technical audience, and each parameter has a perceivable meaning [61].

Due to their simplicity, support of inconsistent knowledge, and circle causalities for knowledge modeling and inferring, FCM was applied to many diverse scientific areas including engineering [79], medicine [55, 68], business [85], software engineering [36, 67], environmental sciences [29, 46], politics [8], and so on. Most of the applications concern knowledge modeling and decision making tasks (i.e. [1, 3, 4, 6, 8, 9, 12, 21, 23, 25, 30, 34, 37, 42, 47, 48, 50–53, 58, 61, 62, 68, 72, 74]).

Also, a number of FCM modeling methodologies and/or FCM extensions for modeling systems have been proposed [49]. These FCM-based approaches refer either to FCM extensions or to enhance FCM structures inheriting characteristics and advantages of other intelligent techniques. The current extensions are usually designed to solve three FCM drawbacks [49], uncertainty modeling (FGCM, iFCM, BDD-FCM, RCM), dynamic issues (DCN, DRFCM, FCM, E-FCM, FTCM, TQFCM), and rule-based knowledge representation (RBFCM, FRI-FCM). The extensions of conventional FCM seem to be a useful trend for overcoming FCM limitations.

The ability of FCMs to improve their operation on the light of experience (learning of the connection matrix) is a crucial issue in modeling. The adaptation of the connection matrix (known as weight matrix) can be carried out by diverse unsupervised and evolutionary type learning methods, such as unsupervised learning based on the Hebbian method [51–53, 57], supervised ones with the use of evolutionary computation [5, 11, 17, 18, 59, 74–76] and/or gradient-based methods [38, 86]. In most known approaches to learning FCMs, the set of concept labels C is provided a-priori by expert, and only the weight matrix is drawn from raw data.

This chapter is devoted to the presentation of methods and learning algorithms for FCM-based modeling. FCMs will be proved to be useful to exploit the knowledge and experiences that human have accumulated for years on the operation of a complex system. Also, it will be shown how the FCM-based methods and its learning capabilities have been used for decision analysis and support research. These methodologies and algorithms contribute to engineers' intention to construct intelligent decision support systems, since the more intelligent a system is, more symbolic and fuzzy representation it utilizes [25, 70, 79].

2 Theoretical Background

Fuzzy Cognitive Map is a combination of fuzzy logic and cognitive mapping, and it is a way to represent knowledge of systems which are characterized of uncertainty and complex processes. FCMs were introduced by [31, 32] and since then they have gradually emerged as a powerful paradigm for knowledge representation [66]. They provide a more flexible and natural mechanism for knowledge representation and reasoning, which are essential to intelligent systems [40, 55, 64, 80, 81].

A FCM consists of factors (concepts/nodes) which represent the important elements of the mapped system, and directed arcs, which represent the causal relationships between the factors. The directed arcs are labeled with fuzzy values in the interval [0, 1] or $[-1, +1]$, that show the strength of impact between the concepts. The fuzzy part allows us to have degrees of causality, represented as links between the concepts of these diagrams. This structure establishes the forward and backward propagation of causality, admitting the knowledge base to increase when concepts and links between them are increased.

Each of FCM's edges is associated with a weight value that reflects the strength of the corresponding relation. This value is usually normalized to the interval [0, 1] or $[-1, +1]$. The matrix E stores the weights assigned to the pairs of concepts. We assume that the concepts are indexed by subscripts i (cause node) and j (effect node).

In the simplest case, it is possible to distinguish Binary Cognitive Maps (BCM) for which the concept labels are mapped to binary states denoted as $A_i \in \{0, 1\}$, where the value 1 means that the concept is activated. The weights of BCM are usually mapped to the crisp set, i.e., $e_{ij} \in \{-1, 0, 1\}$. The value 1 represents, positive causality, understood e.g. such way, that the activation (change from 0 to 1) of concept c_i occurs concurrently with the same activation of concept c_j or that deactivation (change from 1 to 0) c_i occurs concurrently with the same deactivation of concept c_j. The value -1 represents the opposite situation, in which the activation of c_i deactivates the concepts c_j or viceversa. The $e_{ij} = 0$ means that there are no concurrently occurring changes of the states of the concepts. In FCMs, each node quantifies a degree to which the corresponding concept in the system is active at iteration step.

Usually, experts develop an FCM or a mental model manually based on their knowledge in a related area. At first, they identify key domain aspects, namely concepts. Secondly, each expert identifies the causal relationships among these concepts and estimates causal relationships strengths. This achieved digraph (FCM) shows not only the components and their relationships but also the strengths (Fig. 1).

Once the FCM is constructed, it can receive data from its input concepts, perform reasoning and infer decisions as values of its output concepts [32, 79].

3 Fuzzy Cognitive Map Reasoning

For FCM reasoning process, a simple mathematical formulation is usually used. Values of the concept C_i in time t are represented by the state vector $A_i(k)$, and the state of

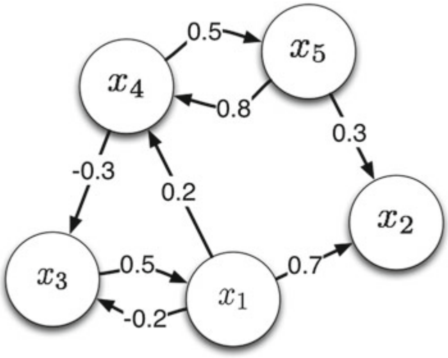

Fig. 1 This figure is a simple FCM representation is illustrated which has five generic vertices (F_1 – F_5) and the weights (weighted edges) showing the relationships between concepts

the whole FCM could be described by the state vector $A(k) = [A_i(k), \ldots, A_n(k)]$, which represents a point within a fuzzy hypercube $I^n = [0, 1]^n$ that the system achieves at a certain point.

The whole system with an input vector $A(0)$ describes a time trace within a multidimensional space I^n, which can gradually converge to an equilibrium point, or a chaotic point or periodic attractor within a fuzzy hypercube. To which attractor the system will converge depends on the value of the input vector $A(0)$.

The value A_i of each concept C_i in a moment $k + 1$ is calculated by the sum of the previous value of A_i in a precedent moment t with the product of the value A_j of the cause node C_j in precedent moment k and the value of the cause-effect link e_{ij}. The mathematical representation of FCMs has the following form:

$$A_i(k+1) = f\left(A_i(k) + \sum_{j=1}^{N} A_j(k) \cdot e_{ji}\right) \tag{1}$$

where $f(\cdot)$ is a threshold (activation) function [82, 83]. Sigmoid threshold function gives values of concepts in the range [0, 1] and its mathematical type is:

$$f(x) = \frac{1}{1 + e^{-m \cdot x}} \tag{2}$$

where m is a real positive number and x is the value $A_i^{(k)}$ on the equilibrium point [79, 82]. A concept is turned on or activated by making its vector element 1 or 0 or in [0, 1]. The transformation function is used to reduce unbounded weighted sum to a certain range, which hinders quantitative analysis, but allows for qualitative comparisons between concepts [79].

New state vectors showing the effect of the activated concept are computed using method of successive substitution, i.e., by iteratively multiplying the previous state vector by the relational matrix using standard matrix multiplication $A^k = A^{k-1} + (A^{k-1} \cdot W)$. The iteration stops when a limit vector is reached, i.e., when $A^k = A^{k-1}$

or when $A^k - A^{k-1} \leq e$; where e is a residua, whose value depends on the application type (and in most applications is equal to 0.001). Thus, a final vector A_f is obtained, where the decision concepts are assessed to clarify the final decision of the specific decision support system.

4 FCM for Decision Support

Real-world problems are not static, the environment changes continuously while decision makers attempt to make a choice, and that it also changes as a result of those choices. In fact, most of real-world decision making is dynamic. Critical decisions in finance, sales, engineering, manufacturing, and other fields need interrelated resource-constrained decisions under hardly complex and uncertain environments.

Overall, decision support includes selecting the optimal strategy for reaching goals, from several strategies. The risks and uncertainties associated with each alternative shape a set of constraints with influence over this process [7]. Real-world issues are often composed by several elements interrelated in so complex ways. In addition, they are frequently dynamic, since they evolve with time by the interactions among elements [63].

Intelligent DSS often incorporates Artificial Intelligence (AI) techniques of knowledge representation and rule-based inferencing. Intelligent DSSs have resulted from the use of artificial intelligence techniques to improve the performance of more traditional systems. AI techniques are used in DSS knowledge bases and inferential procedures [47].

One promising tool for modeling and controlling complex systems is the FCM, and it has emerged as alternative tool for representing and analyzing the systems behavior. FCMs illustrate different aspects in the system's behavior and these concepts interact with each other showing the dynamics of the system.

The main goal of building a FCM around a problem is to be able to forecast the outcome by letting the relevant issues interact with one another. In this sense, it can be used for finding out whether a decision is consistent with the whole set of stated causal assertions [63]. FCM application may contribute to the effort for more intelligent control methods and for the development of autonomous decision making systems.

By using FCMs for decision support, we also get the following benefits [63]:

- Simplicity. By transforming decision problems into causal graphs, decision makers with no technical background can easily understand all of the components in a given problem and their relationships.
- Simulation and prediction. With FCMs, it is possible to determine the most critical factor that appears to affect the target variable and to simulate its impact.
- Timeliness. By relying on FCM models, the decision maker has a strong support, and hence is able to decide faster.

- Reliability. By relying on FCM models from a reputable source, decision makers have the guarantee, or the expectation, that it was built with all the required care, including extensive testing and some validation techniques.
- Investment. FCM models is a way to save the know-how and ingenuity of the best decision makers; to turn a volatile asset into a permanent one.
- Efficiency. Decision makers can aim at the best decisions in their fields of excellence, and for the remainder rely on someone else's expertise modeled in FCMs. In this sense, FCM models could be an efficiency trigger.
- Visual modeling. FCMs provide an intuitive, yet precise way of representing concepts and reasoning about them at their natural level of abstraction.

In addition, FCMs represent knowledge efficiently, handle fuzziness, model situations including uncertain descriptions, adaptive to different situations, and it is flexible to new knowledge.

5 FCM Models/Methodologies

5.1 Rule-based FCMs

Rule-based Fuzzy Cognitive Maps (RB-FCM) are a FCM evolution covering several types of interrelations, not just monotonic causality [15, 16]. RB-FCM represents the complex real-world qualitative systems dynamics with feedback and allow the simulation of events modeling their impact in the system.

RB-FCM are iterative fuzzy rule based systems dealing feedback with fuzzy mechanisms. RB-FCM timing and innovative methods with uncertainty propagation. RB-FCM proposes additional types of relations between concepts as follows causal, inference, alternatives, probabilistic, opposition, conjunction, and so on. Moreover, they include a new fuzzy operation (Fuzzy Carry Accumulation) to model qualitative causal relations (Fuzzy Causal Relations) (Figs. 2 and 3).

In addition, RB-FCM represent time in different ways. The RB-FCM modeler must be able to identify the implicit time in each relationship. Base Time (B-Time) represents the highest level of temporal detail that a simulation can provide in the RB-FCM model (the resolution of the simulation). B-Time must always be implicit while designing each rule in RB-FCM, because if B-Time is one day the meaning of a rule is different than the B-Time is one year.

5.2 Dynamical Cognitive Networks

Dynamical Cognitive Network (DCN), proposed by [40], improves FCM by quantifying the concepts and introducing nonlinear, dynamic functions to the edges. There-

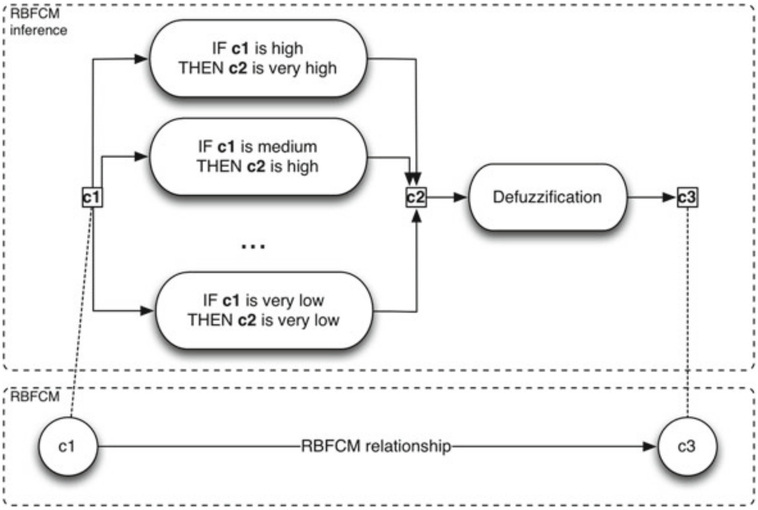

Fig. 2 Rule-based fuzzy cognitive maps. It is illustrated with a couple of nodes (c_1 and c_3) and a RBFCM relationship between them. Fuzzy rules and defuzzification process to compute the new state c_3

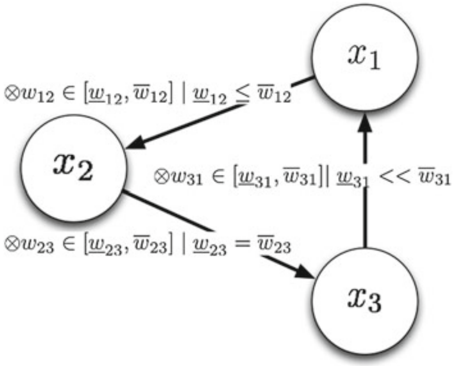

Fig. 3 This figure shows the three kind of relationships in FGCM. The relationship between x_2 and x_3 is a *white* one, between x_1 and x_2 is a *grey* one, and between x_3 and x_1 is a *black* one. FCMs just represent white relationships

fore, DCNs are able to model the dynamic nature of causal processes and perform sensible inference robustly.

DCN relies on the Laplacian framework to represent the causal relationships. The transformation between fuzzy knowledge and Laplacian functions imposes more efforts to DCN modelers. Each DCN node (concept) have its own value set, according on how accurately it needs to be represent.

In this sense, DCNs are more flexible and scalable than conventional FCMs. A DCN can be as simple as a Cognitive Map, a FCM, or as complex as a nonlinear dynamic system. DCNs consider the causal inference factors: the value of the cause, the value of the causal relationship and the degrees of the effect. DCNs improve FCMs by quantifying the state's concepts and introducing non-linear, dynamic functions to the edges.

The value set of the DCN (Φ_G) is the product space of the spaces ($\Phi_{v\in G}$), where Φ_v are the spaces of the concepts which G contains. It is then defined as follows:

$$\begin{aligned}\Phi_G &= \prod_{v\in G} \Phi_v \\ &= \{x|x = (x_1, \dots, x_n)^T,\ x_i \in \Phi_{v_i}\ i = 1, \dots, n\}\end{aligned} \tag{3}$$

where G is a digraph representing the DCN adjacency matrix. The concept value set of a concept v is an order set denoted by Φ_v; every element of the set is a possible state of the concept.

Every DCN concept has its own value set (a binary set, a triple set, a fuzzy set, or a real interval) according to its properties. Moreover, FCMs does not handle dynamics.

5.3 Fuzzy Grey Cognitive Maps

Fuzzy Grey Cognitive Map (FGCM) is an FCM-based generalization designed for environments with high uncertainty, under discrete incomplete and small data sets [65] and it is based on Grey Systems Theory. The FGCM nodes are variables and the relationships between them are represented by grey weighted directed edges. An interval grey weight between the nodes x_i and x_j is denoted as $\otimes w_{ij} \in [\underline{w}_{ij}, \overline{w}_{ij}]$ and it has a lower limit ($\underline{w}_{ij}$) and an upper limit ($\overline{w}_{ij}$). FGCMs represent the human intelligence better than FCM, because it is able to represent unclear relations between nodes and incomplete information about the modeled system better than FCMs do.

The state values of the nodes are updated in an iterative process with an activation function, which is used to map monotonically the grey node value into the range [65].

$$\begin{aligned}\otimes\mathbf{C}(t+1) &= f\Big(\mathbf{C}(\mathbf{t}) \cdot \mathbf{A}(\otimes)\Big) \\ &= f\Big(\otimes\, \mathbf{C}^*(t+1)\Big) \\ &= f\Big((\otimes c_1^*(t+1), \otimes c_2^*(t+1), \dots, \otimes c_n^*(t+1))\Big) \\ &= \Big(f(\otimes c_1^*(t+1)), f(\otimes c_2^*(t+1)), \dots, f(\otimes c_n^*(t+1))\Big) \\ &= \Big(\otimes\, c_1(t+1), \otimes c_2(t+1), \dots, \otimes c_n(t+1)\Big)\end{aligned} \tag{4}$$

where $A(\otimes)$ is the grey adjacency matrix, and $f(\cdot)$ the grey activation function. Usually, the grey activation function is a unipolar grey sigmoid

$$\otimes w_i(t+1) \in \left[\frac{1}{1+e^{-\lambda\cdot \underline{w}_i^*(t+1)}}, \frac{1}{1+e^{-\lambda\cdot \overline{w}_i^*(t+1)}}\right] \quad (5)$$

or a grey hyperbolic tangent

$$\otimes w_i(t+1) \in \left[\frac{e^{\lambda\cdot \underline{w}_i^*(t+1)} - e^{-\lambda\cdot \underline{w}_i^*(t+1)}}{e^{\lambda\cdot \underline{w}_i^*(t+1)} + e^{-\lambda\cdot \underline{w}_i^*(t+1)}}, \frac{e^{\lambda\cdot \overline{w}_i^*(t+1)} - e^{-\lambda\cdot \overline{w}_i^*(t+1)}}{e^{\lambda\cdot \overline{w}_i^*(t+1)} + e^{-\lambda\cdot \overline{w}_i^*(t+1)}}\right] \quad (6)$$

5.4 Intuitionistic FCMs

Intuitionistic FCMs (iFCM) cope with the inability of the FCM models to co-evaluate the hesitancy introduced into the modeled problems due to imperfect facts, indecision and lack of information [49]. iFCM proposal is effective with numeric, reproducible examples, on process control and decision support.

iFCMs include the Intuitionistic Fuzzy Sets (IFS) to handle the experts' hesitancy in their judgements. It improves conventional FCM through the intuitionistic theory so that it models the degree of hesitancy in the relations defined by the experts (Fig. 4).

The experts propose the cause-effect relations between two concepts, and the degree to which the expert hesitates to express that relation. IFS is a generalization of conventional fuzzy sets since the IFS membership is a fuzzy logical value rather than a single truth value.

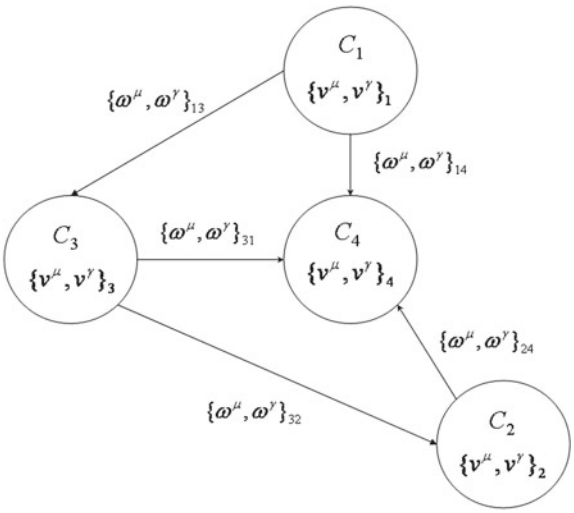

Fig. 4 A relation between a couple of nodes (x_1 and x_2) in iFCM-II. Each node has an impact weight and a hesitancy weight

iFCM-I proposal just considers the hesitancy of the influence between a couple of concepts. On the other hand, iFCM-II introduced hesitancy in the determination of concept values [49]. The hesitancy of the element x of a fuzzy set A is defined as follows

$$\pi_A(x) = 1 - \mu_A(x) - \gamma_A(x) \tag{7}$$

The iFCM-I iterative reasoning process is computed as follows

$$c_i(t+1) = f\left((2 \cdot c_i(t+1)) + \sum_{i=1}^{n}((2 \cdot c_j(t+1)) \cdot \zeta_{ji} \cdot w^{\mu}_{ji} \cdot (1 - w^{\pi}_{ji}))\right) \tag{8}$$

where $c_i \in [0, 1], i = 1, \ldots, n$ represent real node values at iteration k, $w^{\mu}_{ji} \in [0, 1]$ and $w^{\pi}_{ji} \in [0, 1]$ represent the impact weight and the hesitancy weight and factor ζ_{ji} models the sign (positive or negative) impact between the related concepts.

iFCM-II considers that nodes $i = 1, \ldots, n$ are modeled with linguistic variables represented by IFSs as follows

$$L^{c_i}_n = \{\langle x, v^{\mu}_i(x), v^{\gamma}_i(x) | x \in E^+\rangle\} \tag{9}$$

5.5 Dynamic Random Fuzzy Cognitive Maps

Dynamic Random Fuzzy Cognitive Maps (DRFCM) improves conventional FCMs with the nodes' activation probability and including a nonlinear dynamic function within the inference process [2]. The main proposal of the DRFCMs is focused on the dynamic causal relationships. The edges' weight are updated during the FCM dynamics to adapt them better to the new conditions. DRFCM considers on-line adaptive procedures of the system like real-world problems.

The node's state on the DRFCM (the probability of activation of a given concept c_i) is computed as follows

$$p_j = \min\{\varphi^+_j, \max\{r_i, \varphi^-_j\}\} \tag{10}$$

where

$$\varphi^+_j = \max_{i=1\ldots n}\{\min\{q_i, w^+_{ij}\}\} \tag{11}$$

$$\varphi^-_j = \max_{i=1\ldots n}\{\min\{q_i, w^-_{ij}\}\} \tag{12}$$

$$r_j = \max_{i=1\ldots n}\{w^+_{i,j}, w^-_{ij}\} \tag{13}$$

where r_j is the fire rate, and w_{ij} represents how node c_i have influence over the node c_j. If the relationship between both nodes is direct then $w^+_{ij} > 0$ and $w^-_{ij} = 0$. On the other hand, if the former relationship is inverse then $w_{ij}^{-} > 0$ and $w_{ij}^{+} = 0$. Finally, if doesn't exist a relationship among them, then $w_{ij}^{+} = w_{ij}^{-} = 0$.

5.6 Fuzzy Cognitive Networks

Fuzzy Cognitive Networks (FCNs) is an extension of FCMs [13, 33]. The edges' weights are updated in each iteration providing a quicker and smoother convergence. FCNs store the formerly operational situations in a fuzzy rule database avoiding intensive interference with the real-world system updating.

FCNs always get equilibrium points with a continuous differentiable sigmoid-like activation functions with non expansive (or even contractive) properties.

FCNs' adjacency matrix is extracted from physical system historical data. Moreover, FCNs are in continuous interaction with the system they model. The main contribution is the updating mechanism that get feedback from the real-world system and its storage of the ongoing knowledge throughout the system dynamics (Fig. 5).

The FCN's updating process takes into account feedback node states from the real-world system. The proposed updating rule is based on the conventional delta rule as follows

$$\begin{aligned}\delta_j(k) &= c_j^{system}(k) - c_j^{FCN}(k)\\ &= c_j^{system}(k) - \left(1 + e^{-\left(\sum_{i=1, i\neq j}^{n} c_i^{system}(k)\cdot w_{ij}(k) + c_j^{system}(k)\right)}\right)^{-1}\end{aligned} \tag{14}$$

$$w_{ij}(k) = w_{ij}(k-1) + a\cdot\delta_j(k-1)\cdot(1-\delta_j(k-1))\cdot c_j^{FCN}(k-1) \tag{15}$$

where a is the learning rate and $\delta_j(k)$ is the error at iteration k, usually set at $a = 0.1$, $c_i^{FCN}(k)$ refers i to the response of the FCN at k iteration, when the nodes take their state values from the system's feedback.

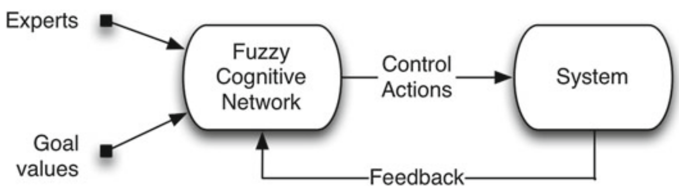

Fig. 5 This figure illustrates the interactive operation of a FCN-based system. The experts offer information related to the structure and the initial weights of the FCN. The desired values represent the system's goals

5.7 Evolutionary Fuzzy Cognitive Maps

Evolutionary Fuzzy Cognitive Maps (E-FCM) simulate real-time concepts states [14]. Their use was examined to model the complex and dynamic causal-related context variables. E-FCM models every temporal state value, which is named as Evolving State in the running process.

Nodes states evolve in real-time, based on their internal states, external assignment, even external causalities. The nodes update their internal states in an asynchronous way with a tiny mutation probability. The causal relationship E represents the strength and probability of the causal effect between a couple of nodes. This proposal considers a couple of system's uncertainty fuzziness and randomness as follows

$$E = [W, S, P_m] \tag{16}$$

where W is a vector of relationships weights, S is a vector of the signs of causal relationships, P_m is a vector of the causal edges probabilities, and m the number of edges.

The E-FCM causal weights can be computed as the statistical correlation of the input data (changes in the presynaptic nodes) and output data (changes in the postsynaptic nodes) if training datasets are available.

$$w_{ij} = \frac{Cov(c_i, c_j)}{\sqrt{var(c_i) \cdot var(c_j)}} \tag{17}$$

where $var(c_i)$ is the variance of the changes in the node state c_i, and $Cov(c_i, c_j)$ is the co-variance of the changes in node state c_i and the changes in node state c_j.

The updating rule is computed as follows

$$\begin{aligned} \Delta c_i(t+T) &= f\left(k_1 \cdot \sum_{j=0}^{n} \Delta c_j(t) \cdot w_{ij} + k_2 \cdot \Delta c_i(t)\right) \\ c_i(t+T) &= c_i(t) + \Delta c_i(t+T) \end{aligned} \tag{18}$$

where T is the time for concept i to update its value (Evolving Time schedule), and k_1 and k_2 are two weight constants.

E-FCM allows different update time schedule for each node, an asynchronous update of the concepts' state. As a result, nodes can evolve in a dynamic and probabilistically way.

5.8 Fuzzy Time Cognitive Maps

Fuzzy Time Cognitive Maps (FTCM) is an FCM extension including time in node's edges [56]. FTCMs model the delay of the influence between the presynaptic node over the postsynaptic one. The relationships between a couple of nodes has two values, the conventional weight and the time lag.

$$\varpi = \{w_{ij}, t_{ij}\} \mid t_{ij} \geq 1 \tag{19}$$

FTCM introduces dummy nodes for value-preserving and translate the FTCM with time delays to unit-time delays (Fig. 6). In addition, it allows comparison of the results between the model dynamics of FTCM and FCM for analyzing time delay effects on the system.

5.9 *Fuzzy Rules Incorporated with Fuzzy Cognitive Maps*

Fuzzy Rules Incorporated with FCMs (FRI-FCM) extends conventional FCM inheriting the rule-based representation of RB-FCMs to describe the systems under a connected point of view [72]. FRI-FCM translates the reasoning mechanism of conventional FCMs to a set of fuzzy IF-THEN rules. FRI-FCM inherits the representation of RB-FCMs to represent the causality underlying the modeled systems.

The FRI-FCM proposal is a four-layer fuzzy neural network designed to enhance the capability of conventional FCMs to automatically identify membership functions and quantify the causalities from raw data [72].

FRI-FCM makes comprehensive use of the dimensional data underlying input vectors state and avoids troublesome degrading of the fuzzy rules activations when the input dimensions are increasing [47].

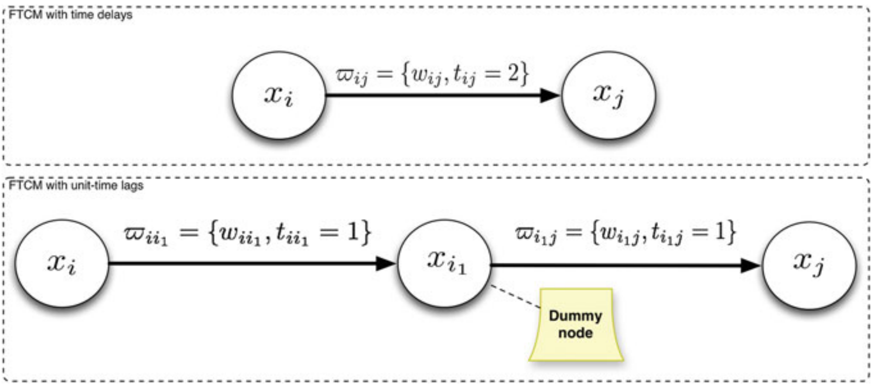

Fig. 6 This figure shows a FTCM with time delays in the upper side and its translation in a unit-time FTCM with dummy nodes

5.10 Fuzzy Cognitive Maps Extensions Comparison

Table 1 shows advantages, disadvantages of each FCM modeling method and in which domain, it is suggested for decision support. In this sense, we propose the following kinds of domains:

As a result, DCN, DRFCM, FCN, and FTCM are suitable for Type I domains where the environments are dynamic and it could include time delays. FGCM and iFCM are better for Type II where the real world has a high uncertainty level. For Type III domain the best approaches are Rule-based FCM, FGCM, iFCM, and FRI-FCM and for Type IV EFCM is the best modeling option.

6 Learning Algorithms for FCMs

The learning approaches for FCMs are concentrated on learning the connection matrix E, i.e. causal relationships (edges), and their strength (weights) based either on expert intervention and/or on the available historical data. According to the available type of knowledge, the learning techniques could be categorized into three groups; Hebbian-based, population-based and hybrid, combining the main aspects of Hebbian-based and evolution-based type learning algorithms [45].

They have been compared recently in a review work [45], where their main features were described and the degree of success of each one was pinpointed. However, after

Table 1 FCM extensions comparison

FCM extension	Advantages	Disavantages	Domain
Rule-based FCM	Include fuzzy rules	Complex inference	Type III
Dynamical cognitive network	Nonlinear dynamic functions	Higher modeling efforts	Type I
Fuzzy Grey CM	Include model uncertainty	Higher modeling efforts	Type II Type III
Intuitionistic FCM	Include model uncertainty	Higher modeling efforts	Type II Type III
Dynamic random FCM	Nonlinear dynamic function	Complex inference	Type I
Fuzzy cognitive network	Quicker and smoother convergence Always convergence	Complex inference	Type I
Evolutionary FCM	Real-time simulation Dynamic variables Different update schedule	Higher modeling efforts Complex inference	Type IV
Fuzzy time cognitive map	Represent time delays	Non-static analysis	Type I
Fuzzy rules incorporated with FCM	Include fuzzy rules	Neural network topology	Type III

Type I	Dynamic systems with uncertainties and/or time delays.
Type II	Extremely uncertain environment.
Type III	Human decision making oriented.
Type IV	Real-time systems and control.

this review study, new learning methodologies were emerged and investigated for constructing FCMs especially from data.

The following three subsections describe each algorithm category from the three groups, presenting also, new learning algorithms for evolutionary-based and hybrid techniques as well as their domain applications. At the end of this section, the main advantages and disadvantages of each one learning category are described showing the appropriateness of each one according to the problem domain.

6.1 Hebbian-based Methods

Dickerson and Kosko were the first who attempted the suggestion of a simple Differential Hebbian Learning (DHL) method [19, 20], which is based on Hebbian theory [26]. During DHL learning the values of weights are iteratively updated until the desired structure is found. In general, the weights in the connection matrix are modified only when the corresponding concept value changes. The main drawback of this learning method is that the formula updates weights between each pair of concepts taking into account only these two concepts and ignoring the influence from other concepts.

An improved version of DHL learning, namely Balanced Differential Algorithm (BDA), was introduced by Huerga [28]. That algorithm eliminates one of the limitations of DHL method by taking into account the entire concept values that change at the same time when updating the weights. More specifically, it takes into consideration changes in all concepts if they occur at the same iteration and has the same direction; however it was applied only to binary FCMs, which limits its application areas.

One year later, Papageorgiou and her colleagues introduced two unsupervised Hebbian-based learning algorithms, such as Active Hebbian Learning (AHL) and Nonlinear Hebbian Learning (NHL) which were able to iteratively adjust FCM weights and thus the learning of FCMs was mainly based on experts' intervention [12, 48, 50–52, 55]. In NHL approach, experts are required to suggest nodes that are directly connected and only these edges are modified during learning.

The experts have to indicate sign of each edge according to its physical interpretation and only the non-zero edges are updated. Also, the experts have to define decision concepts and specify range of values that these concepts can take. The validation is based on checking whether the model state satisfies these constrains. In a nutshell, the NHL algorithm allows obtaining model that retains initial graph structure imposed by expert(s), and therefore requires human intervention before the learning process starts.

In AHL approach [52] experts determine the desired set of concepts, the initial structure, as well as the sequence of activation concepts. A seven-step AHL procedure, which is based on Hebbian learning, is iteratively used to adjust the weights to satisfy predefined stopping criteria. This approach exploited the task of determination of the sequence of activation concepts.

Later, Stach and coworkers [76] proposed an improved version of the NHL method, called Data-Driven Nonlinear Hebbian Learning (DD-NHL), which is based on the same learning principle as NHL. However, it takes advantage of historical data (a simulation of the actual system) and uses output/decision concepts to improve the learning quality. An empirical comparative study have shown that if historical data are available, then the DD-NHL method produces better FCM models when compared with those developed using the generic NHL method.

6.2 Population-based Methods

In the case of population-based algorithms, the experts are substituted by historical data and the corresponding learning algorithms or optimization algorithms are used to estimate the entries of the connection matrix E. The population-based learning algorithms are usually oriented towards finding models that mimic the input data. They are optimization techniques, and for this reason, they are computationally quite demanding. Several population-based algorithms, such as evolutionary strategies [34], genetic algorithms [23, 74], real coded generic algorithm—RCGA [73–75], Swarm Intelligence [43], Chaotic Simulated Annealing [4], Tabu search [6], game-based learning [37], Ant Colony Optimization [21], extended Great Deluge algorithm [89], Bing Bang-Big Crunch [87] for training FCMs have been proposed.

Due to the need of developing new approaches for an automated generation of fuzzy cognitive maps using historical data, some innovative and promising learning algorithms have been proposed recently. For example, an Ant Colony Optimization (ACO) algorithm was presented in order to learn FCM models from multiple observed response sequences. Experiments on simulated data suggest that the proposed ACO based FCM learning algorithm is capable of learning FCM with at least 40 nodes. The performance of the algorithm was tested on both single response sequence and multiple response sequences. The ACO approach was compared to these algorithms through experiments. The proposed ACO algorithm outperforms RCGA, NHL and DD-NHL in terms of model error and SS mean measures when multiple response sequences are used in the learning process [21].

Also, a new learning algorithm, which is called Big Bang-Big Crunch, was proposed for an automated generation of Fuzzy Cognitive Maps from data. Two real-world examples, namely a process control system and radiation therapy process, and one synthetic model are used to emphasize the effectiveness and usefulness of the proposed methodology.

Moreover, the evolutionary mechanism of Cellular Automata (CA) was used to learn the connection matrix of FCM [18]. One-dimension cellular automata were used to code weight parameters, and the cellular states were chosen within the range [0, 1] to form a cell space. In order to guide the optimization direction effectively and accelerate the speed of convergence, a mutation operator was added in the algorithm. This approach was applied on modeling the short-term stock prediction. The data come from Shanghai Securities Exchange, dating from 2002-02-27 to 2002-06-20, 52 days of them were used for training and the rest were used for testing. However, through the experimental analysis, the system error was fluctuating randomly, which explains the non-convergence of the evolution of CA.

A new adaptation algorithm focused on FCM design and optimization, the so-called Self-Organizing Migration Algorithms (SOMA), was proposed by Vascak [84] and was compared also to other methods like particle swarm optimization, simulated annealing, active and nonlinear Hebbian learning on experiments with catching targets for future purposes of robotic soccer. Obtained results showed the advantageous characteristics of the proposed method which are apparent and useful for other application domains.

Moreover, supervised learning using gradient method was proposed by Yastrebov & Piotrowska [86], as a modification of the weights in the direction of steepest descent of error function. Although this gradient-based method seems a promising approach, it needs further theoretical foundation and experimental analysis.

Little research has been done on the goal-oriented analysis with FCM. A methodology for decision support was suggested, which uses an immune algorithm to find the initial state of system in given goal state. The proposed algorithm takes the error objective function and constraints as antigen, through genetic evolution, and antibody that most fits the antigen becomes the solution [35].

6.2.1 Evolutionary Approaches for Prediction Tasks

The prediction of multivariate time series is one of the targeted applications of evolutionary fuzzy cognitive maps (FCM). The objective of the research presented in [22] was to construct the FCM model of prostate cancer using real clinical data and then to apply this model to the prediction of patient's health state. Due to the requirements of the problem state, an improved evolutionary approach for learning of FCM model was proposed. The focus point of the new method was to improve the effectiveness of long-term prediction [22]. The evolutionary approach was verified experimentally using real clinical data acquired during a period of two years. A preliminary pilot-evaluation study with 40 men patient cases suffering with prostate cancer was accomplished. The in-sample and out-of-sample prediction errors were calculated and their decreased values showed the justification of the proposed approach for the cases of long-term prediction.

In the theoretical part, addressing these requirements of the medical problem, a multi-step enhancement of the evolutionary algorithm applied to learn the FCM was introduced. The advantage of using this method was justified theoretically and then verified experimentally [41].

6.2.2 Learning Approaches for Classification Tasks

Papakostas et al. [55] implemented FCMs for pattern recognition tasks. In their study, a new hybrid classifier was proposed as an alternative classification structure, which exploited both neural networks and FCMs to ensure improved classification capabilities. A simple GA was used to find a common weight set which, for different initial state of the input concepts, the hybrid classifier equilibrate to different points. Recently, Papakostas et al. [54] presented some Hebbian-based approaches for pattern recognition, showing the advantages and the limitations of each one.

Another very challenging learning category, which has also been applied for classification tasks and recently emerged, is the Ensemble learning [49]. This ensemble learning method inherits the main ideas of ensemble based learning approaches, such as bagging and boosting. FCM ensemble learning is an approach where the model is trained using non linear Hebbian learning (NHL) algorithm and further its performance is enhanced using ensemble techniques. The Fuzzy Cognitive Map ensembles were used to learn the produced FCM by the already known and efficient data driven NHL algorithm. This new proposed approach of FCM ensembles, applied to a case study regarding the identification of autism, showed results with higher classification accuracy instead of the NHL alone learning technique.

6.3 Hybrid Learning Methods

In this type of FCM learning methodology, the learning goal is to modify/update weight matrices based on initial experience and historical data at a two stage process. The algorithms proposed in the literature target different application requirements and try to overcome some limitations of FCMs. Little literature exists towards this direction [42, 88]. Papageorgiou and Groumpos [42], proposed for first time a hybrid learning scheme composed of Hebbian type and differential evolution algorithms and showed its applicability for in real-world problems for decision making tasks.

Later, Ren [60] presented a hybrid FCM learning method combining NHL and Extended Great Deluge Algorithm (EGDA). This hybrid learning approach has the efficiency of NHL and global optimization ability of EGDA. The FCM is trained at first with the use of NHL, in order to get a set of weights close to optimization structure, and then using EGDA the model is optimized for error minimization. The results were on a simple FCM structure, therefore more complex structures need to be experimented to approve this type of learning.

Another hybrid scheme using RCGA and NHL algorithm was presented by Zhu and Zhang [88], and investigated in a problem of partner selection. Their algorithm inherits the main features of each one learning technique, of RCGA population-based algorithm and NHL type, thus combining expert and data input. Although the first results are encouraging, more research would be essential.

6.3.1 Learning Algorithms Advantages and Limitations

Most of the FCM learning algorithms are devoted to the FCM modeling and optimization. They adapt the weight matrix using the available knowledge from experts and/or historical data. The produced FCM model after training follows system's/problem's characteristics. In the case of evolutionary computation techniques, the FCM design is based on the minimization of an error/cost or fitness function. The fitness function for each population-based algorithm might be modified according to the problem type [45]. Some studies have shown that the population-based algorithms increase FCM functionality, robustness and have generalization abilities [45].

Table 2 describes the main applications of FCM learning algorithms which concern the modeling/design, optimization, prediction and decision support. Also the main domains of each one FCM-based application are apposed in Table 2.

Each one learning category has its advantages and limitations, which make it appropriate to specific type of problems according to the data and knowledge availability. Table 3 gathers the most significant advantages and limitations of each one learning category. It is highlighted the usefulness of each one FCM modeling/design and optimization.

Table 2 Learning algorithms for FCM modeling, optimization, prediction and decision support

Description	Learning algorithms	Domain
FCM modeling/design	DHL, AHL, DD-NHL, NHL-PSO, Extended Great Deluge Algorithm (EGDA), NHL-ECGA, NHL-RCGA, memetic PSO, Tabu search, Simulated annealing, Evolution strategies, RCGA, Parallel RCGA, Sparse RCGA, Divide & Conquer, Immune algorithm.	Industrial process control, mineral processing, game world, radiotherapy modeling, partner selection problem, Robotic soccer navigation
FCM optimization	ACO, Cellular Automata, Big Bang-Big Crunch, Gradient-based, migration algorithms, Differential Evolution (DE).	Numerical examples, one tank process control, Robotic soccer navigation, radiotherapy optimization
FCM prediction/classification	Hebbian-based (AHL, NHL), DD-NHL, GA, Ensemble learning, evolutionary FCMs for time series prediction	Pattern recognition, Classification, Time-series prediction
FCM-based decision support	GA for multi-objective decision, genetic algorithm, Differential Evolution (DE), PSO, Hybrid algorithm (NHL-DE)	Medicine, politics, e-business company, squad of soldiers in combat

Table 3 FCM learning comparison

	Advantages	**Limitations**
Hebbian-based	Connections have a physical meaning	Small deviations of weights from the initial ones
	Connections keep their signs	Dependence on experts
	No time consuming	Dependence on initial states and connections
	Easy of use	Higher simulation errors
	No multiple historical data	Low generalization ability
Population-based	Model concepts with precise values	Learn FCM from multiple observed response sequences
	Cost function optimization	Large number of historical data
	Low simulation error	Large number of processors
	Increase functionality	Time consuming
	Robustness	Adjustment of enough learning parameters
	Generalization ability	Availability of historical data
		Problem with convergence issues

One challenge is to develop efficient semi-automated algorithms to encounter the limitations/problems, presented in Table 3, such as hybrid and ensemble learning algorithms. The semi-automated methods are preferred if some structural constraints have been imposed on the map by the experts. The hybrid learning approaches, which are based on functionalities of Hebbian and population-based learning algorithms and inherit the advantages and disadvantages of both of them, emerge less limitations as most of them can overcome from the fusion of both computational methods. Thus, their operation could be more advantageous in the case of modeling complex systems and systems with time evolving.

If the only criterion is the quality of the model's dynamic behavior then the fully automated genetic optimization seems to be the best solution [74, 75, 78]. The population-based methods have wider applicability due to their ability to learn FCMs from multiple observed response sequences; they are able to predict time-series, to classify patterns, to simulate chaotic behavior, to model the evolving virtual systems, etc [45].

The main drawback of the population-based learning methods is that they provide solutions that are hard or impossible to interpret and which may lead to incorrect static analysis. Some experimental results that concern both static and dynamic properties of the FCMs learned with the genetic-based methods are promising [73].

7 Example Case Study on FCM Design Using Learning Methods

An example process control problem which was described in [51] was selected to show the effectiveness of each one learning algorithm for FCM design. We concentrate our presentation results on FCM design and adaptation methods using learning algorithms described previously. This process control problem is a well-established case study as it was used by most researchers to experimentally analyze and test their suggested learning techniques. A brief description of how this FCM model can be used to perform various tasks of analysis and simulations in order to obtain useful knowledge about the system being modeled, is presented in [73].

This chemical process problem consists of a tank with three valves that influence the amount of liquid within the tank. Valve 1 and valve 2 empty two different kinds of liquid into the tank, and during the mixing of the two liquids a chemical reaction takes place. Valve 3 opens when a proper mixing of the two liquids is accomplished.

A gauge sensor located inside the tank measures the specific gravity of the produced liquid. The desired quantity of the liquid within the tank depends (a) on the value of the specific gravity G, which should range between a minimum (G_{min}) and a maximum value (G_{max}), and (b) on the height H of the liquid within the tank, which should also range within a minimum H_{min} and a maximum value H_{max}. In this case process control aims to maintain the values of G and H within the desired ranges, which are:

$$0.74 \leq G \leq 0.80 \tag{20}$$

$$0.68 \leq H \leq 0.74 \tag{21}$$

The FCM model for this system involves the following five concepts:

Concept 1 (c_1) represents the amount of liquid as measured by its height H within the tank; it depends on the operational state of valves 1, 2 and 3.

Concept 2 (c_2) represents the state of valve 1; it may be closed, open or partially open.

Concept 3 (c_3) represents the state of valve 2; it may be closed, open or partially open.

Concept 4 (c_4) represents the state of valve 3; it may be closed, open or partially open.

Concept 5 (c_5) represents the specific gravity G of the liquid within the tank.

Since the monitored parameters of this problem are the specific gravity and the height, the decision concepts (DC) of the cognitive map are the concepts c_1 and c_5. These concepts are connected as illustrated in the form of a graph shown in Fig. 7, which also shows the weights associated with directed connections between all pairs of the concepts.

We use the process control system in Fig. 7 to investigate the quality of models learned using the state-of-the-art learning methods which exist in the literature. The usage of different FCM development methods may result in different maps. Following that, we focus on the central theme of this chapter which is the design of FCM-based models, defining concepts relevant to a given system and weighted connections (weights) between the selected concepts.

More specifically, the following learning approaches have been implementing to learn this FCM model: AHL, NHL, NHL-DE, DDNHL, RCGA, PSO, ACO, memetic

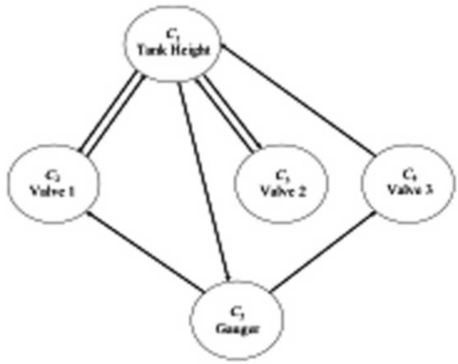

Fig. 7 This figure shows the tank control model

PSO, and Big Bang-Big Crunch. These nine different learning methodologies were tested experimentally in this process control problem. The simulation results of the conventional FCM model which describes the process control, were used as data to learn the FCM model [74].

Since the RCGA and other evolutionary-based methods were initialized with a 100 randomly generated maps, whereas the three Hebbian-based methods use just a single map, the experiments for all Hebbian-based were repeated 100 times using the 100 initial maps generated for the RCGA and method. The final output was selected as the map that provides simulations either with the lowest value of the simulation-error or with the minimum cost function.

Table 4 presents a summary of the results for the nine learning approaches applied in this process control problem. Both matrix-error and calculation-error (concerning either simulation error or cost/fitness function minimization) were calculated to quantify the quality with respect to both the static and the dynamic analysis. The average values together with the corresponding standard deviations (shown in brackets) are reported.

$$Matrix - error = \frac{1}{N \cdot (N-1)} \sum_{i=1}^{N} \sum_{j=1}^{N} (w_{ij}^{estimated} - w_{ij}^{real}) \tag{22}$$

where $w_{ij}^{estimated}$ and w_{ij}^{real} are the estimated weights after learning and real (initial) weights respectively. The simulation error is computed as follows

$$Simulation - error = \frac{1}{N \cdot (K-1)} \sum_{k=1}^{K-1} \sum_{j=1}^{N} |DC_i^{estimated} - DC_i^{real}| \tag{23}$$

where $DC_i^{estimated}$ and DC_i^{real} are the estimated and real values of decision concepts (DC), K is the number of available iterations to compare and N is the number of concepts. The cost function is calculated as follows

Table 4 Applied learning methods in a case study problem

Learning method	Weight matrix error	Error calculation (Simulation error or cost function)		Authors
AHL	0.303 (0.187)	0.069	Simulation-error	[Papageorgiou et al. 2004]
NHL	0.236 (0.162)	0.064	Simulation-error	[Papageorgiou et al. 2003]
NHL-DE	0.192 (0.034)	10^{-4}	Fitness function	[Papageorgiou & Groumpos, 2005]
DDNHL	0.245 (0.145)	0.056	Simulation-error	[Stach et al. 2008]
RCGA	0.255 (0.154)	0.001	Cost function	[Stach et al. 2004, 2007, 2010]
PSO	0.186 (0.032)	10^{-4}	Fitness function F(W)	Papageorgiou et al. 2004, Petalas et al. 2005
ACO	0.193 (0.036)	10^{-8}	Fitness function F(W)	Ding et al. 2011
Big Bang-Big Crunch	N/A	$1.57x10^{-6}$	Cost function	Yesil and Urbas, 2010
Memetic PSO	0.191 (0.034)	10^{-8}	Fitness function F(W)	Petalas et al. 2005

$$Cost - function = \frac{1}{N \cdot (K-1)} \sum_{k=1}^{K-1} \sum_{j=1}^{N} (DC_i^{estimated} - DC_i^{real})^2 \tag{24}$$

It is observed that the weight matrix-error values obtained with maps learned using the population-based methods are substantially lower than the errors of the AHL, NHL and DDNHL. This happens due to the small deviations of the learned weights around their initial values. The ACO, PSO, Big Bang-Big Crunch have shown better performance regarding the quality of the produced maps than the RCGA and Hebbian-based models. In the case of AHL, the matrix error increases as all the zero weights are updated to new non-zero values.

Concerning the simulation-error values obtained with maps learned using the Hebbian-based methods are higher than the errors of the other population-based approaches. In spite of the relatively different connection matrix generated by population-based algorithms, the error/cost function or fitness function minimization is very small (equals 0.001 if we consider only the final state). This observation can be generalized, based on experiments reported in the literature (e.g. reference [77]), to a statement that the structurally different maps can generate very similar simulations. The population-based approaches find a number of suboptimal solutions, which in the case of PSO and memetic PSO can be a large one. This is acceptable due to the operation of the evolutionary approaches for optimization tasks.

Summarizing, population-based methods outperform Hebbian-based in terms of model error. The evolutionary learning algorithms use fitness functions for design and optimization tasks, thus defining the problem constraints more efficiently in learning approach.

8 Conclusions and Future Directions

FCM-based methods and computational learning algorithms have emerged attention throughout recent years for modeling and decision support tasks. Many successful applications in diverse domains clearly imply the effectiveness of these methodologies and learning techniques devoted to FCM modeling and decision making.

There is a considerable number of methodologies and learning approaches for FCMs resulted from several years of research and are exploited in this chapter. They emerged to eliminate the drawbacks and limitations of the conventional FCMs, thus improving and automating FCM modeling and construction. It is a research challenge for proposing powerful or efficient FCM-based methodologies and learning algorithms for modeling the complex and difficult tasks of systems evolving.

Models developed by experts are vulnerable to subjectivity of expert(s) beliefs and could be difficult to be developed for complex problems that involve dozens of concepts. Although maps developed by experts provide an accurate static analysis of FCM model, they may lead to inaccurate dynamic analysis.

These limitations motivated researchers towards the use of learning algorithms that would provide models with a more accurate representation of FCM system. The hybrid learning approaches, seem to be more feasible than Hebbian-type or population-based type in order to design an FCM, and this is a promising direction for FCM learning. Therefore, new approaches are required for training FCMs effectively which will increase their potential application in practice.

Recent interest in new FCM methodologies and computational algorithms suggests that these will be the main direction for future research. Even though the first step towards automatic construction of FCM from data was made, there are problems that still need to be overcome.

Although there are many recent attempts toward modeling and learning of FCMs, the application of FCM technique to a wide variety of scientific areas makes crucial the development of a commonly used tool that can assist the creation and simulation of FCMs. Few attempts have been made towards the creation of such a tool, ie. FCMapper (http://www.fcmappers.net/), jfcm (http://jfcm.megadix.it/), FCM designer tool, FCModeler tool.

Although many scientists construct their own FCMs, using experts knowledge and experience, there is no solid and standard representation of them that would make them easily reusable and transportable. There is not any standard software or programming tool that would simulate these FCMs, so every scientist has to create his own program and software system for simulating and analyzing FCMs.

The development of a software system would be very useful in research community because it could be able to assist the creation and simulation of dynamic FCMs, facilitate knowledge sharing and reuse of this knowledge and include learning algorithms and theoretical foundations for a dynamic behavior as well.

Finally, more research is needed on modeling, learning, automatic construction, knowledge representation and software tools development. New theoretical contributions could be included in current or emerging FCM extensions as well.

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Chapter 2
Fuzzy Cognitive Maps as Representations of Mental Models and Group Beliefs

S. A. Gray, E. Zanre and S. R. J. Gray

Abstract Fuzzy Cognitive Maps (FCM) have found favor in a variety of theoretical and applied contexts that span the hard and soft sciences. Given the utility and flexibility of the method, coupled with the broad appeal of FCM to a variety of scientific disciplines, FCM have been appropriated in many different ways and, depending on the academic discipline in which it has been applied, used to draw a range of conclusions about the belief systems of individuals and groups. Although these cognitive maps have proven useful as a method to systematically collect and represent knowledge, questions about the cognitive theories which support these assumptions remain. Detailed instructions about how to interpret FCM, especially in terms of collective knowledge and the construction of FCM by non-traditional 'experts', are also currently lacking. Drawing from the social science literature and the recent application of FCM as a tool for collaborative decision-making, in this chapter we attempt to clarify some of these ambiguities. Specifically, we address a number of theoretical issues regarding the use of Fuzzy Cognitive Mapping to represent individual "mental models" as well as their usefulness for comparing and characterizing the aggregated beliefs and knowledge of a community.

S. A. Gray (✉) · E. Zanre
Department of Natural Resources and Environmental Management, University of Hawai, Honolulu, HI, USA
e-mail: stevenallangray@gmail.com

E. Zanre
e-mail: ezanre@hawaii.edu

S. R. J. Gray
Coastal and Marine Research Center, University College Cork, Cork, Ireland
e-mail: s.gray@ucc.ie

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1 Introduction

There is a wealth of literature from the fields of cognitive science, psychology, and systems science that discusses the use of individuals' knowledge structures as representations or abstractions of real world phenomena. However, before we can begin our discussion of how Fuzzy Cognitive Mapping (FCM) contributes to these fields, we must first reconcile the various definitions and approaches in the literature used to characterize internal cognitive representations of the external world. Understanding the theoretical foundations of concept mapping, cognitive mapping, mental models and the notion of "expertise" in the elicitation of a subject's knowledge is of particular interest to our discussion on FCM construction and interpretation. Further, we discuss issues related to analyzing FCMs collected from non-traditional experts, which is a growing area of research that seeks to characterize group knowledge structure to inform community decision-making and compare knowledge variation across groups. In this chapter, we address: how FCM can be used to understand shared knowledge and what trade-offs should be considered in the selection of FCM data collection techniques.

2 Concept Mapping, Cognitive Mapping and Mental Models as Representations of Knowledge Structures

FCM has its roots in concept and cognitive mapping. Concept maps are graphical representations of organized knowledge that visually illustrate the relationships between elements within a knowledge domain. By connecting concepts (nodes) with semantic or otherwise meaningful directed linkages, the relationships between concepts in a hierarchical structure are logically defined [49, 55]. The argument for representing knowledge with concept maps emerges from constructivist psychology, which postulates that individuals actively construct knowledge by creating mental systems which serve to catalogue, interpret and assign meaning to environmental stimuli and experiences [61]. Knowledge "constructed" in this manner forms the foundation of an individual's organized understanding of the workings of the world around them, and thus influences decisions about appropriate interaction with it. Influenced by cognitive psychology's developmental theory of assimilation and accommodation, as theorized by the Swiss cognitive psychologist Jean Piaget, the use of concept maps as representations of an individual's organized knowledge is further supported. According to Piaget's developmental theory of learning, individuals' assimilate external events and accommodate them to develop a mental structure that facilitates reasoning and understanding [17, 58]. Using this theoretical framework, concept maps can be elicited to represent an organized understanding of a general context, thereby providing an illustrative example of a person's internal conceptual structure [49].

Another form of structured knowledge representation commonly referred to in the social science literature is cognitive mapping. A cognitive map can be thought of as a concept map that reflects mental processing, which is comprised of collected information and a series of cognitive abstractions by which individuals filter, code, store, refine and recall information about physical phenomena and experiences. Popularized by psychologist Edward Tolman as a replication of a geographical map in the mind, the term has since taken on a new meaning. Robert Axelrod [5] was the first to use the term in reference to the content and structure of individuals' minds, thereby shifting its applied meaning from referring to a map that is cognitive, to a map of cognition [14, 27]. Using Axelrod's definition, cognitive maps are visual representations of an individual's 'mental model' constructs, and are therefore analogous to concept maps that represent a person's structured knowledge or beliefs.

Although both concept and cognitive maps are often used as external representations of internal mental models, it is important to note that these graphical representations and mental models are not the same. Cognitive maps, of which FCMs are an extension, are themselves extensions of mental models, but are distinct since cognitive maps are physical constructs, whereas mental models only exist in the mind [14]. First introduced by Craik [11], today the notion of mental models and their usefulness for understanding individual and group decision-making is a widely accepted construct in the social science literature [1, 28], and justifies the methodological appropriation of FCM as external representations of a person's internal understanding. It is hypothesized that in order to successfully achieve a given objective, individuals must possess sufficient knowledge of their immediate environment in order to craft appropriate responses to a given decision context [47]. In such contexts, mental models are considered to provide the structures that form the basis of reasoning [28]. The perceived utility of internal mental models in decision making contexts lies in their simplicity and parsimony, which permits complex phenomena to be interrogated and salient components selected to form judgments. Inferring causal relationships between a range of factors based on available evidence or beliefs facilitates the generation of workable explanations of the processes, events and objects an individual may encounter within their environment. By encoding these inferences into a heuristic structure, individuals can accrue knowledge incrementally over time, thereby offsetting the limitations of human cognition under conditions of complexity and uncertainty [65]. This process enables individuals to construct an internal model that both integrates their existing relevant knowledge of the world, as well as meets the requirements of the domain to be explained. To enable individuals to make a context-appropriate decision, mental models mediate between knowledge stored in the long-term memory and knowledge that is constructed in the short-term working memory [48]. Therefore, it is hypothesized that individuals constantly rely on mental models to structure their understanding, explain the world, and to some extent, make decisions that reflect this internal process of reasoning.

Combining the notion of "mental modeling" with cognitive mapping, FCM utilizes fuzzy logic in the creation of a weighted, directed cognitive map. FCMs are thus a further extension of Axelrod's definition of cognitive maps, and can therefore similarly be considered a type of mental model representation [21, 29, 35, 52].

Given FCMs may serve as semi-quantitative, detailed representations of individual and/or group knowledge structures, either through aggregation of individual's models, or through group FCM building exercises, they are attracting increased attention in applied research contexts seeking to promote collective decision-making or better understand community knowledge [3, 18, 52]. Using the imprecise nature of common language, FCM permits individuals to interpret and express the complexity of their environment and experiences by combining their knowledge, preferences and values with quantitative estimations of the perceived relationships between components within a particular context of interest [28, 29, 39, 52]. Similarly, from a social science research perspective, employing FCMs as representations of mental models can generate understanding of how different people filter, process and store information, as well as elucidate how these perceptions may guide individuals decisions and actions in a particular context [7]. In a manner analogous to the *mental modeling* that structures an individual's cognitive decision making process, eliciting the reasoning and predictive capacity of experts' mental constructs via FCM has proven to be a useful decision support tool [2, 18, 21, 52]. Although FCM have been proposed as a method to understand mental models, issues regarding whose knowledge is represented, how group knowledge is collected and interpreted, and what constitute best practices for combining mental models in different applied research contexts, have largely not been addressed.

3 Traditional 'Western' Expertise and Non-traditional Expertise

The collection of FCMs as representations of mental models can be divided into two general categories in terms of 'whose knowledge is being structured?'. The first, and perhaps most long standing use, is related to FCMs as representations of "traditional" expert knowledge. There is a long history of representing expert knowledge systems using FCM and fuzzy-logic in areas of research where system uncertainty is high and empirical data to validate a hypothesized model is unavailable or costly to collect. This FCM research encompasses a wide range of applications including: risk assessment [25, 43], work efficiency and performance optimization [29, 71] strategic deterrence and crisis management [38, 57], scenario/policy assessment [3, 32] spatial suitability and prediction mapping [4, 45] and environmental modeling and management [2, 24, 26, 40, 60]. FCM based on expert knowledge, attempts to make tacit, expert knowledge more explicit in an effort to represent complex systems and their inherent dynamics that would otherwise not be well understood. "Traditional western experts" in this sense reflect the common use of the term and characterize social elites including physicians [6], scientists [10, 24], and engineers [3]. By collecting mental models from experts considered to hold the 'best' knowledge about a system, structure is provided to what would otherwise be loosely-linked, highly complex, or unavailable understanding of a system domain.

The second and more recently emerged category of FCMs as representations of mental models, are those collected from non-traditional western experts. These

FCMs are most often employed in participatory planning and management and/or environmental decision-making contexts, and are primarily used to gain an understanding of how stakeholders internally construct their understanding of their world or a particular issue of interest [33, 34]. For example, non-traditional expert FCMs have been elicited from bushmeat hunters in the Serengeti [50], fishermen [40, 70], pastoralists and farmers [16, 51] as well as a range of other stakeholders during participatory planning and modeling contexts [10, 18, 30, 44, 52, 56] Collecting FCMs from non-traditional experts serves as a way to characterize community understanding of a system or collect data intended to help characterize a system that might not be represented by information provided by traditional experts alone [7, 33]. Though there may be some degree of overlap in the need for or desire to use tacit or local knowledge to inform the decision making process, the appropriation of FCM in the collection of local stakeholder knowledge is commonly associated with decision-making in the local community context rather than to pool expert knowledge in conditions of uncertainty, where data is limited or not comprehensively linked [34]. Since knowledge exists on a continuous spectrum of expertise from novice to expert, and the degree of expertise is not usually easily determined, the collection of FCMs from non-traditional experts has been largely influenced by research questions and to date, there has been little consideration of the differentiation or potential protocols of FCM collection from experts and non-traditional experts.

4 Disentangling Group Knowledge

In addition to questions associated with 'whose knowledge is being structured?', there are also research context dependent issues associated with FCM in terms of appropriately representing group knowledge. FCMs are often collected from groups of individuals and aggregated as a way to support decision-making and promote understanding of system dynamics. However, interpreting the cognitive structures of FCMs within the group context raises questions about what this pooled knowledge represents, and how it is useful for research, analysis and interpretation. Although the literature defines mental models as individual's internal representations of the world, consensus is currently lacking with regard to the theoretical basis of shared cognition as it relates to concept and cognitive mapping. Therefore, there are still questions about what collated representations of individual mental models represent [31, 67]. In the literature, this ambiguity is demonstrated by the variable use of research methods and terms employed in the study of shared cognition [8, 46]. To date, the FCM literature has largely ignored this ambiguity, despite the fact that FCMs are strongly influenced by the individual characteristics and cognitive processes of those who construct them [59], as well as the method by which FCMs are aggregated and analyzed [53]. While it is commonly accepted that individuals within a given community are exposed to the same "reality", it is also acknowledged that their interpretation of that reality may not be shared [12, 67]. This is because individual mental models are socially-mediated, created with diverse knowledge abstractions, reliant on personal experience and highly dependent on prior knowledge [65]. As evidence of this, the aggregation of individuals' knowledge structures has been shown to show considerable variation and when aggregated, the group level "knowledge structures" sometimes fail to reflect the sum of individual members' mental models [31, 67].

FCMs have been proposed as a unique tool for aggregating diverse sources of knowledge to represent a "scaled-up" version of individuals' knowledge and beliefs [52]. The product of the aggregation of individual's FCMs is sometimes referred to as a "social cognitive map" and is often considered a representation of shared knowledge [18, 52]. The concept of shared knowledge in the form of social cognitive maps has been used in a variety of distinct applications using of FCMs including: to gain a more comprehensive understanding of complex systems; to describe consensus in knowledge among individuals and to define differences in individual and group belief or knowledge structures. Further, as FCM evolves beyond its foundations as representations based on traditional expert systems towards the integration of more non-traditional expert knowledge for participatory engagement, it is necessary to understand the nature and appropriateness of FCM aggregation in order to ensure that interpretations are theoretically sound. Therefore, in an effort to further expand the appropriation of FCM to a new generation of social science researchers, it is of critical importance to: (1) understand what is meant by "shared" knowledge of individuals and (2) establish data collection protocols based on common FCM research goal typologies.

5 Understanding the Meaning and Measurement of 'Shared Knowledge' with FCM

There is little consensus across the literature regarding the aspects of knowledge that are shared in group decision-making [8]. Differences in interpretation of "shared knowledge", however, tend to emerge along disciplinary lines generated largely from the organizational behavior and social psychology literature. For example, shared team knowledge has been described as knowledge relevant to team work and task work [8, 63] while others have referred to shared cognition as an inter-subjective process related to transactive memory shared within a community, which influences learning, and therefore, the knowledge held within a group [46]. Still other researchers promote the idea of collective learning through shared frames of reference, or alternatively, through achieving consensus, which reflects shared beliefs among individuals [5, 31, 67]. In essence, studies of shared knowledge highlight the importance of identifying pre-existing discrete dimensions of structural and content knowledge found across individual mental models [8].

In an applied research context, FCM have implications for assessing the degree of shared knowledge distributed across individuals by using a range of structural measures. Comparing FCMs allows researchers to uncover trends in reasoning, as evidenced by similarities in cognitive map structure, to be used to measure the degree of conceptual agreement. Research focused on capturing pre-existing knowledge in a community seeks to understand similarities in how individuals and groups conceptualize contexts of inquiry on a systems level [34]. Understanding the degree of shared knowledge through FCM is important to explaining some aspects of social dynamics since shared knowledge is important for promoting trust, cooperation and since it may influence interaction between individuals and groups [19].

In terms of specific structural measurements available to researchers, the last ten years have seen considerable advances in both network and FCM analyses. These advances have yielded a range of routine metrics to uncover shared knowledge structure by measuring discrete dimensions of an individual's mental model structure, thereby permitting comparisons across individuals and groups (see Table 1 for a summary) [18, 52]. Although we assume the reader is familiar with the basic FCM collection and transcription techniques of cognitive maps into matrices [35], we briefly outline common measures facilitated through matrix calculations. The calculation of these measures allows the degree of shared knowledge to become estimated when the FCM modeling activity is standardized across individuals or groups. Based generally in network analysis, FCM can be analyzed for any number of dimensions, which can detect differences in how individuals view the dynamics and components in a given domain. For example, the amount of connections indicates increased or decreased structural relationships between system components or the degree of connectedness between components that influence system function and emergent properties. Centrality score of individual variables represents the degree of relative importance of a system component to system operation. Number of transmitting, receiving, or ordinary variables and the complexity scores indicate whether the system is viewed as largely comprised of driving components or whether the outcomes of driving forces are considered (i.e. that some components are only influenced). Higher complexity scores have been associated with more "expert views" of systems [42, 64] and therefore it is assumed that the FCMs generated by individuals with deeper understanding of a domain will have higher complexity scores relative to others with less understanding. Density scores are associated with the perceived number of options that are possible to influence change within a system as the relative number of connections per node indicate the potential to alter how a given system functions. Hierarchy scores indicate the degree of democratic thinking [41] and may indicate whether individuals view the structure of a system as top-down or whether influence is distributed evenly across the components in a more democratic nature. Centrality scores for an overall FCM indicate the overall perceived degree of dynamic influence within a system.

Although the implications for understanding shared structural knowledge through FCM are somewhat straight forward given the structural metrics available, understanding the degree of shared content knowledge across individuals using FCM is as clear quite as clear. In their review, Cannon-Bowers and Salas [8] outline that shared content includes aspects of knowledge such as task knowledge (both declarative and procedural), contextual knowledge, attitudes, beliefs, expectation and predictions. Although these dimensions of knowledge are more tightly linked to the team

Table 1 Structural metrics that can be applied to matrix forms of FCMs (adapted from Gray)

Mental model structural measurement	description of metric and cognitive inference
N (Concepts)	Number of variables included in model; higher number of concepts indicates more components in the mental model [52]
N (Connections)	Number of connections included between variables; higher number of connections indicates higher degree of interaction between components in a mental model [52]
N (Transmitter)	Variables that only have forcing functions; indlicates the number of variables that influence other system variables, but are not influenced by other variables. Sometimes referred as "driver" variables [15]
N (Receiver)	Variables that only have receiving functions; indicates number of variables that are influenced by other variables but do not influence other variables [15]
N (Ordinary)	Variables with both trasmitting and receiving functions; indicates the number of variables that influence but are also influenced by other variables [15]
Centrality	Absolute value of either (a) overall influence in the model (all + and – relationships indicated, for entire model) or (b) influence of individual concepts as indicated by positive (+) or negative (−) values placed on connections between components; indicates (a) the total influence (positive and negative) to be in the system or (b) the conceptual weight/importance of individual concepts [35]. The higher the value, the greater the importance of all concepts or the individual weight of a concept in the overall model
C/N	Number of connections divided by number of variables. The lower the C/N score, the higher the degree of connectedness in a system [52]
Complexity	Ratio of receiver variables to transmitter variables. Indicates the degree of resolution and is a measure of the degree to which outcomes of transmitter/driving forces are considered. Higher complexity indicates more complex systems thinking [15, 52]
Density	Number of connections compared to number of all possible connections. The higher the density, the more potential management polices exist [15, 22]
Hierarchy index	Index developed to indicate hierarchical to democratic view of the system. On a scale of 0-1, indicates the degree of top-down down (score 1) or democratic perception (score 0) of the mental model [41]

decision-making literature, there are still general implications for FCM, however this research area of FCM is somewhat underdeveloped. For example, comparing the outcomes of scenario analyses across several FCM through "clamping" the same variables [35] may allow for qualitative interpretation of how a domain may react under an established pre-set condition to be compared which is thought to be analogous to scenario heuristics used by individual decision-makers [69]. By evaluating these scenario outputs, researchers can make inferences regarding the degree of shared expectations and predictions across individual mental models or different aggregated group models. Additionally, coding or grouping FCM variables into discrete categories may provide a useful means by which agreement or concurrence of a particular problem and for a given system can be identified and assessed. Employing complementary tools, such as standardized surveys, may facilitate the assessment of attitudes and beliefs which could be correlated with quantitative FCM structural measurements [34]. When used in tandem, such an approach may improve understanding and help disentangle the interaction between of structural and content knowledge, and develop more robust assessments.

6 Research Aim: Typologies and Trade-offs of FCM Data Collection

In addition to ambiguities associated with FCMs as representations of mental models and their implications for understanding and measuring shared knowledge, the literature to date has also not dealt with the issue of knowledge heterogeneity or routine variations of FCM collection procedures toward different research goals. The theory behind both mental models and FCM suggest that their usefulness for decision-making significantly depends upon the quality of knowledge used in their construction [36, 68]. Consideration of the potential implications of integrating diverse sources of knowledge using FCMs is timely, particularly given their utility as a participatory modeling approach and as a tool for operationalizing diverse sources of knowledge for improved system understanding, multi-objective multi-stakeholder decision support and expansion to investigate general community understanding [20, 33, 34]. Additionally, assessments of expert selection methods, qualification of expert knowledge, and assessment of knowledge quality are currently lacking [13]. In an effort to provide some clarity on these issues, we identify 4 possible FCM collection strategies related to individual FCM collection and group FCM generation using freely associated or predetermined/standardized concepts (Table 2). Further, we outline the research goals afforded by each method and compare the tradeoffs of each FCM collection technique.

6.1 Collecting Individual FCM or Facilitating Group Modeling?

FCM and other cognitive mapping techniques have a unique methodological history since they can be used both as a measurement tool for use in applied research, but can also serve as an intervention to promote model-based reasoning and social learning in group settings. Differences in their appropriation are partially determined on the basis of whether FCM are constructed by individuals to be analyzed and manipulated by researchers, or whether groups construct them socially as an external representation of shared knowledge that can also be revised.

In an applied research context, the difference between individual and group map creation rests on the research context, which may seek to characterize individual

Table 2 Tradeoffs of different FCM data collection techniques

Model collection technique	Aggregation technique	Methodological tradeoffs
Individual mental model: Standardized concepts provided	Average individual FCMs together; assessment of expertise and weighting individual FCMs may be required for small sample sizes [8]	Pros • Aggregated models permit standardized functional analysis and scenario modeling • Careful expert selection can improve model exactness and reduce sample size demands • Standardization of concepts allow for large sample sizes to be collected and aggregated to draw conclusions about the knowledge of large communities • Standardized concepts facilitate ease of aggregation Cons • Model element chosen may not reflect full range of system components perceived by individuals • Interviews required first to generate list of standardized components • Multi-person multi-objective decision making validity dependent upon concept and expert selection • Constraining model components may bias FCM construction and significantly constrain representation of a domain

(continued)

Table 2 (continued)

Model collection technique	Aggregation technique	Methodological tradeoffs
Individual mental model: Concepts chosen freely by individuals	Researcher subjectively condenses individuals mental model concepts and then averages individual mental models together to produce a group model	Pros • Facilitates equitable multi-person multi-objective decision making across diverse knowledge domains to be guided by the individuals constructing the model [9, 35] • Model confidence requires larger sample sizes determined by an accumulation curve [52] • Allows for full representation of domain components as perceived by individuals • Weighting is not necessary with sufficiently large sample sizes Cons • Larger role of the researcher in interpreting and condensing domain components when group model is developed • Concept condensation is time intensive and subjective • Group validation of aggregated model required to ensure representativeness • Sufficient sample size may be costly to collect

(continued)

Table 2 (continued)

Model collection technique	Aggregation technique	Methodological tradeoffs
Group model: Standardized concepts provided to group and collectively modeled	Group creates model together, percent agreement may be useful for deciding group model structure [8]	Pros • Time efficient data collection compared to allowing groups to select concepts or individual mental model collection • Providing concepts allows for scaffolding of group model building • Real-time revision of model is possible as participant time allows • Detailed discussion of structural agreement possible • Facilitates social learning Cons • Group members should be experts in the domain of inquiry since the provision of predefined concepts limits the capture of variability in individuals' knowledge/ideas • Model's meaning is limited to the group context since socially constructed, negotiated, and validated [31] • Knowledge represented dependent upon group power dynamics [62, 66] • Expert facilitation skills necessary to moderate group dynamics and ensure group model is not biased toward views of more vocal/forceful individuals

(continued)

Table 2 (continued)

Model collection technique	Aggregation technique	Methodological tradeoffs
Group model: Concepts chosen by individuals, but condensed and modeled collectively	Concept brainstormed then condensed, group creates model together; percent agreement may be useful for deciding group model structure [8]	Pros • Accommodates diverse knowledge domains of group members, pools unconstrained knowledge into map construction • Time efficient compared to individual mental model collection • Facilitates social learning Cons • Model's meaning is limited to the group context since it is socially constructed, negotiated, and validated [31] • Knowledge represented dependent upon group power dynamics [62, 66] • Expert facilitation skills necessary to moderate group dynamics and ensure group model is not biased toward views of more vocal/forceful individuals • Group modeling activity and map may deviate from original domain slightly given conceptual freedom and group dynamics

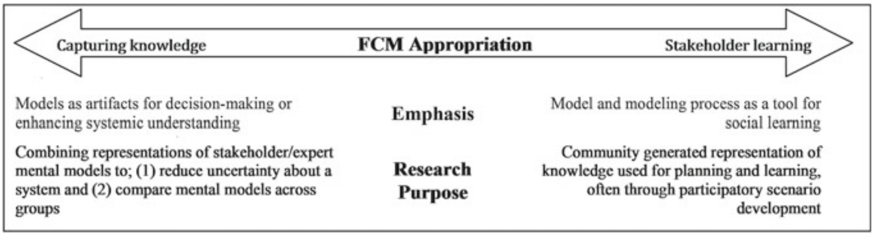

Fig. 1 Conceptual model of spectrum of FCM appropriation

or community understanding, promote social learning, or a mixture of the two (see Fig. 1). The strengths of individual model development include the ability of the researcher to standardize and aggregate model variables at will, as well as the ability to ensure that the resulting model representation meets the research goals. Since the collection of individual FCMs are not influenced by group dynamics, which can often be prone to power struggles, individual models provide a more robust representation of individual understanding, reveal differences in individual concepts, and highlight unbiased consistencies or inconsistencies in knowledge through comparison. This potentially allows for more equitable knowledge representation, which may more accurately characterize collective knowledge compared to group FCM construction. However, collecting individual FCMs may be resource intensive, and knowledge heterogeneity across maps may complicate aggregation and related structural and scenario-based analyses.

Conversely, an alternative option is to engage in group modeling, whereby a group of participants constructs an FCM as a collective. Group FCM construction is most often aligned with research priorities that seek to promote and represent the outcome of social learning. In these research contexts, more emphasis is placed on model building as a process, and less emphasis placed on capturing individual-level representations of knowledge. The FCM is therefore an outcome of social interaction and represents the group construction of knowledge, achieved through the collective sharing of aspects of individuals' mental models. Group modeling is often less resource intensive compared to the collection of individual models since members of a community can be organized to create a model in a workshop or group setting. In these cases, model aggregation reflects community knowledge, and the role of the researcher is less pronounced since more control of group knowledge representation is afforded to the community. Given that the integration of individuals' knowledge structures is socially negotiated in the group model building context, the resulting consensus model is ultimately dependent upon the personalities, strength of expertise, relationships and level of equality of the group. It may, however, be difficult to accurately assess the distribution of contributed knowledge across group membership or weight each member's expertise. In such contexts, the resulting FCM is most appropriately used as a tool for creating consensus related to the context of inquiry, and for facilitating group discourse for the promotion of shared understanding and collective learning. The model itself represents a socially negotiated form of collective knowledge that can be used to represent community understanding; however, it cannot be scaled down to represent individual understanding [23].

6.2 Standardizing Concepts or Free Association of Concepts?

Related to the choice of FCM collection is the question of whether to construct FCMs using a list of standardized concepts or freely associated concepts. The standardization of concepts involves providing participants with the same list of predefined concepts from which to construct their individual FCMs On the other hand, FCM elicitation through free association of concepts allows individuals to populate FCMs with their own freely chosen concepts [18, 52].The standardization method facilitates knowledge combination via aggregation of individuals' maps by eliminating the need for the researcher to subjectively categorize and reduce the large quantity of concepts typically resulting from FCM elicitation using free association. However, while easing the task of model aggregation and reducing the role of the researcher in determining the concept aggregation scheme, time investment in stakeholder discussions and preliminary research is still required to define an appropriate list of standardized concepts. Additionally, when model concepts are standardized, accumulation curves cannot be used to determine the appropriate sample size of individuals [52]. Further, although standardizing model structures facilitates the ease of scenario modeling with aggregated maps, the reliability of model structure and function may be biased since predefined concepts shape individuals' cognitive abstractions [59, 64]. Therefore, variation in knowledge perceived by individuals with high degrees of knowledge heterogeneity may not be captured. To mitigate some of these challenges in the group contexts with standardized concepts, it is recommended that researchers attempt to reduce knowledge variability and increase reliability of knowledge contributions by attempting to homogenize expertise by the type of experts constructing FCMs. These homogenized expertise FCMs can then be integrated with other groups FCMs after they are collected. It is important to note, however, that homogenized expertise also has trade-offs associated with it since map construction with overlapping expertise may limit the application of FCM as a tool for facilitating multi-person, multi-objective decision making in diverse group settings. In more heterogeneous expert contexts, freely associated concepts provide obvious advantages; however, this freedom has the ability to overwhelm individuals, especially if they are non-traditional experts, or if FCM or concept mapping is not a familiar activity.

Despite the notion that standardized concepts pose some analytical constraints, some research benefits are provided in terms of measuring shared knowledge. For example, in a group context, the use of standardized concepts may scaffold participants and promote social learning as a result of the group discussion and through the model validation process. Additionally, there are also considerations of ease of collection that should be considered in the selection of FCM collection techniques. While the research objective should be the first criteria used to inform FCM collection, availability of funding, and/or staff and participant time availability often influence the choice of data collection as well. When resources are limited, standardized concepts offer many benefits by facilitating the collection of larger sample sizes, which can be useful in drawing conclusions about the knowledge of communities and take less time to elicit as well as to aggregate. In the group context, they can also save time which may permit real time revision, and therefore create a more useful discussion of structural agreement. In contrast, FCM collection using freely associated concepts can require increased time dedicated to FCM elicitation, aggregation, analysis and follow-up validation.

While there are variations on FCM collection options, careful consideration of the research goals as well as the community and expert context should be undertaken so that methodological limitations are diminished to the greatest extent possible. Obviously, hybrid methods that combine pre-selected components and freely associated concepts are also possible, and to some extent can mitigate drawbacks associated with both options.

7 Conclusions

Structuring human knowledge through the collection of FCMs has obvious use beyond simply characterizing traditional expert systems, and also provides a way to represent community understanding as a form of scaled up "mental modeling". As the field of FCM continues to evolve and the usefulness of FCM continues to be seen through novel appropriations, continued research is needed to establish best practice standards which match specific techniques with different research contexts, backed by discipline appropriate theoretical foundations. Although FCM provide a powerful tool for both traditional experts and non-traditional experts to model complex systems, evaluate structural differences between the knowledge held by groups and individuals, and functionally determine the dynamic outcome of this understanding, there are still issues regarding the interpretation of FCMs as artifacts of individual knowledge and group beliefs. In this chapter, we have sought to provide a theoretical background to inform the collection and interpretation of FCM as representations of shared knowledge when individual FCMs are aggregated together, compared across individuals within the context of group interaction, or created collectively by individuals within a group context. More specifically, we can summarize the lessons learned as follows:

- When FCMs are used as representations of individual mental models or group knowledge or beliefs, the research objective should be carefully aligned with the appropriate cognitive theory and data collection method.
- FCMs, like all concept maps, have the ability to be used as both measurements of individual and group understanding and as a tool to promote social learning to facilitate group decision-making. Researchers should be clear about their appropriation when drawing conclusions about FCM as representation of knowledge and beliefs.

- Researchers engaged in FCM research should justify, based on tradeoffs, the selection of FCM data collection and aggregation techniques.
- Continued evaluation of existing methods, and the development of new methods, is currently needed in the areas of aggregation tests, sample size sufficiency, knowledge heterogeneity, and expert credibility.

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Chapter 3
FCM Relationship Modeling for Engineering Systems

O. Motlagh, S. H. Tang, F.A. Jafar and W. Khaksar

Abstract Semantic graphs like fuzzy cognitive map (FCM) are known as powerful methodologies commonly used in control applications, as well as in relationship modeling. Besides, FCM is used as a systematic way for analyzing real-world problems with numerous known, partially known and unknown factors. This chapter discusses FCM application in relationship modeling context using some agile inference mechanisms. A sigmoid-based activation function is discussed with application in modeling hexapod locomotion gait. The activation algorithm is then added with a Hebbian weight training technique to enable automatic construction of FCMs. A numerical example case is included to show the performance of the developed model. The model is examined with perceptron learning rule as well. Finally a real-life example case is tested to evaluate the final model in terms of relationship modeling.

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O. Motlagh (✉) · F. A. Jafar
Faculty of Manufacturing Engineering, Universiti Teknikal Malaysia Melaka, 76100 Melaka, Malaysia
e-mail: omid@utem.edu.com

F. A. Jafar
e-mail: fairul@utem.edu.com

W. Khaksar · S. H. Tang
Faculty of Engineering, Department of Mechanical and Manufacturing, University Putra Malaysia, 43400 Selangor, Malaysia
e-mail: weria@eng.upm.edu.my

S. H. Tang
e-mail: saihong@eng.upm.edu.my

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1 Introduction

Fuzzy cognitive map (FCM) [1–3] is a graph-like semantic model including nodes (concepts) and edges (events) whereby concepts activate one another repeatedly depending on weights of events. FCM is proven to be capable of causal inference and is applicable to complex decision problems where numerous interlinked dependent variables influence one another. FCM also supports group decision making by aggregating multiple decision makers' views on a specific problem [4], as well as supervisory control [5]. Accordingly FCM has been used in variety of applications in combination with learning and optimization techniques [6–11]. There are many approaches used to train FCM (matrix weights) mainly based on genetic algorithms (GA) [6–8], and Hebbian algorithms [9–11]. However, despite many modifications in terms of weight training, neural activation in FCM has remained intact and rather follows the initial models [2].

Like other neural models, FCM activation involves two steps. In the first step, the effects of the concepts on one another have to be calculated. A concept C_j receives influence from all concepts $\{C_1 \ldots C_n\}$ including itself in an n-node FCM graph while each concept C_i causes an effect of $C_i.e_{ij}$ on concept C_j. The parameter e_{ij} itself is the weight of the connecting event from C_i towards C_j. Accordingly, the sigma in Eq. 1 shows the total aggregated influence on concept C_j received from all concepts within the FCM graph. In the second step, this amount has to be squashed within a certain bound, e.g., 0 to 1, using an activation function before it could be assigned to C_j. The activation function in most cases is a sigmoid function around a fixed value (particularly 0.5) while other threshold functions such as *tanh* can be employed as well [5].

$$c_j^{(k+1)} = \left(1 + e^{-\sum_{i=1}^{n} c_i^{(k)}.e_{i,j}}\right)^{-1}, \quad \text{and} \quad j \in \{1 \ldots n\} \tag{1}$$

$$c_j^{(k+1)} = g\left(c_j^{(k)} + \alpha \sum_{i=1}^{n} c_i^{(k)}.e_{i,j}\right), \quad \text{and} \quad g_{(x)} = (1 + e^{-\lambda x})^{-1} \tag{2}$$

Using the definition formula (Eq. 1) the weight of each concept C_j is defined entirely a new regardless of its previous value. Alternatively, incremental formula allows for including the previous weight of a concept to determine its new value (Eq. 2). The incremental method is meant to increase influence of concepts on their own weights and is therefore more realistic in terms of decision outputs. Its only difference is in adding squashed value of each concept from previous cycle (k) to a fraction of total effect on it during new cycle (k+1). This method is used in most FCMs [10], where $0< \alpha <1$ is the gain, and $\lambda > 0$ is steepness of sigmoid activation function.

Upon completion of activation steps, FCM is already updated with new concepts' values. The algorithm then continues cyclically until a convergence is obtained which means all concepts weights have reached ultimate stable values without further changes. Only upon convergence FCM can be interpreted for results or decision outputs in contrast to chaotic and oscillatory situations where concepts keep varying indefinitely and do not show results.

2 FCM Activation

Sigmoid activation has been conventionally used in FCMs. While resulted inference models have been the key components in most of the research on FCM, yet there are shortcomings being overlooked when it comes to real-life situations. The first drawback is that there is a certain value about which the new concepts weights are squashed during every cycle of the dynamic map. This diminishes the influence of the very initial concepts' weights, i.e., those with which FCM cycles start, and therefore, the knowledge of the initial concepts which could be less prone to uncertainty will not be utilized. On the other hand, the second drawback is that the weights of the events, which are more likely to carry error especially at early stage of training, remain intact through cycles unless a larger learning rate is chosen. Large learning rate itself means a risk of overlooking the solution. In other words, events' weights play much more important role than initial concepts weights while in most applications the events' weights are relatively more vulnerable to error compared to the initial concepts' values read from sensors or given at training set. While in real-life a concept which is not receiving any influence from others should remain intact by converging to its initial value, it will approach a fixed value of 0.5 if function of Eq. 1 is applied.

In contrast to the above viewpoint, one may discuss that FCM's lack of sensitivity to initial concepts' values is sometimes advantageous especially when it comes to noisy and unreliable data. Therefore, it could be regarded as a short coming if the performance of FCM is known to be sensitive to the initial weight setting and architecture [12]. In fact, an FCM advantage is to handle incomplete and noisy inputs. However, it must be noted that this could be achieved only upon sufficient training prior to receiving noisy input at nodes. An untrained FCM should rather rely on inputs' initial values at its nodes than weights of edges.

Another drawback of existing formula is that they usually result into crisp decisions by converging some nodes toward 1 (upper bound) and the rest to 0 (lower bound). Accordingly, having no gray values in between makes it difficult to interpret FCM outputs. Again, a troublesome situation is about nodes which do not receive any influence from others, and yet their values increase or decrease with no reason causing misleading outputs.

2.1 Static Systems Versus Dynamic Scenarios

Many researchers have spotted the problem of lack of concept of time, i.e., practically each causal has a different time delay [13, 14]. Being one of the challenging problems in FCM-based modeling, time related and dynamic variables may not be realistically analyzed without including notion of time into FCM inference. One approach here is to defined sequence of activation or priority based activation. However, agile inference or obtaining convergence at shortest time still serves as the baseline of time-related inference whether or not a notion of time is included in activation sequence. In other words, handling both static systems and dynamic scenarios could be guaranteed using agile FCM inference. Therefore, an alternative solution is to activate FCM nodes concurrently while minimizing the inference period to its extreme to achieve highest frequency of sampling.

From this perspective, the conventional activation models in Eqs. 1 and 2 lead to relatively slow convergence. Stability at nodes take long time in most cases that is due to extreme fluctuations of nodes especially in the case of (Eq. 1), and therefore FCM does not respond to dynamic stimuli as it only receives new inputs once the previous set of inputs have been digested. This problem makes FCM overlook transient and dynamic data when it comes to dynamic scenarios.

2.2 Cumulative Neural Activation

Through modification of the incremental model, a cumulative activation function has been developed [3] to resolve the above problem. Here, the activation function is a sigma around a concept's own previous value instead of a fixed value as used in previous models. Accordingly, concepts values could be accumulated to show more realistic behaviors in terms of sensitivity to their initial values. Therefore, the function of (Eq. 3) allows for direct influence of initial concepts' weights on their converged final values as the activation threshold during each cycle (k+1) is determined based on the previous values at cycle (k).

Accordingly, concepts do not show much fluctuation and rather follow smooth variations over successive activation cycles. This characteristic makes convergence both more likely and faster. In fact even in the cases of chaotic and oscillatory maps still the outputs could be interpreted as long as the concepts show continuous and meaningful variations. And most importantly, without including a time concept, FCM has shown inherent time-related behaviors as discussed. Gray outputs have been made possible as the outputs do not need to approach lower and upper bonds to secure a convergence. And lastly, having each decision concept's value linked with its previous value, the network could be interrupted anytime to supply updated inputs values to meet real-time requirements.

$$c_j^{(k+1)} = f\left(\sum_{i=1}^{n} c_i^{(k)}.e_{i,j}\right) \text{and, } f_{(x)} = \frac{\gamma\, c_j^{(k)} e^{\lambda x}}{\gamma\, c_j^{(k)} \left(e^{\lambda x} - 1\right) + 1} \qquad (3)$$

where, $j \in \{1 \ldots n\}, 0 < \gamma < 1$

2.3 An Agile FCM Method

Since the developed model secures FCM convergence at relatively less number of activation cycles compared to other activation functions, it is assumed that it also could facilitate faster weight training, regardless of the training algorithm employed. This assumption has examined through a number of examples some given in the following sections. It is shown that the activation function of (Eq. 3), added with any of the conventional weight training models (e.g., in this case a modification of the Hebbian rule, and the perceptron rule), could result into both faster convergence and more accurate weight training. Fast convergence facilitates close to real-time computation and accurate matrix of weights satisfies realistic relationship modeling in real-life systems.

As the chapter continues, the application of the developed FCM in modeling dynamic variables will be examined through some real-life case study. The walking cycle of the hexapods is modeled without the need for inclusion of a time concept. Accordingly, the capability of the model in responding to transient stimuli will be discussed in more details using MATLAB graphics. A Hebbian training model is developed for construction of FCM and is then tested using a simple numerical example case. The problem of modeling simple mechanism has been resolved as another convincing case study.

3 Case Studies

3.1 Legged Locomotion

Tripod gait and ripple gait are two of the cyclic walking behaviors commonly adopted by smaller and bigger insects, respectively. Hexapod walking in bio-inspired robotics is defined as mimicking six-legged locomotion, which depending on number of joints in each leg known as degree of freedom (DoF) involves solving for complex Jacobeans to facilitate alternative support and swing phases of robot's feet. Figure 1 illustrates a leg during the support phase to describe the phenomena of locomotion on land. Based on the law of action-reaction, by exerting repulsive force to the ground,

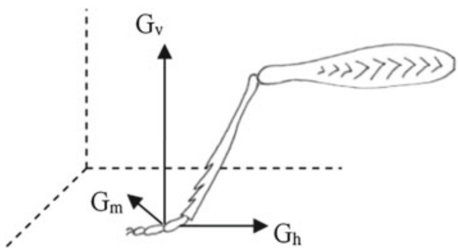


Fig. 1 The components of the ground reaction force

the animal (or robot) is pushed forward due to the ground reaction force being a resultant of three components $G^{\rightarrow} = Gv^{\rightarrow} + Gh^{\rightarrow} + Gm^{\rightarrow}$ [16]. As the vertical component Gv supports the weight, the horizontal Gh and mediolateral Gm components push the animal to forward and lateral directions, respectively. The animal limbs alternatively experience support with non-zero horizontal force followed by a swing phase to facilitate forward loco-motion. As soon as all six limbs switch between the phases alternatively, it is said that an entire walk cycle or stride period T_s has completed.

Assuming the animal's straight forward locomotion, there are two simple locomotion principles to develop the expert-defined FCM of this case study. The first principle (P1) is based on the vertical component of the reaction force on each leg, i.e., reflecting a portion of the animal's weight G_V. Based on (Eq. 2), during an entire stride T_S each leg bears a fraction of the animal's weight W depend on the number of legs, e.g., 6 in this case, and when one or more legs go for swing, the others shall bear more weight to maintain the equation.

The second principle (P2) involves with horizontal component or G_h. While the vertical component is measurable, i.e., equal to W/6, the horizontal component is more difficult to be measured as many dynamical forces are involved, e.g., extent of propulsion force and friction with the surface. Accordingly, the developed FCM setup should be flexible enough to accept any range of weights for the matrix of events or the causal links.

Figure 2a shows an insect with limbs at Front Left, Front Right, Middle Left, Middle Right, Hind Left, and Hind Right, or FL, FR, ML, MR, HL, HR, respectively. The two gaits of locomotion namely tripod (Fig. 2b) and ripple (Fig. 2c) are described by numbering the sequence of the swing legs during an entire stride. It could be seen that while in the ripple gait limb swing one by one, in the tripod gait limbs swing

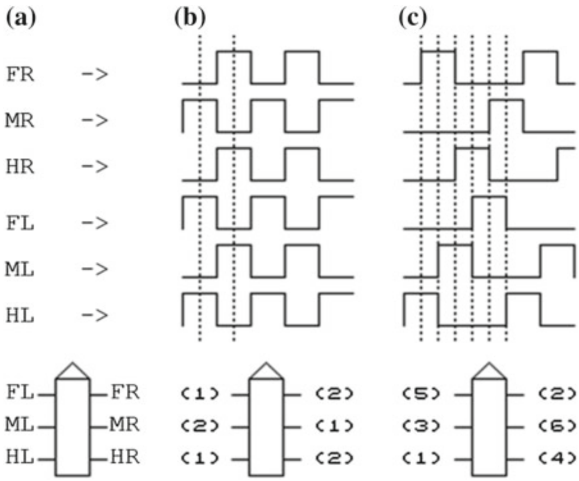
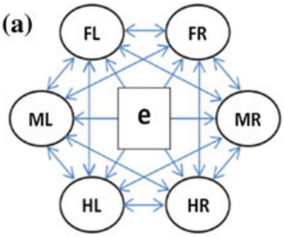


Fig. 2 **a** Hexapod limbs, **b** Alternative tripod gait, **c** Ripple locomotion gait

(a)



(b)

e1:	FL	FR	ML	MR	HL	HR
FL	+1	-1	0	0	0	0
FR	-1	+1	0	0	0	0
ML	0	0	+1	-1	0	0
MR	0	0	+1	-1	0	0
HL	0	0	0	0	+1	-1
HR	0	0	0	0	+1	-1

(c)

e2:	FL	FR	ML	MR	HL	HR
FL	+3	0	-2	-1	0	0
FR	0	+3	-1	-2	0	0
ML	0	0	+3	0	-2	-1
MR	0	0	0	+3	-1	-2
HL	-2	-1	0	0	+3	0
HR	-1	-2	0	0	0	+3

Fig. 3 **a** FCM governed by matrix e, **b** event matrix e1, **c** event matrix e2

three by three alternatively, also known as the alternative tripod gait. The FCM of Fig. 3a has been developed based on the two principles of locomotion. The event matrix (e) is obtained from the normalized resultant of event matrix 1 (e_1 in Fig. 3b) and event matrix 2 (e_2 in Fig. 3c) which are defined based on locomotion principles *P1*, and *P2*, respectively.

$$\frac{1}{T_s}\int_0^{T_s} G_v dt = \frac{W}{n}, \quad n = 6 \; for\; hexapods \tag{4}$$

According to *P1*, when a limb goes for support it bears part of the total weight. However, the main support is given to its neighboring limb, e.g., to FR when FL goes for support, which is due to the fact that before a limb goes from swing to support, its neighboring limb has had a tough period of standing alone under the load while the other limbs have been paired together for bearing similar loads, e.g., a pair of HL and HR. Therefore, in e_1, each limb should have a negative causal link (e.g., -1) towards its neighboring limb to reduce its load and a positive feedback link towards itself (e.g., +1) to transfer the excess of load from the neighboring limb to itself. Other links in e_1 are set to 0 with the assumption that the animal's body is long and its weight is distributed evenly among its limbs.

As for the principle *P2* assuming equal coefficient of friction at feet and equal power of propulsion at all limbs, the only considerable dynamical forces are the effects of pushing and pulling among the limbs as appears in the form of compression or stretch within the animal's body. Both kinds of forces facilitate a swing in that limb to relax and therefore the respective event weights in e_2 are represented with

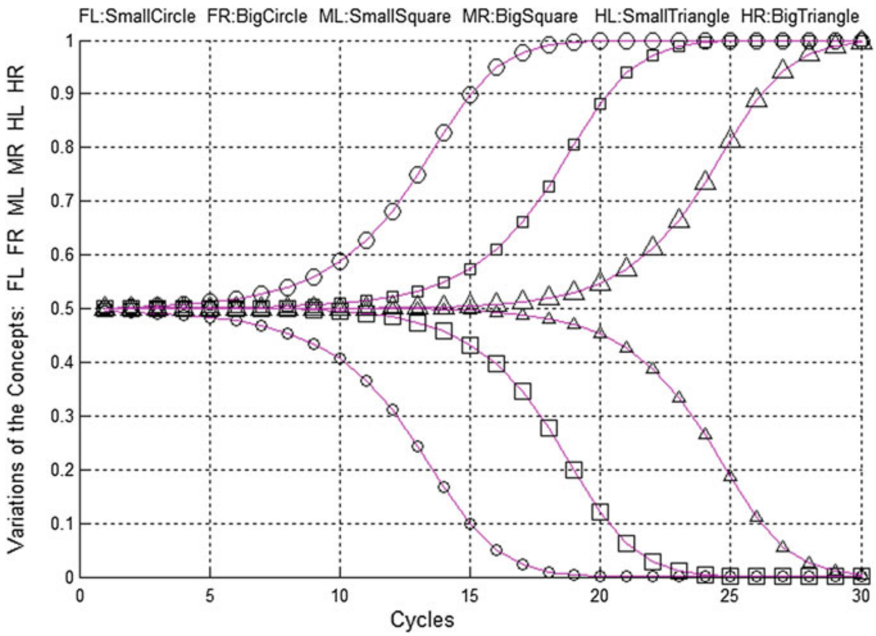


Fig. 4 A small stimuli at FL causes FL and then MR and HL to swing

negative amounts (i.e., encouraging swing). Each limb has a pulling effect (e.g., −2) on the other limb at its rear and on the same side of the body through stretching, e.g., FL on ML. The diagonal pulling forces (e.g., ML on MR) are weaker (e.g., −1) as the distance between the points of attachment of limbs to the body is longer and therefore stretch in less intense.

The pushing forces as resulted from contraction of the animal's body cause sending a limb for swing, which in this case the rear limbs encourage the front limbs for swing to facilitate forward locomotion. Each limb however has positive feedback towards itself for two reasons: first to go for support and therefore to let another limb experience a relaxing swing, and second to balance out the entire event matrix using a positive value, e.g., +3. The resultant event matrix is obtained from (Eq. 5) to generate normalized weights within the standard range of (−1, +1).

A MATLAB code was generated based on the above principles. Considering a hexapod weighing 30 g at a rest position, which means each leg supports 5 g on average, the goal is to mimic the two gaits of tripod and ripple forward locomotion. Simulation result in Fig. 4 shows the situation for tripod gait, where a tiny stimuli at the front left limb, i.e., FL intension for swing, causes more limbs to go for swing which are MR and HL. A tripod consisting of FR, ML, and HR remains to support the excess of the weight as the other three limbs start to swing.

$$e = (1 + \exp -(k_1 e_1 + k_2 e_2))^{-1}, k_1 > 0 \quad \text{and} \quad k_2 > 0 \tag{5}$$

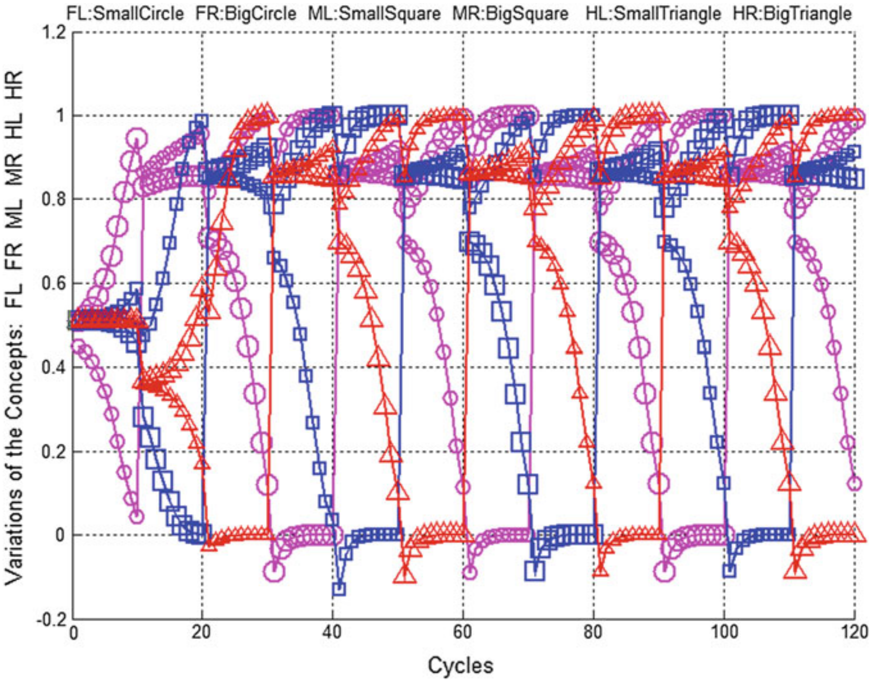


Fig. 5 Mimicking ripple gait by allowing any limb to experience a support phase right after a relaxing swing

The stimuli are supplied through the nodes by replacing concept value of FL at rest from 5 g to 4.95 g, while increasing the other values from 5 g to 5.01 g. The concepts' values then change through the FCM cycles towards 0 g (or 0 in the graph) representing swing, and 10 g (or 1 in the graph) representing support. However, it must be noted that the key factor to attain the tripod gait is that when a limb starts to swing, it should not be sent for support until the other two limbs have started their swing as well. As soon as the two tripods (i.e., for swing and support) have been formed, the limbs at swing should be sent to replace the limbs at support.

Alternatively, another gait of locomotion could be achieved if the above condition is not set, i.e., a limb at swing may immediately advance forward and go for support so that another limb can start to swing. Figure 5 shows this situation as any swing leg is immediately experiencing a support phase by giving it external stimuli, which is through an increase in its weight. It is observed that the FCM is able to respond to any dynamic changes in the inputs and accordingly takes an appropriate action by sending the correct limb to swing. The sequence of swing legs is obtained as HL, FR, ML, HR, FL, MR that is comparable with that of Fig. 2c. The FCM is relatively fast in generating decision outputs signifying the effectiveness of the developed activation function as discussed in Eq. 3.

3.2 A Numerical Case Study

The notion of Hebbian rule could be applied to FCM for learning concept values assuming the network has reached its steady state values, known as state of convergence. This is useful for learning datasets of certain network configurations, storage and retrieval applications, look-out tables, and crisp control systems where different sets of concepts values and their relationships are known and need to be memorized. An example of such applications is given in Table 1 (part 1) for learning 10 known inputs (x1 … x10) each with 6 concepts C1–C6 within the range (0, 1). Each pattern could be a known situation, configuration, desired set of values, etc., of a system of concern. While the patterns to be memorized are known, the initial weights of the causal links Wi which could attain such patterns is unknown and therefore is chosen randomly within (−1,1).

It must be noted that the 10 given input vectors (x1 … x10) are chosen in such a way to generate 10 distinct patterns (p1 … p10), which otherwise would generate less number of patterns. Through the application of Hebbian rule the tuned weights *wFCM* could be obtained as shown Table 1 (part 2). The memorized patterns (p1 … p10) are closely similar with input vectors. For better analogy, values close to 0.9 are bolded. The entire algorithm consists of FCM activation (Eq. 3) and a modified Hebbian rule given in Eq. 6 to generate weights symmetrically around zero.

$$\Delta w_{ij} = \alpha.sign\left(w_{ij}\right).x_i y_j - \varphi y_j w_{ij} \quad and \quad w_{ij}^{(n+1)} = w_{ij}^{(n)} + \Delta w_{ij} \tag{6}$$

In contrast to the method in [17], this model follows the basic Hebbian rule without squashing the generated weights at iterations. However, it is more difficult to determine the values of the learning and decay factors in order to retain weights within the range of (−1,1). Alternatively, by replacing the forgetting part of the rule with a squashing function (Eq. 7) more flexible learning rates could be applied, e.g., $\alpha = 0.1$, which gives better results. The tuned matrix of weights is guaranteed to be within (−1,1) and the patterns are closely analogous with the input vectors.

$$w_{ij}^{(n+1)} = w_{ij}^{(n)} + \alpha.sign\left(w_{ij}\right) x_i y_j \tag{7}$$

$$w_{ij}^{(n+1)} = 2/\left(1 + e^{-\mu w_{ij}^{(n+1)}}\right) - 1$$

In order to examine the algorithm, the input vector x = {0.1, 0.1, 0.1, 0.9, 0.9, 0.9} is triggered with both the initial weights matrix, and the tuned weights matrix. The outputs are mapped to {0.2214 , 0.4999 , 0.1101 , 0.9753 , 0.8355 , 0.4603} in Fig. 6a and {0.1083, 0.1081, 0.0927, 0.9086, 0.8946, 0.8912} in Fig. 6b, respectively, which qualitatively show he effectiveness of the developed model through analogy. The tuned FCM was also tested with similar input vectors (with slight deviations) which would classify each similar input as belonging to the respective trained pattern.

Table 1 Learning 10 distinct input vectors

Part 1 : INPUT VECTORS AND INITIAL WEIGHTS MATRIX										
x –>	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10
	:	:	:	:	:	:	:	:	:	:
C1 –>	0.1000	**0.9000**	**0.9000**	0.1000	**0.9000**	0.1000	**0.9000**	0.1000	0.1000	**0.9000**
C2 –>	0.1000	0.1000	**0.9000**	0.1000	**0.9000**	0.1000	**0.9000**	0.1000	0.1000	**0.9000**
C3 –>	0.1000	0.1000	**0.9000**	**0.9000**	**0.9000**	0.1000	0.1000	**0.9000**	0.1000	**0.9000**
C4 –>	0.1000	0.1000	**0.9000**	**0.9000**	0.1000	**0.9000**	0.1000	**0.9000**	0.1000	**0.9000**
C5 –>	0.1000	0.1000	0.1000	**0.9000**	0.1000	**0.9000**	0.1000	0.1000	**0.9000**	**0.9000**
C6 –>	0.1000	**0.9000**	0.1000	**0.9000**	0.1000	**0.9000**	0.1000	0.1000	**0.9000**	**0.9000**
wi =	0.6294	-0.4430	0.9143	0.5844	0.3575	0.4121				
	0.8116	0.0938	-0.0292	0.9190	0.5155	-0.9363				
	-0.7460	0.9150	0.6006	0.3115	0.4863	-0.4462				
	0.8268	0.9298	-0.7162	-0.9286	-0.2155	-0.9077				
	0.2647	-0.6848	-0.1565	0.6983	0.3110	-0.8057				
	-0.8049	0.9412	0.8315	0.8680	-0.6576	0.6469				
Part 2 :	HEBBIAN LEARNING WITH WEIGHTS DECAY (Eq. 7) with $\alpha = \varphi = 0.01$									
Tuned matrix:										
WFCM =	0.8185	-0.7519	0.5763	0.4684	0.3908	0.4415				
	0.6816	0.7380	-0.5457	0.4375	0.3766	-0.2831				
	-0.5637	0.6671	0.8119	0.6629	0.5204	-0.4096				
	0.4413	0.5360	-0.6752	-0.7470	-0.6282	-0.5414				
	0.2976	-0.3536	-0.4105	0.5273	0.7447	-0.6786				
	-0.4345	0.3675	0.4411	0.5582	-0.7588	0.8370				
Stored patterns:										
p –>	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10
	:	:	:	:	:	:	:	:	:	:
	0.1117	**0.9326**	**0.9683**	0.0925	**0.9555**	0.1377	**0.9712**	0.1022	0.1012	**0.9647**
	0.1114	0.0844	**0.9633**	0.2498	**0.9449**	0.1629	**0.9094**	0.2460	0.1124	**0.9636**
	0.1018	0.2036	**0.9131**	**0.9130**	**0.9474**	0.0636	0.1041	**0.9112**	0.1041	**0.9151**
	0.1185	0.2339	**0.9546**	**0.9602**	0.3211	**0.9344**	0.2168	**0.9104**	0.2411	**0.9801**
	0.1060	0.0811	0.1672	**0.8970**	0.2491	**0.8516**	0.1788	0.0979	**0.9046**	**0.9409**
	0.0944	**0.9591**	0.0531	**0.8194**	0.0789	**0.8622**	0.1061	0.0465	**0.9058**	**0.8369**

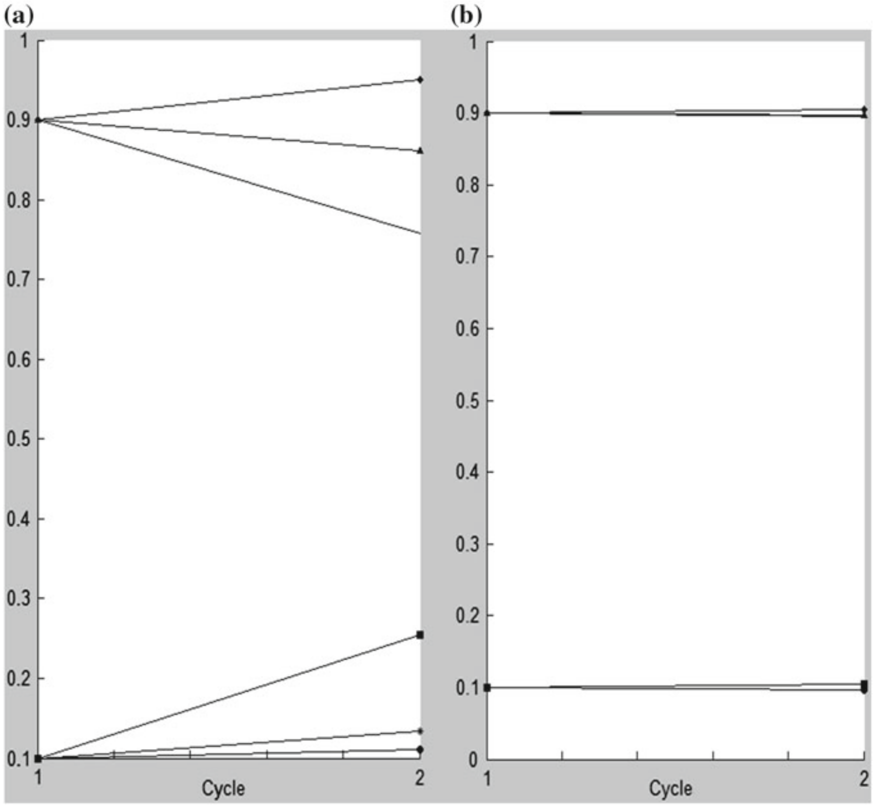


Fig. 6 **a** FCM with random matrix (*wi*), **b** FCM with tuned matrix (*wFCM*)

This generalization capability makes the model capable of application as FCM-based classifier.

It must be noted that in both Hebbian models in Eqs. 6 and 7, the learning rule updates weights with values of the same polarity, which makes the system depend

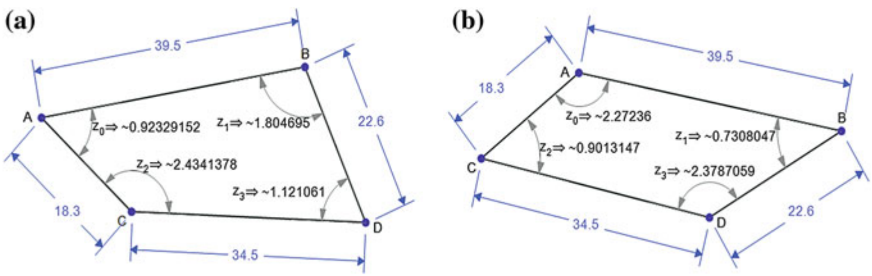


Fig. 7 A 4-bar mechanism at two different poses

on expert for initial setting of weights polarity. Although this is not a major problem for most small scale FCMs where experts have no difficulty in determining the sign of the causal links [17], but it could be troublesome when it comes to larger FCMs with tens of causal links. Also as another consequence, the minimum cost solution is not guaranteed and the algorithm may take longer time to find a solution, while on the other hand limit cycles are also likely to occur. Therefore, such inability of the learning rule to cross zero should be resolved using modified models, or other rules such as perceptron or simulated annealing.

3.3 Modeling a Simple Mechanism

To achieve expert-independency, the inference model was examined with the perceptron learning rule (Eq. 8) subjected to simulated annealing to ensure uniqueness of the solution. By allowing zero-crossing along weight training cycles it is observed that a unique solution is obtained with optimally tuned weights regardless of their polarity (i.e., expert initial settings) which guarantees lowest cost to solution. The learning rate α should be set to a small value to reduce the risk of missing the global solution. On the other hand, a very small α would degrade the algorithm in terms of real-time response since the smaller the learning rate, the longer the tuning process may take, or in the event of fixed number of training cycles, the less accurate finalized weights will be obtained. Accordingly, α=0.01 is shown to be optimal through experiments.

As a case study, in this section a simple 4-bar mechanism is analyzed using the developed relationship modeling tool. Figure 7 developed in Geometry Expressions Software, shows two poses of a randomly generated 4-bar linkage having four angles which vary dependently to maintain a sum of 2π radian. This configuration is much like nodes within an entirely interrelated FCM. The edges of the FCM graph however could not be represented by the existing four links. Instead, due to having four links, the FCM includes $16 = 4^2$ links or edges. The goal is to solve for a matrix of weights which could describe the behavior of the system in Fig. 7.

$$\Delta w_{ij} = \alpha \left(x_j - y_j\right) .x_i \tag{8}$$

Accordingly, in order to obtain a real-life numerical dataset, different poses of the 4-bar system are generated whereby each pose (p) indicates a set of angles A, B, C, D represented as nodes z0, z1, z2, z3 of the FCM. A dataset P including 5 records P: {p1…p5} was obtained in the same manner as given in Table 2. Then, the algorithm is run to find a unique solution for matrix of weights by training using the database given in Table 2.

While the initial node values come from real-life dataset of Table 2, the 4x4 matrix of weights is initially from random amounts within (-1,+1), i.e., w_{init} as shown in Fig. 8a. The method was tested several times using different random weight matrices. However, a single unique solution ($w_{trained}$) was obtained for the FCM matrix as

Table 2 Dataset obtained from 4-bar system of Fig. 7 (angles are in radian)

Poses of joints A, B, C, D recorded as FCM node values z0, z1, z2, z3	Z0	z1	z2	z3
P1 =	0.1827	1.9352	3.5008	0.6646
P2 =	0.4623	1.9809	3.0521	0.7880
P3 =	0.9233	1.8047	2.4341	1.1211
P4 =	1.4847	1.4078	1.7751	1.6156
P5 =	2.0152	0.9619	1.1848	2.1213

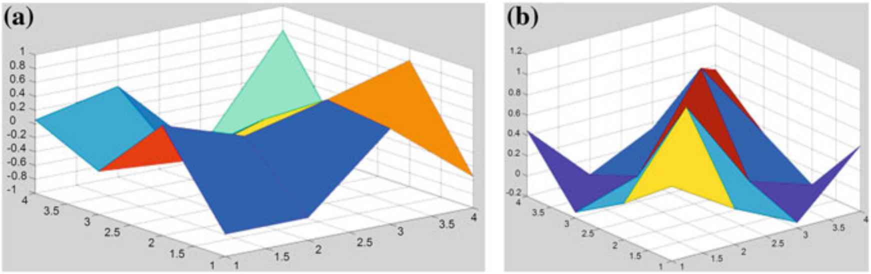


Fig. 8 **a** Initial and **b** Trained weights matrices

Table 3 Training in terms of memorizing states, and corrective capability

Part 1: Memorized states with RMS error of less than 4.2e-4	**z0**	**z1**	**z2**	**z3**
P1 =	0.1827	1.9352	3.5008	0.6646
P2 =	0.4623	1.9809	3.0521	0.7880
P3 =	0.9233	1.8047	2.4341	1.1211
P4 =	1.4847	1.4078	1.7751	1.6156
P5 =	2.0152	0.9619	1.1848	2.1213
Part 2: Correcting noisy inputs with maximum error of 0.0202				
An original test data:	z0 = 2.7513, z1 = 0.2381, z2 = 0.3430, z3= 2.9508			
Noisy test data given to FCM:	z0 = 2.6513, z1 = 0.2381, z2 = 0.2430, z3= 2.9508			
Corrected test data:	z0 = 2.7578, z1 = 0.2223, z2 = 0.3569, z3 = 2.9169			

shown in Fig. 8b. On the other hand, the memorized dataset as given in Table 3 (part 1) showed a maximum RMS error of 4.2e-4 being the cost to the solution.

To ensure the soundness of the solution, the following test record is considered: z0 = 2.7513, z1 = 0.2381, z2 = 0.3430, z3 = 2.9508. A considerable noise is inserted into the data by reducing the values of z0 and z2 each by 0.1 rad. The noisy input is then given to FCM to rectify which the converged result showed only slight RMS error of 0.0202 compared against the original test data as shown in Table 3 (part 2).

It is shown using the above example that the developed FCM is capable of modeling the existing relationships of the four joint angles. However, a remaining issue is that how the obtained weights could be interpreted and linked with the actual relationships among nodes, i.e., length of the four links. In other words, although the trained

FCM matrix is already proven to mimic the behavior of the 4-bar mechanism, yet each figure of the FCM matrix should be interpreted and somehow linked with one or more of the actual links. Interpretation of weights is mathematically complex to link 16 pieces of data from a 4x4 FCM matrix to the 4 actual links in the mechanism (Fig. 7).

However, there are facts supporting the soundness of the result. For example without any supervision and or boundary settings, it is seen that the training algorithm has tuned the weights in a perfectly symmetric way. In Fig. 8b, it is observed that every w_{ij} is equal to w_{ji} signifying the fact that the resultant effect of such linkage between joints *i* and *j* (i.e., sum of the forces exerted by one node on the other) is mutually equal which is true in reality.

4 Conclusion

A new FCM-based methodology was discussed for relationship modeling that is applicable to both dynamic and static systems. The respective cumulative activation model along with FCM tuning was described through a number of example cases. The tuned FCM showed to manage relationship modeling among nodes, as well as corrective capability to rebuild noisy inputs. The future work involves with application of the developed FCM on more cases of natural and real-life problems including spatio-temporal analysis of human motion, animal locomotion, NP-hard and complex problems.

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Chapter 4
Using RuleML for Representing and Prolog for Simulating Fuzzy Cognitive Maps

Athanasios Tsadiras and Nick Bassiliades

Abstract Fuzzy Cognitive Map (FCM) technique is broadly used for decision making and predictions by experts and scientists of a wide range of disciplines. The use of the FCMs would be even wider if a standardized representation of FCMs was developed and a system that would simulate them was constructed. Having such a system, decision makers would be able to create and examine their own developed Fuzzy Cognitive Maps, and also distribute them e.g. through Internet. In this chapter, (a) we propose a RuleML representation of FCMs and (b) we present the design and implementation of a system that assists experts to simulate their own FCMs. This system, which is developed using the Prolog programming language, makes the results of the FCM simulation directly available to other cooperative systems because it returns them in standard RuleML syntax. In the chapter, the design choices of the implemented system are discussed and the capabilities of the RuleML representation of FCM are presented. The use of the system is exhibited by a number of examples concerning an e-business company.

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A. Tsadiras (✉)
Department of Economics, Aristotle University of Thessaloniki, GR-54124
Thessaloniki, Greece
e-mail: tsadiras@auth.gr

N. Bassiliades
Department of Informatics, Aristotle University of Thessaloniki, GR-54124
Thessaloniki, Greece
e-mail: nbassili@auth.gr

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1 Introduction

Scientists from various disciplines are using Fuzzy Cognitive Map (FCM) as a method for taking decisions and making predictions. To take decisions through FCM, the simulation of the FCM model is required. This can be a difficult task, especially from those scientists that do not have the required computer skills. Furthermore, the degree of expertise of the domain experts involved in the FCM construction is vital for the successful construct of an FCM.

In this chapter we try to cope with the following problems that FCMs face at the present time:

1. There is no standard representation of FCMs that would make them easily reusable and transportable.
2. There is no standard software that would simulate FCMs. Nowadays every scientist has to create his own software system.
3. No repository of FCMs exists to assist their dissemination.

In the chapter, these problems are handled by developing:

1. an XML representation of FCMs, which is based on RuleML [1], a popular rule interchange format for the web,
2. a Prolog-based simulation system that can assist FCM authors to simulate their scenarios in FCMs.

The basic assumption that we make is that FCMs closely resemble rules, since they represent causality relations between concepts, something that matches with the logical implication semantics of rules.

In the Sect. 2 of this chapter, a short introduction to FCMs and related literature is given. Section 3 discusses the representation capabilities of RuleML while Sect. 4 presents the proposed RuleML representation of FCMs. Section 5 explains the design of the Prolog-based simulation system that simulates FCMs represented in RuleML. Section 6 concerns the implementation and demonstration of the system's capabilities. Finally, conclusions and recommendations for further research are presented in Sect. 7.

2 Fuzzy Cognitive Maps and Related Literature

Kosko introduced in 1986, Fuzzy Cognitive Maps (FCMs) [2, 3], based on Axelord's work on Cognitive Maps [4]. FCMs are considered a combination of fuzzy logic and artificial neural networks and many researchers have made extensive studies on their capabilities (see for example [5–9]). An example of an FCM concerning an e-business company (modified version of the model presented in [10]), is given in Fig. 1. In this figure, the nodes represent the concepts that are involved in the FCM model and the directed arcs between the nodes represent the causal relationships between the corresponding concepts. Each arc is accompanied by a weight that defines the type

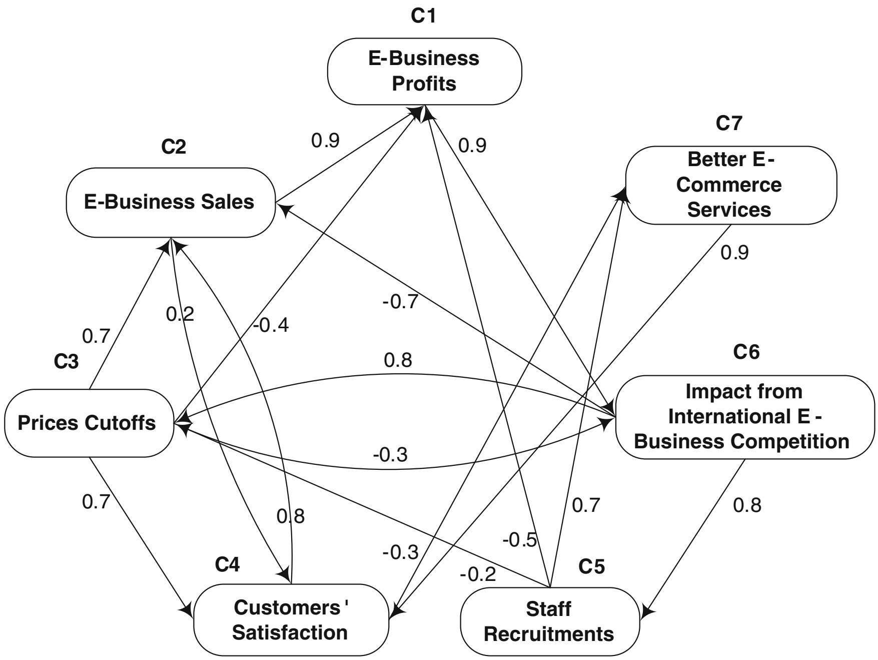


Fig. 1 An FCM concerning an imaginary e-business company (modified version of the model presented in [10])

of the causal relation between the two nodes. A positive (negative) causal relation between two concepts C_i and C_j means that an increase of the activation level of concept C_i will increase (decrease) C_j and also a decrease of concept C_i will decrease (increase) C_j.

The level of activation of each concept C_i at time step t is determined by number A_i^t, i=1,...,n with n to be the number of concepts of the FCM. The weight of the arc that connects C_i and C_j is defined as w_{ij}. The FCM system is updating in a synchronous manner which means that A_i^{t+1}, i=1,...,n is calculated by one of the following formulas:

1. $$A_i^{t+1} = f_M(A_i^t, S_i^t) - dA_i^t \tag{1}$$

   using Certainty Neurons [9] or

2. $$A_i^{t+1} = f_M\left(w_{1i}A_1^t, f_M(w_{2i}A_2^t, f_M(..., f_M(w_{n-1,i}A_{n-1}^t, w_{n,i}A_n^t)))\right) - dA_i^t \tag{2}$$

   using Recursive Certainty Neurons [11]

where,

- $S_i^t = \sum_j w_{ji} A_j^t$ is the sum of the weight influences that concept C_i receives at time step t from all other concepts,
- d is a decay factor and

- $$f_M(A_i^t, S_i^t) = \begin{cases} A_i^t + S_i^t(1 - A_i^t) = A_i^t + S_i^t - S_i^t A_i^t & \text{if} A_i^t \geq 0, S_i^t \geq 0 \\ A_i^t + S_i^t(1 + A_i^t) = A_i^t + S_i^t + S_i^t A_i^t & \text{if} A_i^t < 0, S_i^t < 0 \left|A_i^t\right|, \left|S_i^t\right| \leq 1 \\ (A_i^t + S_i^t)/\left(1 - \min(\left|A_i^t\right|, \left|S_i^t\right|)\right) & \text{if} A_i^t S_i^t < 0 \end{cases} \quad (3)$$

is the function that was used for the aggregation of certainty factors at the MYCIN expert system [12].

Many attempts have been made recently in order to develop methods for training and learning of FCMs [13–15]. Despite that, the development of a commonly used tool that can assist the creation and simulation of FCMs remains crucial because of the application of FCM technique to a wide variety of scientific areas. Attempts that have been done towards the creation of such a tool are the following:

- FCM Constructor is a knowledge acquisition system that builds an FCM by direct knowledge acquisition [16].
- The FCM Designer Tool is a tool in Spanish which allows the design of the structure of the FCMs [17]. The tool handles casual relationships as rules.
- FCMapper is an FCM analysis and visualization tool based on MS Excel (http://www.fcmappers.net/).
- The Fuzzy Cognitive Map applet is an on line calculator and downloadable Java application for FCM computations (http://www.ochoadeaspuru.com/fuzcogmap/index).
- A Java standalone library for FCM computations exists in http://jfcm.megadix.it/.
- FCModeler tool is a Java interface that reads and displays data from an Excel spreadsheet of links and nodes [18].

An FCM tool should also facilitate knowledge sharing and reuse of knowledge in order to deal with semantic interoperability between different systems. Attempts towards this point are the following:

- Jung [19] proposed ontological Cognitive Maps (ontoCM) as an extension to Cognitive Maps that additionally provides semantic information by ontology that is organized on a tree-like hierarchical structure.
- Carvalho [20] studied the semantics of FCMs for the modeling and simulation of complex social, economic and political systems.

In our study, we propose the use of RuleML for the representation of FCM that promotes interoperability between different systems and reuse of knowledge.

3 Representing Capabilities of RuleML

The Rule Markup Language (RuleML) is a markup language designed for the interchange of various types of Web rules in an XML format that is uniform across various rule languages and platforms [1]. RuleML was developed to express both forward (bottom-up) and backward (top-down) rules in XML for deduction, rewriting, and further inferential-transformational tasks. The specification of RuleML constitutes a modular hierarchical family of Web sublanguages, whose root accesses the language as a whole and whose members identify customized, combinable subsets of the language. Each of the family's sublanguages has an XML Schema definition, addressed by a URI, which permits inheritance between sublanguage schemas and precise reference to the required expressiveness.

Logic rules are in the form A→B, whereas A is called antecedent or condition of the rule, while B is the consequent or the conclusion of the rule. The usual semantics of a rule is that whenever the condition is true, then the conclusion is also true. In other words, the existence of the antecedent causes the existence of the consequent (assuming that existence of something in an e.g. database is equivalent to being true).

An FCM consists of factors (concepts / nodes) which represent the important elements of the mapped system. The strength of the causal relationships between the factors is determined by the directed weighted arcs. Consequently, it is natural to think of rules as a way to represent these causal relationships between concepts. Other scientists also followed this idea, e.g. the FCM system of Jose & Contreras [17], handles casual relationships as rules.The concept nodes are equivalent to things being true, whereas the directed arc is equivalent to the implication operation of a rule between the concepts.

For this reason, we have chosen a rule-based representation of FCMs as a basis for a standard representation language. Moreover, we have chosen RuleML, a de-facto web rule standard, as a candidate language for representing and exchanging FCMs on the Web. The latest version 1.0 of the RuleML standard is employed, coupled with an additional controlled vocabulary in order to cover all the representational requirements of FCMs. This is detailed in the next section.

4 Representation of FCMs Using RuleML

In this section we present how FCM causal relationships can be represented as rules in RuleML. The presented representation is an improved representation of that presented in [21].

An FCM contains a number of arcs that represent causal relationships between its concepts, as it can be seen in Fig. 1. All these relationships have the following form:

Concept1 "**influences**" *Concept2* "**with weight**" *W*.

These FCM causal relationships can be represented in RuleML as rules. In RuleML1.0[1], the above abstract relationship can be represented as follows:

```
<Implies>
     <if>
            <Atom>
                   <op>

                          <Rel>Concept1</Rel>
                   </op>
            </Atom>
     </if>
     <then>
            <Atom>
                   <degree>
                          <Data>W</Data>
                   </degree>
                   <op>
                          <Rel>Concept2</Rel>
                   </op>
            </Atom>
     </then>
</Implies>
```

It can be noticed that such rules are in propositional logic because the atoms in RuleML are not needed to have arguments, since concepts in FCM are atomic with no parameters. For example, the arc in Fig. 1 between concepts C2:"E_Business Sales" and C4:"Customer Satisfaction " with weight 0.2, presents the following causal relationship:

E_Business Sales **influences** *Customers Satisfaction* **with weight** *0.2*.

It can be represented by the following RuleML rule:

```
<Implies>
     <if>
            <Atom>
                   <op>
                          <Rel> e_business sales </Rel>
                   </op>
            </Atom>
     </if>
     <then>
            <Atom>
                   <degree>
                          <Data>0.2</Data>
                   </degree>
                   <op>
                          <Rel> customers satisfaction </Rel>
                   </op>
            </Atom>
     </then>
</Implies>
```

[1] http://ruleml.org/1.0/

Of course, we need a RuleML rulebase with N rules as the above, in order to represent a complete FCM with N arcs/causal relationships. Moreover, for the representation of an FCM statements like the following are required:

Concept "**is set to**" *Value.*

Such statements mean that the activation level of the specific concept should be kept steady to that certain value through the whole simulation process. In RuleML, such statements can be represented as facts about concepts referred to by rules, in the following manner:

```
<Atom>
     <degree>
           <Data>Value</Data>
     </degree>
     <op>
           <Rel>Concept</Rel>
     </op>
</Atom>
```

For example, according the above, to represent in RuleML that "E-Business Sales are set to 0.3" or "E-Business Sales are set to low", the following RuleML code is needed.

```
<Atom>                                  <Atom>
  <degree>                                <degree>
    <Data>0.3</Data>                        <Data>low</Data>
  </degree>                               </degree>
  <op>                                    <op>
    <Rel> e_business sales </Rel>           <Rel> e_business sales </Rel>
  </op>                                   </op>
</Atom>                                 </Atom>
```

A similar representation is required in FCM, for statements like the following:

Concept "**is initially set to**" *Value.*

Statements like the above mean that the activation level of the specific concept initially (at time step 0) is set to the specific value and afterwards, the concept is free to interact with other concepts and to change this value accordingly. In RuleML such statements can be presented again by facts, augmented with an additional "system" modifier argument whose value is the constant "dynamic" from the controlled vocabulary for FCMs.

```
<Atom>
  <degree>
    <Data>Value</Data>
  </degree>
  <op>
    <Rel>Concept</Rel>
  </op>
  <Ind iri="&ctrl;#dynamic"/>
</Atom>
```

So for example, to represent in RuleML that "E_Business Sales are initially set to 0.8" or "E_Business Sales are initially set to high", the following RuleML code is needed.

```
<Atom>                                  <Atom>
  <degree>                                <degree>
    <Data>0.8</Data>                        <Data> high </Data>
  </degree>                               </degree>
  <op>                                    <op>
    <Rel> e_business sales </Rel>           <Rel> e_business sales </Rel>
  </op>                                   </op>
  <Ind iri="&ctrl;#dynamic"/>             <Ind iri="&ctrl;#dynamic"/>
</Atom>                                 </Atom>
```

Other parameters of FCM that must be specified are:

1. the type of transfer function that should be used through the simulation (either the mycin function for Eq. (1) or the recursive function for Eq. (2)),
2. the value of the decay factor d,

In order to represent these global simulation parameters in RuleML, a relative "system" modifier fact is created containing the required information. This atom is of the form:

```
<Atom>
    <op>
        <Rel iri="&ctrl;#transformation-function"/>
    </op>
    <Ind>TRANS_FUN</Ind>
    <Data>DECAY_VALUE</Data>
</Atom>
```

where **TRANS_FUN** is either *mycin* or *recursive* and **DECAY_VALUE** is a decimal between 0 and 0.5. For example:

```
<Atom>
    <op>
        <Rel iri="&ctrl;#transformation-function"/>
    </op>
    <Ind>mycin</Ind>
    <Data>0.1</Data>
</Atom>
```

Notice that the operator of the "system" fact is defined in the controlled vocabulary for FCMs. The name of the transformation function though is not within the controlled vocabulary in order for the RuleML representation for FCMs to be extensible and adaptable to any FCM simulator system and not to be restricted to the specific transformation functions of our system.

Having defined the above representation of FCM in RuleML, the FCM of Fig. 1 can be presented as it appears in Fig. 2:

The controlled vocabulary for FCM is minimal, consisting of one system relation name and one constant only. The mechanism for handling controlled vocabularies in RuleML is open to the application. We have chosen to represent the vocabulary using RDF/RDFS as it is shown below.

```
<?xml version="1.0" encoding="UTF-8"?>
<!DOCTYPE RuleML [    <!ENTITY ctrl "http://lpis.csd.auth.gr/ontologies/2013/fcm.rdf">       ]>
<RuleML xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
xsi:schemaLocation="http://ruleml.org/spec http://www.ruleml.org/1.0/xsd/datalog.xsd"
xmlns="http://ruleml.org/spec">
        <Assert>
                <Atom>
                        <op>
                                <Rel iri="&ctrl;#transformation-function"/>
                        </op>
                        <Ind>mycin</Ind>
                        <Data>0.1</Data>
                </Atom>
                <!--  Rules of an FCM concerning an  E_Business company. -->
                <!--  Rule 1 e_business profits influence e_competition with weight 0.9. -->
                <Implies>
                        <if>
                                <Atom>
                                        <op>
                                                <Rel>e_business profits</Rel>
                                        </op>
                                </Atom>
                        </if>
                        <then>
                                <Atom>
                                        <degree>
                                                <Data>0.9</Data>
                                        </degree>
                                        <op>
                                                <Rel>e_competition</Rel>
                                        </op>
                                </Atom>
                        </then>
                </Implies>
                <!--  Rule 2 e_business sales influence e_business profits with weight 0.9.. -->
                <Implies>

….

                </Implies>

                <!--  fact 1. staff recruitments are set stable to 0.3. -->
                <Atom>
                        <degree>
                                <Data>0.3</Data>
                        </degree>
                        <op>
                                <Rel>staff recruitments</Rel>
                        </op>
                </Atom>
                <!--  fact 2.e_competition is set initially to 0.5. -->
                <Atom>
                        <degree>
                                <Data>0.5</Data>
                        </degree>
                        <op>
                                <Rel>e_competition</Rel>
                        </op>
                        <Ind iri="&ctrl;#dynamic"/>
                </Atom>
        </Assert>
    </RuleML>
```

Fig. 2 RuleML representation of FCM shown in Fig. 1

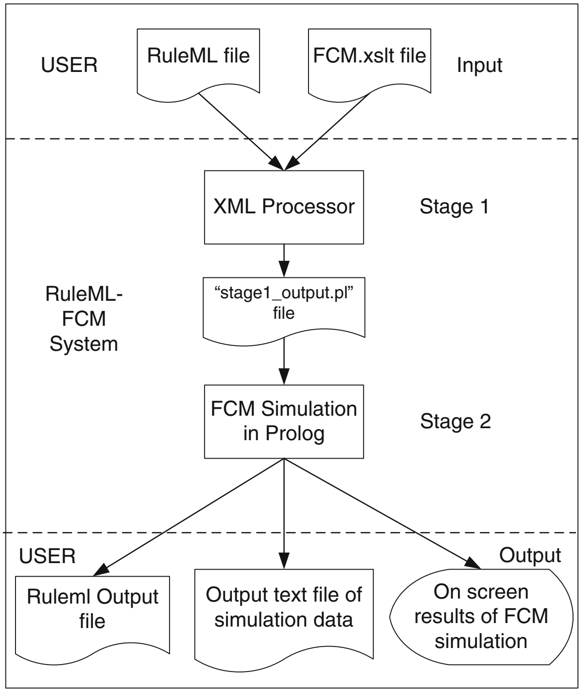


Fig. 3 Stages for the simulation of FCM represented in RuleML

```
<?xml version="1.0"?>
<rdf:RDF
    xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
    xmlns="http://lpis.csd.auth.gr/ontologies/2013/fcm.rdf#"
    xmlns:rdfs="http://www.w3.org/2000/01/rdf-schema#"
  xml:base="http://lpis.csd.auth.gr/ontologies/2013/fcm.rdf">
  <rdfs:Class rdf:ID="transformation-function"/>
  <rdfs:Resource rdf:ID="dynamic"/>
</rdf:RDF>
```

Notice that the relation name is equivalent to an RDFS class, whereas the constant name is an instance of the generic rdfs:Resource class. If we had named slots in the controlled vocabulary for the FCMs, we would have also used RDF properties.

5 Design of the RuleML-FCM Simulation System

Having represented the FCM in RuleML, the next step is that of simulating the represented FCM. The stages for the simulation of scenarios imposed to FCMs, are shown in Fig. 3.

In Stage 1 of the simulation system (a) the RuleML file that represents the FCM and (b) the XSLT file of Fig. 4, are inputted to an XSLT processor which performs

```
<?xml version="1.0" encoding="UTF-8"?>
<!DOCTYPE stylesheet [
          <!ENTITY ctrl "http://lpis.csd.auth.gr/ontologies/2013/fcm.rdf"> ]>
<xsl:stylesheet version="2.0" xmlns:xsl="http://www.w3.org/1999/XSL/Transform"
xmlns:n="http://ruleml.org/spec">
          <xsl:output method="text" version="1.0" encoding="UTF-8" indent="no"/>
          <xsl:template match="/">
                    <xsl:apply-templates select=".//n:Assert"/>
          </xsl:template>
          <xsl:template match="n:Assert">
                    <xsl:apply-templates select=
"n:Atom[n:op/n:Rel/@iri='&ctrl;#transformation-function']" mode="function"/>
                    <xsl:apply-templates select="n:Implies"/>
                    <xsl:apply-templates select="n:Atom[n:op/n:Rel/text()]"/>
          </xsl:template>
          <xsl:template match="n:Implies">
                    with_weight(influences(<xsl:apply-templates select=
"n:if//n:Rel"/>,<xsl:apply-templates select="n:then//n:Rel"/>),<xsl:value-of select=
"n:then//n:degree/n:Data"/>).
          </xsl:template>
          <xsl:template match="n:Atom" mode="function">
          use(<xsl:value-of select="lower-case(n:Ind)"/>).
          decay_is_set_to(<xsl:value-of select="n:Data"/>).
</xsl:template>
          <xsl:template match="n:Atom">
                    <xsl:choose>
                              <xsl:when test=
"n:Ind/@iri='&ctrl;#dynamic'">initially(</xsl:when>
                              <xsl:otherwise>is_set_to(</xsl:otherwise>
                    </xsl:choose>
                    <xsl:apply-templates select=".//n:Rel"/>, <xsl:value-of select=
".//n:degree/n:Data"/>).
          </xsl:template>
          <xsl:template match="n:Rel">
                    [<xsl:for-each select="tokenize(normalize-space(text()), '\s+')">
                              <xsl:value-of select="lower-case(.)"/>
                              <xsl:if test="position()!=last()">,</xsl:if>
                    </xsl:for-each>]
          </xsl:template>
</xsl:stylesheet>
```

Fig. 4 XSLT file for transforming the RuleML representation to a textual FCM representation for the simulation of FCM

with_weight(influences(*Concept1_name_in_list_form* **,** *Concept2_name_in_list_form* **,** *Weight* **).**
is_set_to(*Concept_name_in_list_form* **,** *Weight* **).**
initially(*Concept_name_in_list_form* **,** *Weight* **).**
use(*mycin/recursive* **).**
decay_is_set_to(*Value* **).**

Fig. 5 RuleML Generic Prolog statements of the XSLT transformation

an XSL transformation and produces at the output, a Prolog file having statements of the forms shown in Fig. 5.

In the statements of Fig. 5:

- "*Concept_name_in_list_form*" is a list of one or more words.
- "*Weight*" is either a number in the interval [-1,1], or a linguistic value such as "*very low*", "*low*", "*average*", "*high*" and "*very high*". These linguistic values during

```
use(mycin).
decay_is_set_to(0.1).

with_weight(influences( [e_business,profits] , [e_competition] ), 0.9).
with_weight(influences( [e_business,sales] , [e_business,profits] ), 0.9).
….
with_weight(influences( [e_competition] , [staff,recruitments] ), 0.8).
with_weight(influences( [better,e_services] , [customers,satisfaction] ), 0.9).

is_set_to( [staff,recruitments] , 0.3).
initially( [e_competition] , 0.5).
```

Fig. 6 Content of the "stage1_output.pl" file containing the transformation of the RuleML representation of the FCM shown in Fig. 1, in Prolog statements

the next phase of our system will be translated to the values 0.1, 0.3, 0.5, 0.7, 0.9, respectively.

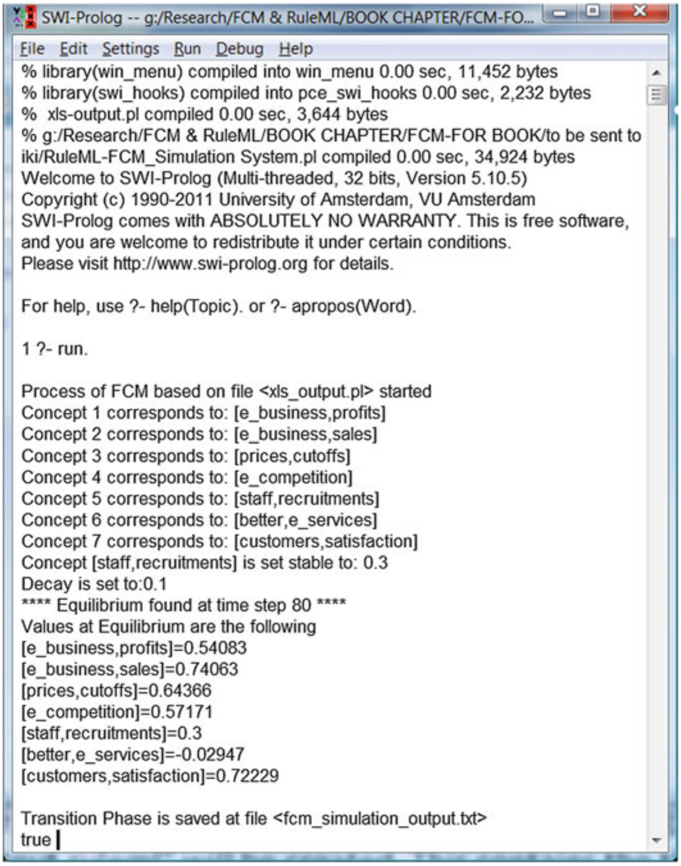
- *"Value"* of the decay factor is a numerical value in the interval [0, 0.5].

Using the above transformation in Stage 1, the RuleML representation of the FCM of Fig. 2 is transformed to that shown in Fig. 6. These statements will be saved to a "stage1_output.pl" file and automatically is inputted to the Prolog subsystem of FCM simulation.

The simulation of the FCM is performed in Stage 2 of the system (see Fig. 3), by a program written in the Prolog programming language [22]. An earlier version of this application is presented in [21]. FCM can reach (a) an equilibrium point, (b) a limit circle periodical behaviour or (c) a chaotic behaviour [23]. If an equilibrium point is reached, as shown in Fig. 3,

1. The activation levels of all FCM's concepts at equilibrium are shown on the computer screen,
2. These activation levels are saved to an output file in a RuleML format as a set of facts, to make them available for use by other systems and
3. The activation levels of the concepts of the FCM model through the transition phase towards this equilibrium point are saved as output data into an text file called "fcm_simulation_output.txt", for possible further examination.

If the FCM reaches a limit circle behaviour or a chaotic behaviour then the system simulates 10,000 time steps of interaction and saves the activation levels of the concepts of the FCM model through these 10,000 time steps to the "fcm_simulation_output.txt" file for further examination by a graph plotting software tool.



```
SWI-Prolog -- g:/Research/FCM & RuleML/BOOK CHAPTER/FCM-FO...
File Edit Settings Run Debug Help
% library(win_menu) compiled into win_menu 0.00 sec, 11,452 bytes
% library(swi_hooks) compiled into pce_swi_hooks 0.00 sec, 2,232 bytes
%  xls-output.pl compiled 0.00 sec, 3,644 bytes
% g:/Research/FCM & RuleML/BOOK CHAPTER/FCM-FOR BOOK/to be sent to
iki/RuleML-FCM_Simulation System.pl compiled 0.00 sec, 34,924 bytes
Welcome to SWI-Prolog (Multi-threaded, 32 bits, Version 5.10.5)
Copyright (c) 1990-2011 University of Amsterdam, VU Amsterdam
SWI-Prolog comes with ABSOLUTELY NO WARRANTY. This is free software,
and you are welcome to redistribute it under certain conditions.
Please visit http://www.swi-prolog.org for details.

For help, use ?- help(Topic). or ?- apropos(Word).

1 ?- run.

Process of FCM based on file <xls_output.pl> started
Concept 1 corresponds to: [e_business,profits]
Concept 2 corresponds to: [e_business,sales]
Concept 3 corresponds to: [prices,cutoffs]
Concept 4 corresponds to: [e_competition]
Concept 5 corresponds to: [staff,recruitments]
Concept 6 corresponds to: [better,e_services]
Concept 7 corresponds to: [customers,satisfaction]
Concept [staff,recruitments] is set stable to: 0.3
Decay is set to:0.1
**** Equilibrium found at time step 80 ****
Values at Equilibrium are the following
[e_business,profits]=0.54083
[e_business,sales]=0.74063
[prices,cutoffs]=0.64366
[e_competition]=0.57171
[staff,recruitments]=0.3
[better,e_services]=-0.02947
[customers,satisfaction]=0.72229

Transition Phase is saved at file <fcm_simulation_output.txt>
true
```

Fig. 7 Output of RuleML—FCM simulation system for an FCM concerning an e-business. Scenario #1: "staff recruitments" is set to 0.3. Equilibrium reached after 80 time steps

6 Demonstration of the RuleML-FCM Simulation System

The RuleML-FCM simulation system is implemented in SWI-Prolog (http://www.swi-prolog.org/), following the design described in the previous section. To demonstrate its implementation, the FCM of Fig. 1 will be used, in which "staff recruitment" is set to 0.3. This scenario (let's call it scenario #1) attempts to predict the consequences of a small increase to the number of employees of the e-business company. To examine this scenario, the RuleML representation of FCM of Fig. 1 (as shown in Fig. 2) is saved to a file called "FCM for e-business.ruleml" and inserted to the RuleML-FCM system together with the "fcm.xslt" file of Fig. 4. The output of the system is shown in Fig. 7.

Seven (7) different concepts are identified and one of them, concept "staff recruitment", is set constant to 0.3. After 80 time steps, FCM reaches an equilibrium point

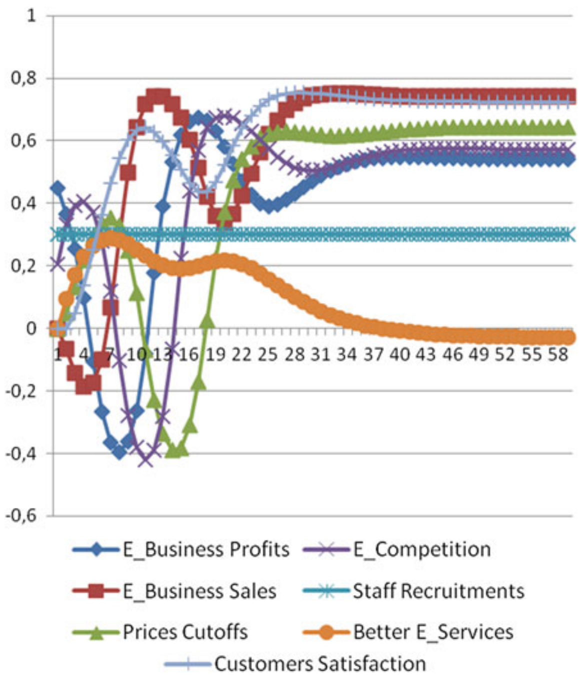


Fig. 8 RuleML Transition phase towards equilibrium for scenario #1

to the state that is presented in Fig. 7. From that, we can conclude that the small increase to the number of employees (0.3), leads to a significant increase to competition from other companies (0.57171). This causes a significant decrease to prices (prices cutoffs = 0.64366) that leads to a significant increase to sales and profit of the ebusiness company (e_business sales = 0.74063 and e_business profits = 0.54083). The satisfaction of the customers is increased (0.72229). The small increase to the number of employees (0.3), did not cause to any change to the quality of the offered e-services (better e_services = −0.02948) because of the large increase to the number of sales.

The data of the interactions during the 80 time steps are saved to an output text file. This file can be processed by a graph plotting software tool and the transition phase towards equilibrium can be exhibited. This transition phase for the case above is shown in Fig. 8. Additionally, a RuleML output file is created, as shown in Fig. 9, containing the activation levels of all FCM's concepts at equilibrium point, represented as RuleML facts. This facilitates the use of FCM's results by other systems, using the common RuleML representation.

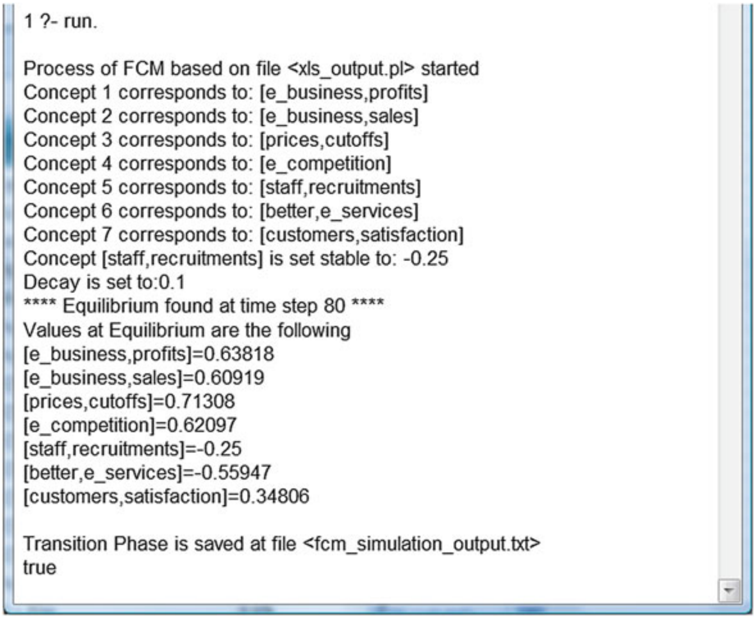
Other "what-if" scenarios can be studies with the system, in order the decision maker to examine the predicted outcomes according to the FCM. In this new scenario #2, we would like to predict the consequences of a small decrease of the number of employees of the e-business company (instead of a small increase which was the case

```
<RuleML xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
         xsi:schemaLocation="http://ruleml.org/spec
                  http://www.ruleml.org/1.0/xsd/datalog.xsd"
         xmlns="http://ruleml.org/spec">
        <Assert>
                <Atom>
                        <degree>
                                <Data>0.72229</Data>
                        </degree>
                        <op>
                                <Rel>customers satisfaction</Rel>
                        </op>
                </Atom>
                <Atom>
                        <degree>
                                <Data>-0.02948</Data>
                        </degree>
                        <op>
                                <Rel>better e_services</Rel>
                        </op>
                </Atom>
                <Atom>
…
…
                </Atom>
                <Atom>
                        <degree>
                                <Data>0.54083</Data>
                        </degree>
                        <op>
                                <Rel>e_business profits</Rel>
                        </op>
                </Atom>
        </Assert>
</RuleML>
```

Fig. 9 RuleML output file representing the activation levels of FCM's at equilibrium for scenario #1

in scenario #1). To simulate this scenario, concept "staff recruitment" is set constant to value "−0.25". Running this new scenario #2, the outcome is that of Fig. 10.

Once again seven different concepts are identified, and one of them, concept "staff recruitment", is set constant to −0.25. After 80 time steps, FCM reached an equilibrium point, with the concepts to be activated to the degree shown in Fig. 10. It can be concluded that according to the FCM predictions, the small decrease of the number of employees leads to a decrease of the quality of the provided e-services (better e-services = −0.55947). The company reacts with severe discounts (prices cutoffs = 0.71308) that cause significant increase in sales and profits (e-business sales = 0.60919 and e-business profits = 0.63818). A small increase of customers satisfaction is predicted (customer satisfaction is 0.34806) while competition is significantly increased (e-competition = 0.62097). A RuleML output file is created, containing the activation levels of FCM's concepts at equilibrium. Additionally, an output text file is created, containing the data of the interactions during the 80 time steps. Based on this data, Fig. 11 is created.



```
1 ?- run.

Process of FCM based on file <xls_output.pl> started
Concept 1 corresponds to: [e_business,profits]
Concept 2 corresponds to: [e_business,sales]
Concept 3 corresponds to: [prices,cutoffs]
Concept 4 corresponds to: [e_competition]
Concept 5 corresponds to: [staff,recruitments]
Concept 6 corresponds to: [better,e_services]
Concept 7 corresponds to: [customers,satisfaction]
Concept [staff,recruitments] is set stable to: -0.25
Decay is set to:0.1
**** Equilibrium found at time step 80 ****
Values at Equilibrium are the following
[e_business,profits]=0.63818
[e_business,sales]=0.60919
[prices,cutoffs]=0.71308
[e_competition]=0.62097
[staff,recruitments]=-0.25
[better,e_services]=-0.55947
[customers,satisfaction]=0.34806

Transition Phase is saved at file <fcm_simulation_output.txt>
true
```

Fig. 10 Output of RuleML—FCM simulation system. Scenario #2: Staff recruitments is set to −0.25. Equilibrium found after 80 time steps

Another scenario (scenario #3) is tried with the system, to examine the consequences of a more severe decrease of the number of the e-business employees, than that of scenario #2. In scenario #3, the concept "*staff recruitment*" is set constant to value "−0.5" (instead of −0.25 of scenario #2). Running this scenario in the system, the outcome is that of Fig. 12. As it is shown in that figure, after 114 time steps, FCM reached an equilibrium point, with the concepts to be activated to the degrees shown in Fig. 12. It can be concluded that according to the FCM predictions, that the severe decrease to the number of employees causes serious problems. The quality of the provided e-services is decreased (better e_services = −0.33472) and the same applies for e-competition (−0.59306). Prices are increased (prices cutoffs = −0.59306), leading to severe decrease in sales and profits (e-business sales = 0.75698 and e-business profits = 0.4687). The transition phase according to the data of the output file is shown in Fig. 13. A RuleML output file is also created, containing the activation levels of FCM's concepts at equilibrium.

To examine the effect of an increase to the prices, scenario #4 is imposed to the system. According to this scenario, "prices cutoffs" is decreased to a degree of −0.3. The output of the systems for this scenario, is that of Fig. 14. After 167 time steps, (as it is shown in Fig. 14) FCM reached an equilibrium point, with the concepts to be activated to the degrees shown in Fig. 14. According to the FCM predictions, this is very bad scenario for the company. Even this small increase in prices leads to severe decrease in sales and profits (e-business sales = −0.67154 and e-business profits

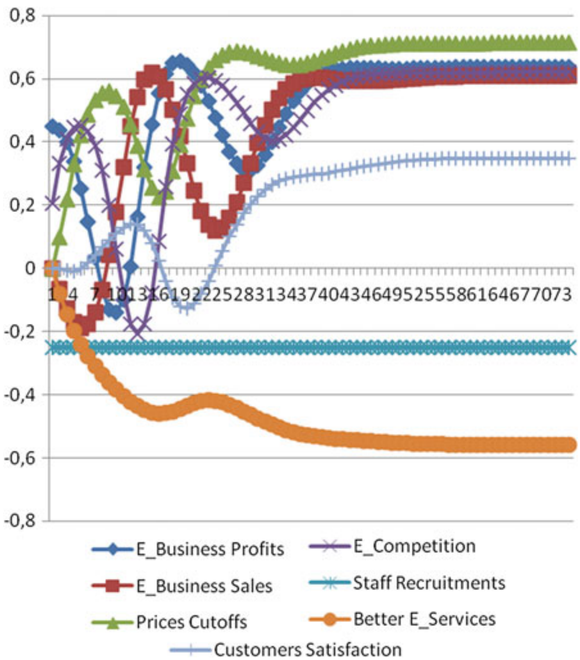
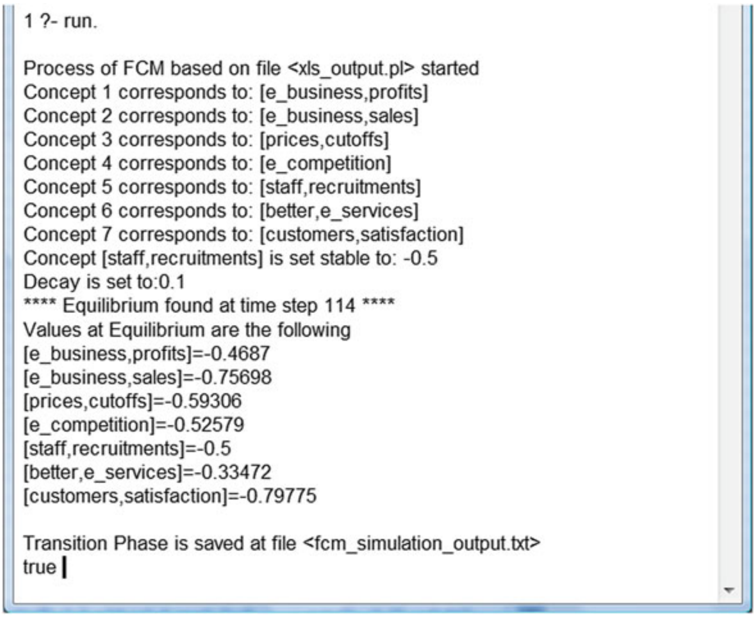


Fig. 11 Transition phase towards equilibrium for scenario #2


1 ?- run.

Process of FCM based on file <xls_output.pl> started
Concept 1 corresponds to: [e_business,profits]
Concept 2 corresponds to: [e_business,sales]
Concept 3 corresponds to: [prices,cutoffs]
Concept 4 corresponds to: [e_competition]
Concept 5 corresponds to: [staff,recruitments]
Concept 6 corresponds to: [better,e_services]
Concept 7 corresponds to: [customers,satisfaction]
Concept [staff,recruitments] is set stable to: -0.5
Decay is set to:0.1
**** Equilibrium found at time step 114 ****
Values at Equilibrium are the following
[e_business,profits]=-0.4687
[e_business,sales]=-0.75698
[prices,cutoffs]=-0.59306
[e_competition]=-0.52579
[staff,recruitments]=-0.5
[better,e_services]=-0.33472
[customers,satisfaction]=-0.79775

Transition Phase is saved at file <fcm_simulation_output.txt>
true

Fig. 12 Output of RuleML—FCM simulation system. Scenario#3:"Staff recruitments" is set to −0.5

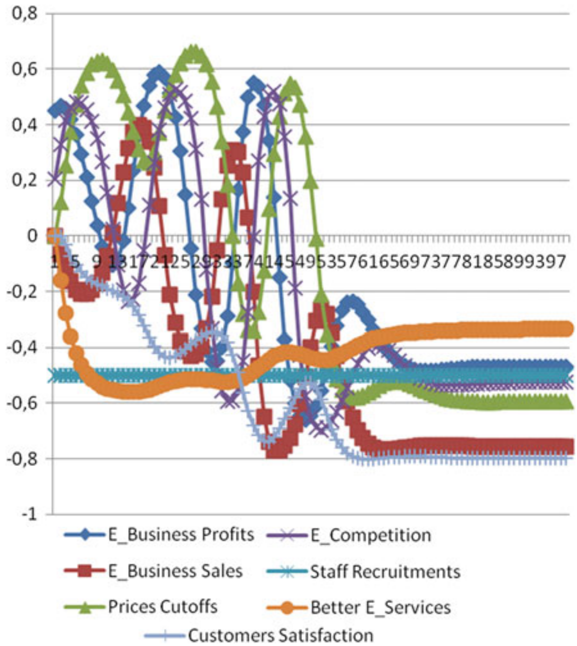
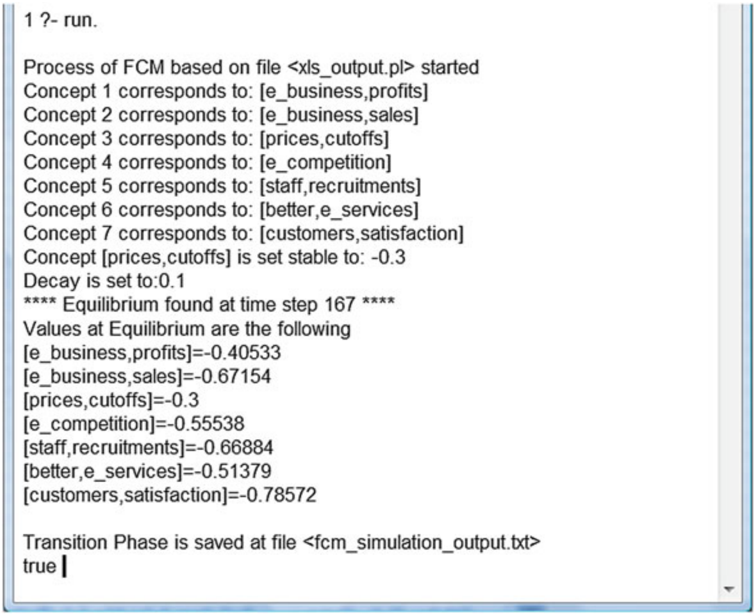


Fig. 13 Transition phase of an FCM concerning a car industry for scenario #3



```
1 ?- run.

Process of FCM based on file <xls_output.pl> started
Concept 1 corresponds to: [e_business,profits]
Concept 2 corresponds to: [e_business,sales]
Concept 3 corresponds to: [prices,cutoffs]
Concept 4 corresponds to: [e_competition]
Concept 5 corresponds to: [staff,recruitments]
Concept 6 corresponds to: [better,e_services]
Concept 7 corresponds to: [customers,satisfaction]
Concept [prices,cutoffs] is set stable to: -0.3
Decay is set to:0.1
**** Equilibrium found at time step 167 ****
Values at Equilibrium are the following
[e_business,profits]=-0.40533
[e_business,sales]=-0.67154
[prices,cutoffs]=-0.3
[e_competition]=-0.55538
[staff,recruitments]=-0.66884
[better,e_services]=-0.51379
[customers,satisfaction]=-0.78572

Transition Phase is saved at file <fcm_simulation_output.txt>
true
```

Fig. 14 Output of RuleML—FCM simulation system. Scenario #4:“prices cutoffs” is set to −0.3

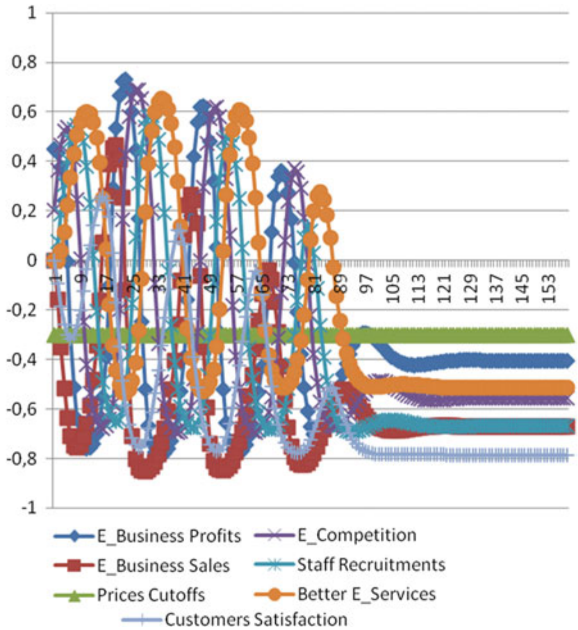


Fig. 15 Transition phase of the FCM for scenario #4. Equilibrium reached after 167 time steps

```
1 ?- run.

Process of FCM based on file <xls_output.pl> started
Concept 1 corresponds to: [e_business,profits]
Concept 2 corresponds to: [e_business,sales]
Concept 3 corresponds to: [prices,cutoffs]
Concept 4 corresponds to: [e_competition]
Concept 5 corresponds to: [staff,recruitments]
Concept 6 corresponds to: [better,e_services]
Concept 7 corresponds to: [customers,satisfaction]
Concept [prices,cutoffs] is set stable to: -0.3
Decay is set to:0.1
Transition Phase is saved at file <fcm_simulation_output.txt>
true
```

Fig. 16 Output of RuleML—FCM simulation system. Scenario#5: "prices cutoffs" is set to −0.3. "price cutoffs" influences "customers satisfaction" with weight 0.4 (instead of 0.7 that is in scenario #4)

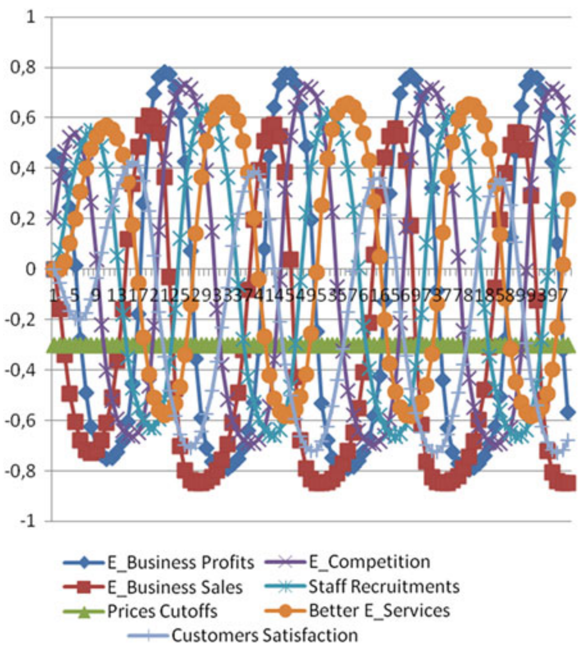


Fig. 17 Transition phase of the FCM for scenario #5. Limit cycle behaviour is reached

= −0.40533). The quality of the provided e-services is decreased and customers satisfaction is severely decreased. A decreased of the number of employees and e-competition is predicted (staff recruitments = −0.66884, e-competition = −0.55538). According to the data of the output file, the transition phase is that of Fig. 15. Similarly to the previous scenario, a RuleML output file is created, containing the activation levels of FCM's concepts at equilibrium.

The RuleML-FCM system can also examine scenarios in which one or more weights of the connections between the FCM's concepts are changed. For example, lets create another scenario (scenario #5), which is similar to scenario #4 ("prices cutoffs" is set to −0.3) but in scenario #5 the weight of the influence of "price cutoffs" to "customers satisfaction" is 0.4, instead of 0.7 that is in scenario#3. In other words, scenario #5 examines how scenario #4 is affected by a change of the strength that "price cutoffs" influences "customers satisfaction". This scenario is imposed to the system and the outcome is that of Fig. 16. No equilibrium point is reached after 10,000 iterations. To examine the dynamical behaviour of this scenario, Fig. 17 is created based on the data of the output file. It is apparent that the FCM enters a limit cycle behaviour where all concepts periodically are getting high and low. For the e-business company, it can be concluded that these concepts will continuously increase and decrease, meaning that there will be strong interactions and no equilibrium for this scenario.

For the e-business company, scenario #5 is better than scenario #4 because the outcome of scenario #4 is very bad while scenario #4 products strong interactions between of the concepts of the FCM but not a equilibrium to a bad position for the e-business company. It is interesting to notice that the results of the same action (increase in prices) can lead to different outcome, even when a single interaction in FCM is changed (weight between "price cutoffs" and "customers satisfaction" in the above case). This indicates that:

1. Experts should be very careful when they create an FCM.
2. Decision makers, by using FCMs, can also be supported in their decisions by examining scenarios that involve the change of the weights between the interactions of the FCM's concepts.
3. Decision makers can also use results of FCM's scenarios in order to examine what structural changes should strategically be done, in order to reach the desired results.

More scenarios can be created and the predicted outcome will be immediately received. This is highly appreciated by decision makers that are willing to examine a number of "what-if" scenarios and check the predicted consequences of these scenarios.

7 Conclusions

In this chapter, a RuleML representation of FCMs is proposed that make FCMs:

- reusable and transferable,
- ready to interact with other systems that interact with RuleML,
- easily managed within a repository, that is important for FCM researchers and practitioners.

Additionally, a program written in Prolog is designed and implemented which:

- Simulate scenarios written in the form of the RuleML representation of FCM.
- Present the equilibrium point of the imposed scenario.
- Produce a RuleML output file that contains the activation levels of FCM's concepts at equilibrium.
- Produce an output file that contains the data of the transition phase to visualize it, if the user wants to.

The use of the system above is illustrated using a number of examples, to prove its utility for decision makers working with FCMs. It was found that:

- The representation of FCMs in RuleML is simple, given that numerous user-friendly XML editors exist.
- No programming skills are required to create and simulate FCMs.
- A number of different scenarios can be examined rapidly and easily, having the decision maker focused on the FCM itself and not to computer technicalities.

In the future we would like to work towards (a) the development of a user-friendly editor for building FCMs, such as a natural language interface to feed directly the Prolog simulator (e.g. in ACE [24]), and/or a graphical/visual RuleML-ware editor, as in [25], (b) the integration of the various functionalities of the system into a single stand-alone web application that will help disseminate FCM research and development.

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Chapter 5
Fuzzy Web Knowledge Aggregation, Representation, and Reasoning for Online Privacy and Reputation Management

Edy Portmann and Witold Pedrycz

Abstract A social Semantic Web empowers its users to have access to collective Web knowledge in a simple manner, and for that reason, controlling online privacy and reputation becomes increasingly important, and must be taken seriously. This chapter presents Fuzzy Cognitive Maps (FCM) as a vehicle for Web knowledge aggregation, representation, and reasoning. With this in mind, a conceptual framework for Web knowledge aggregation, representation, and reasoning is introduced along with a use case, in which the importance of investigative searching for online privacy and reputation is highlighted. Thereby it is demonstrated how a user can establish a positive online presence

1 Introduction

As nowadays more and more humans are social media literate, we bear down on an interconnected information space. However, there are limits to social applications such as blogging, social networks and wikis, concerning information integration, dissemination, reuse, portability, searchability, automation and more challenging tasks like querying. This is where semantic applications come into play, in which knowledge is expressed in a computer-understandable language. With the intention to enable computers to grasp meaning as humans do, the Semantic Web includes layers built on the current Web, which describes concepts and relationships, following

E. Portmann (✉)
Department of EECS, University of California, Berkeley, CA, USA
e-mail: portmann@eecs.berkeley.edu

W. Pedrycz
Department of ECE, University of Alberta, Edmonton, Canada

W. Pedrycz
Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland
e-mail: wpedrycz@ualberta.ca

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logical rules [1]. The vision is to provide humans automated assistance in everyday tasks, for example through incorporating respective Semantic Web technologies into social applications.

From the point of logic, however, it is known that no system could ever be both consistent and complete and that no sufficiently rich interpreted language can fully represent its own semantics [2, 3]. To make the matter worse, there even exists a class of NP-complete problems that basically cannot be solved efficiently by current computers [4]. In contrast, human beings seem to thrive on this; they live and make decisions without knowing all the facts. What is striking is that all these human activities, to a great extend, entail imprecision, uncertainty, and partial truth.

Characterized by Web users needs to have the power to define themselves online (and in life), and by the fact that evermore uncontrolled information is available, in a forthcoming social Semantic Web, a user should be endorsed to manage his online privacy and reputation. To do this reliably, the Semantic Web has to overcome its limitations, by dealing with approximations [5]. On this account, deriving fuzzy meaning from the massive amount of online discussions, and gain a deeper understanding [6] is a key concern of media applications in a social Semantic Web.

This Web is an enhanced Semantic Web that combines its vision with socially accepted applications. Among other things, its applications admit facilitated information integration, dissemination, reuse, portability, searchability, automation and querying. Web users learn by conversations, and create new knowledge in the context of it. A social Semantic Web allows computers to help users create even more knowledge and also to learn from each other (more efficiently). On one hand, computers in the Semantic Web collect, store, remember, search, and combine users Web data, and on the other hand, they draw logical conclusions from and make predictions about these data [7]. Generally speaking, techniques for a social Semantic Web should resemble organic processes more closely than traditional techniques, which are largely based on mathematical logic systems, and which strive for exactness and full truth. Hence, unlike these systems as todays Semantic Web is built on, social Semantic Web applications exploit the given tolerance of imprecision, partial truth, and uncertainty [6].

Using Fuzzy Cognitive Maps (FCM) to address Web knowledge aggregation, representation, and reasoning, in this chapter we present an approximated, yet practicable and robust framework as solution to seize the presented requirements of online privacy and reputation management. The next section provides background knowledge around a social Semantic Web we strive for. Section 3 introduces the notion of using investigative searches for online privacy and reputation management. In Sect. 4, we present the Web knowledge aggregation, representation, and reasoning framework. Based on FCM techniques, approximated ontologies can be derived that quasi represent the Semantic Web's knowledge. Through interactive visualization, an aggregated FCM allows investigative seekers for online privacy and reputation browsing netlike knowledge structures, and support their reasoning. Finally, conclusion and future research directions are outlined in Sect. 5.

2 Towards a Social Semantic Web

This section illustrates the evolution of the Web to a social Semantic Web. Step-by-step we explain how to tackle today's Semantic Web issues using FCMs; to that end, Sect. 2.1 introduces into the Semantic Web; Sect. 2.2 into Web agents; Sect. 2.3 in FCMs; and Sect. 2.4 brings together the previous parts.

2.1 The Semantic Web

The Semantic Web is "*an extension of the current Web in which information is given well-defined meaning, better enabling computer and people to work in cooperation.*" [1]. The prefix *semantics* thereby suggests computer understanding of the meaning of the human-readable Web content. Yet, to teach computers meaning, the difficulty is defining relations from the syntactic structure of a human language to an appropriate model [8]. To tackle this issue, typically *ontologies* are used. In conventional sense, these ontologies explore the nature of being, existence, or reality, as well as the basic categories of being and their relations. They cover topics like what entities exist or can be said to exist, and how such entities can be grouped, related within a hierarchy, and subdivided according to similarities and differences.

In the Semantic Web "*ontologies are conceptual models that capture and make explicit the vocabulary used in a domain or in a semantic application, thereby guaranteeing the absence of ambiguities.*" [9], and Gruber adds, that "*an ontology is readable for both humans and machines. Together with a syntax and semantics, it provides the language by which knowledge-based systems can interoperate, e.g. exchanging assertions, queries, and answers. The ontology determines what "exists" for a system.*" [10]. More formally, an ontology $O \in D$ (i.e., domain) contains different concepts C, the properties P of the concepts C, as well as the relationships R that exist between the concepts C. In such an ontology, the meaning of a symbol is expressed in a specific language L [11]. The outcome is an index of the types of things that are assumed to exist in D from the perspective of a user who uses L for the purpose of talking about D. The types of O represent the predicates, word senses, or concept and relation of L when used to discuss topics in D. It is a description (i.e., a formal specification of a program) of the domain, as it exists for a user or an agent. In the Semantic Web several distinct ontology languages emerged; examples are RDF,[1] RDFS,[2] FOAF,[3] XTM,[4] DAML+OIL,[5] and OWL.[6]

[1] http://www.w3.org/RDF/

[2] http://www.w3.org/TR/rdf-schema/

[3] http://www.foaf-project.org/

[4] http://www.isotopicmaps.org/sam/sam-xtm//

[5] http://www.w3.org/TR/daml+oil-reference

[6] http://www.w3.org/TR/owl2-primer/

In order to integrate data, information, and knowledge from several ontologies, agents are needed that merge the individual ontologies to a new ontology [12]. In this sense, data (showing at the lowest level of abstraction), information (i.e., intermediated level), and knowledge (i.e., highest level among all three) can be shared as well as reused across applications, enterprises, and community boundaries [13]. The next subsection looks at Web agents more precisely, which are used to collect data, information, and knowledge from Semantic Web sources.

2.2 Semantic Web Agents

In the last years, the volume of the Web increased, what led eventually to modern Web search engines prevalence, due in no small parts to Web agents [14]. The Web remains intelligible to its human users because it is steadily analyzed and monitored by these automatic agents. *Reactive agents* perform unsophisticated behavior patterns, whereas *cognitive agents* have considerable better-elaborated behavior patterns (e.g., the ability to pursue goals, plan actions and to negotiate with other agents to reach objectives, etc.). The reactive agents strength, however, is their capability of protruding an emergent global behavior beyond the behavior of individual agents [12].

Today, Web crawlers are basically used to create copies of visited Web pages for later processing by a search engine that index the downloaded pages to provide users fast searches. A crawler takes as input a set of starting pages that are downloaded, parsed and scanned for new links. The links pointing to pages that have not yet been downloaded are superimposed to a central queue of URLs for a later retrieval. Following a set of rules, the crawlers select a new page from the queue to download and to process, is repeated until reaching a (potential) stop criterion.

In order to prepare an ontology, a Web crawler needs to be extended and should not only collect URLs but also other data used. The notion of crawlers can be employed to aggregate existing ontologies in the Semantic Web; examples are the DAML Crawler,[7] the RDF Crawler,[8] or FOAF Scutter,[9] and the OCRA Crawler.[10] These crawlers imply an add-on to traditional reactive Web agents with cognitive behavior.

The aggregated ontologies now need to be aligned following a process, where correspondences between ontologies are determined. Given a set of n crawled ontologies $O = \{O_1, \ldots, O_n\}$ possibly stored at different locations on the Web and in different formats are matched against a new ontology O^{new}. In doing so wrappers $W = \{W_1, \ldots, W_n\}$ help to transform the different formats of the ontologies to the new global ontology O^{new} (see Fig.1).

[7] http://www.daml.org/crawler/

[8] http://ontobroker.semanticweb.org/rdfcrawl/index.html

[9] http://code.google.com/p/slug-semweb-crawler/

[10] http://www.mindswap.org/~golbeck/downloads/ocra.shtml

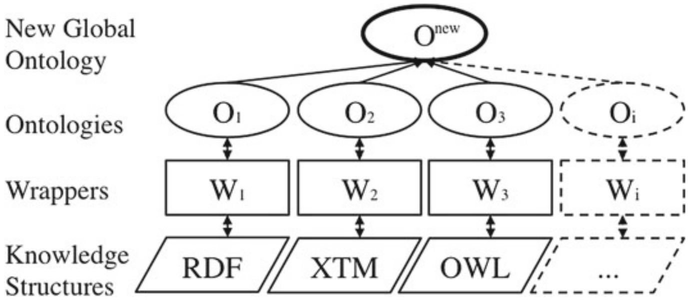

Fig. 1 Ontology alignment using semantic web agents

In order to answer imprecision, uncertainty, partial truth, and approximation, the ontology alignment process should go back to the use of inexact solutions to computationally hard tasks (see next subsection).

2.3 Fuzzy Cognitive Maps

In a distributed and open system as the Semantic Web, it is impossible to avoid heterogeneity of concepts [12]. So what is needed are means automatically rebalance these issues to align ontologies in an organic manner. This means should be powerful enough to negotiate meaning in a real-life approximated context, somehow similar as humans do in everyday communications [15]. For this purpose, fuzzy logic seems eminently suitable, because it mimics human behavior [16], resulting in an enhanced human-computer relationship (i.e., the computer can respond to user in a human way). A combination of fuzzy logic with cognitive maps yields structures that resemble neural networks (i.e., imitating human neurons).

Incidentally, the credit for the creation of cognitive maps is often given to Tolman [17], although the concept dates back to 1913 [18]. To represent social-scientific knowledge, in the seventies Axelrod used an interconnected diagraph [19]. Introduced by Kosko [20], primarily with semi-quantitative attributes [21], a *Fuzzy Cognitive Map (FCM)* is a directed graph with concepts C as nodes and causalities as edges, representing causal relationship between concepts C. Unlike ordinary neural networks, however, FCMs boast high transparency [22]. For an overview of the concept, we may refer to [23, 24]. Using fuzzy logic's epistemic facet [25] allows defining fuzzy ontologies 0 with expressions from natural language L [6]. When the nodes (i.e., concepts) are fuzzy sets then they are called fuzzy nodes. The causalities represent the relationships R with properties P (see Sect. 2.1). However, FCMs that restrict causalities (i.e., edge weights W) to the set $\{-1, 0, 1\}$ are called simple (see Fig. 2); thereby the value of -1 represents full negative, +1 full positive, and 0 denotes neutral relation [21, 26]. Note that using α-cuts [27], complex FCMs can be transformed to simple FCMs.

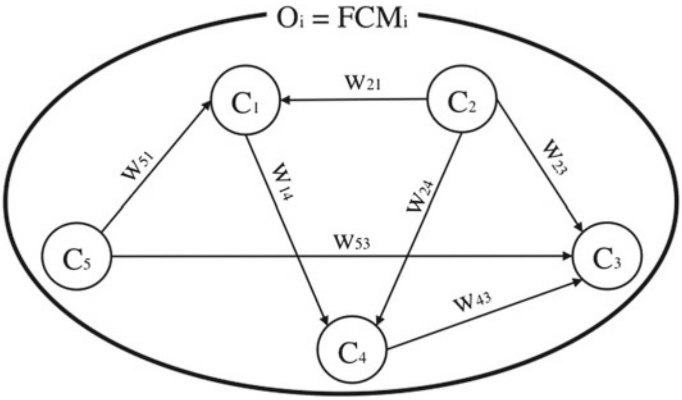

Fig. 2 A simple fuzzy cognitive map

The next subsection highlights how FCMs can be used in order to make the Semantic Web more social.

2.4 *From a Semantic Web to a Social Semantic Web*

This subsection is about the Web evolution to a more social Semantic Web, which combines the Semantic Web vision with socially accepted applications. In order to enable computers better meet human users (e.g., through adaptive interfaces [6, 28]), a social Semantic Web draws on techniques that resemble organic processes more closely than traditional ones. To adaptively address individual human user, an *intelligent interface* exploits carefully the human-inherent tolerance of imprecision, partial truth, and uncertainty [29].

In the social Semantic Web, FCMs can be used to bridge the gap between a human-centered Web and the technique-centered Semantic Web (see Fig. 3): Firstly, based on expert's opinion (see, e.g., [30, 31]) that is ready and stored in Semantic Web ontologies (see, e.g., [12]), they are very simple, thus leading to a quicker social

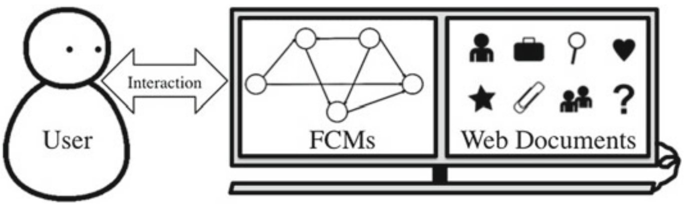

Fig. 3 Fuzzy cognitive maps to bridge the gap between human and computers

acceptance than more complicated systems. Secondly, in an information integration process the different concepts of the Semantic Web ontologies only need to be crawled and wrapped to FCMs, and eventually matched against another FCM. Thereby the combined FCM^{new} naturally averages the FCMs and their corresponding causal descriptions as well as much of their dynamics [32]. Thirdly, as a technique that exposes hidden patterns, when the data happens to be unsupervised, FCMs become reasonable practicable [26]. Through an interactive visualization of the aggregated Web knowledge as FCMs in a human-computer interaction process, a Web user can investigate hidden knowledge patterns [6, 33] eventually allowing reasoning for human and computers (i.e., there is already software that automatically supports human reasoning process such as EYE,[11] Jena,[12] OpenCyC,[13] Pyke,[14] etc.).

Allowing information integration, dissemination, reuse, portability, searchability, automation, and querying, these are all required features of an online privacy and reputation management application. Most of these application start with a Web (reputation) search engine that can benefit from FCMs. The next section introduces into online privacy and reputation management, and underlying idea of investigative search.

3 Investigative Search for Online Reputation Management

This section introduces FCMs in online privacy and reputation management; Sect. 3.1 presents online privacy and reputation management that is becoming increasingly important in a social Semantic Web; and Sect. 3.2 introduces the notion behind investigative Web search for online privacy and reputation management.

3.1 Online Privacy and Reputation Management

Since all organisms seek sustenance and propagation, searches deeply affect our lives [34]. With the advancement of computers to consumer products and the evolution of the Internet as mass medium [35], searching the Web evolved into a daily activity for everyone. Built on crawlers, the Web made searches a lot easier, and, in turn, users put a lot more of their life in the Web.

Since today's life is defined by search results, however, search engines results can include information that is irrelevant or out of context [36]. Modern Web search engines imperil users to quickly rank negative or slanderous results. If one does not protect, someone can post a comment, make a video, create a blog post, file a

[11] http://eulersharp.sourceforge.net/2003/03swap/eye-note.txt

[12] http://jena.apache.org/

[13] http://www.opencyc.org/

[14] http://pyke.sourceforge.net/index.html

complaint, promote a competition, and develop a hate site or worse [37]. These search results can affect negatively a business or career, if the information is fallacious or misleading (e.g., false accusations or exaggerated negative reviews, etc.). Because it is habitually obscure how many have seen that misinformation online or how many have passed along this information offline the extent of the damage can only be estimated.

Web users have to realize that they must play their part in protecting their privacy [38]. Since current laws are insufficient to prevent damaging a users reputation or harvesting private information (e.g., without adequate protection, personal information could be sold by information traders), *online privacy and reputation management* is critical. For this reason a monitoring of a users reputation is advisable, and should not be understood as impudent promotion [36]. Originating from the mindset that everyone should have the power to define himself in life (as well as online), this is rather a form of (self) defense and best practice. When someone is chasing a dream school, job or relationship, the first impression will probably be made online.

The following subchapter introduces the concept of investigatory search as basis for identifying online privacy and reputation. Shaped according Web search engines principles, a reputation search engine can help monitor online reviews from all over the Web, and subsequently establish a positive Web presence [37]. Therewith one can straightforwardly detect personal information from websites that collecting some and help to protect privacy and identity. On this basis it is possible to set the records straight by pushing down false and misleading search results with positive material in one's own control.

3.2 Investigative Web Search Engines

When a user enters a query, a Web search engine examines its Web crawler-produced index (see Sect. 2.2) and provides a list of best-matching websites. The usefulness of a search engine depends on the *relevance* of the returned websites. Traditionally *recall* (i.e., the number of relevant objects that are retrieved from Web data) and *precision* (i.e., the number of retrieved objects that are relevant) are used as quality measurement of a search engine. Yet, Marchionini [34] makes a significant distinction between lookup searches (i.e., traditional view of searching the Web) and exploratory search (i.e., new view that also addresses more investigative searching the Web). This searching investigates more in recall (i.e., maximizing the number of possibly relevant objects that are retrieved) than precision (i.e., minimizing the number of possibly irrelevant objects that are retrieved).

In *investigative search*, different levels of interaction for automatic query reformulation are studied that leverage the traditional measurements of precision and recall but apply them to the results of multiple iterations of user interaction, rather than to a single query response. Ingwersen defines this as "*interactive communication processes that occur during the retrieval of information by involving all the major participants in information retrieval* [...]*, i.e., the user, the intermediary, and the*

IR system." [39]. In an investigative search it is crucial to study the interactions of Popper's *second* and *third world*, to describe and explain them if they can and so to help in organizing knowledge (rather than data and information) for more effective use [40]. Most systems, however, point to data and information, giving physical access via representations to *world one* objects [39, 40]. Investigative search covers a broad class of activities, such as exploring, evaluating, comparing, and synthesizing. Seekers in an investigative search process generally combine querying and browsing strategies to foster investigation (and learning) [34].

Using FCMs it is possible to bring Popper's three worlds together [40]. In the next section, FCMs are employed as help in investigative search for a Web users online privacy and reputation. Thereby aggregated FCMs act as approximated causal Web knowledge (i.e., top-level ontology) that can interactively visualized (e.g., for investigative search), and even support human user with reasoning.

4 Fuzzy Cognitive Maps in the Social Semantic Web

This section presents the Web knowledge aggregation, representation, and reasoning framework; with this in mind, Sect. 4.1 introduces into the conceptual framework; Sect. 4.2 illustrates the aggregation component; Sect. 4.3 the representing component; and Sect. 4.4 the reasoning component. Last but not least, a short use case for this framework is presented in Sect. 4.5.

4.1 Fuzzy Cognitive Maps for Knowledge Aggregation, Representation, and Reasoning

In the Semantic Web different actors have different interests and habits, use different tools and knowledge, and most often, at different levels of detail. These many reasons for heterogeneity lead to diverse forms of knowledge, and, therefore, should be considered in investigating online privacy and reputation. According to Ingwersen, *world knowledge* consists of knowledge structures or cognitive structures, which are "*determined by the individual and its social/collective experiences, education, etc.*" [39]. The connections and influences between individuals and social/organizational knowledge, goals and purpose, preferences, as well as expectations and experiences, are thus reflected in the underlying ontologies. Yet, Web crawlers can aggregate knowledge about a specific domain. At the same time, these agents permit a wrapping of the relevant ontologies to FCMs, FCM_t. Afterwards an alignment of different FCMs leads to the creation of a new FCM from possible overlapping submodels. Thereby the initial ontologies remain unaltered. The aligned FCM^{new} (see Fig. 4) is supposed to contain the knowledge of the respective ontologies (e.g., consequences

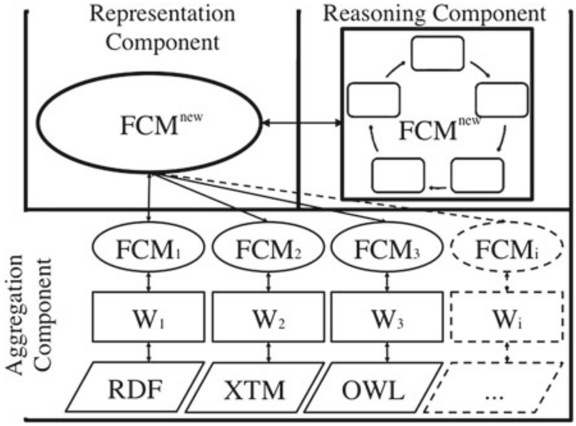

Fig. 4 Web knowledge aggregation, representation, and reasoning framework

of each ontology are consequences of the alignment). Using FCMs, we can calculate an approximated FCM.

Figure 4 illustrates the Web knowledge aggregation, representation, and reasoning framework that can be used to monitor online privacy and reputation. Based on this framework, it is possible to manage online reputation and to establish a transparent Web presents [36] that gets someone noticed for the right reasons. Therewith, using investigative search techniques, supported by FCMs, it is possible to detect personal information from websites the easy way, and help to protect privacy and identity. In the next subsections the three main components of this framework are specified; Sect. 4.2 illustrates knowledge aggregation with FCMs, Sect. 4.3 knowledge representation using FCMs, and Sect. 4.4 support in reasoning based on FCMs.

4.2 Knowledge Aggregation Using Fuzzy Cognitive Maps

A FCMs aggregation yields a new FCM model, FCM^{new}, as a merge of submodels. The development of a FCM often occurs within a group context. In the Semantic Web, ontologies are developed free and/or in a group context. The FCM underlying assumption is that combining incomplete, conflict opinions of different experts may cancel out the effect of oversight, ignorance, and prejudice [41]. The simplest method is to establish the candidate FCM by averaging the corresponding relationship values (i.e., weights w) across all the submodels. Using the FCMs matrix representation, this is carried out by calculating averages of the corresponding cells across all the submodels.

A finite number of FCMs can be combined together to produce the joint effect of all underlying maps. Let $E_1, E_2, \ldots, E_p$ be the adjacency matrices of the maps with $C_1, C_2, \ldots, C_n$, then the combined FCM is obtained by summing up all adjacency matrices $E_1, E_2, \ldots, E_p$. The combined map's adjacency matrix is labeled by $E =$

$\sum_{i=1}^{p} E_t$, with as the number of adjacency matrices and as the number of concepts (see Sect. 2). According to Stach et al., this standard technique can be improved by adding credibility to each submodel [42]. Accordingly, credibility can be computed using in-sample error values (i.e., difference in the original data). The in-sample error assesses the quality of submodels; submodels with low in-sample error obtain higher credibility, and vice versa. Specifically, given submodels and their in-sample values, the aggregation is realized using

$$e_{ij} = \frac{\sum_{s=1}^{S} cr_s \times e_{ij}^s}{\sum_{s=1}^{S} cr_s}$$

where is the credibility o f th submodel (i.e., calculated as 1-in-sample error of the submodel); e_{ij}^s the weight between concept C_i and C_j in the th sub-model.

Using FCMs, the next subs ection illustrates the interactive visualization of the aggregated knowledge.

4.3 Knowledge Representation Using Fuzzy Cognitive Maps

Through dynamic query in terfaces [28] humans are able to adapt to computers and through machine learning techniques (i.e., neural networks) computers can (better) adapt to humans. To support everyday people in their search, dynamic query interfaces should fit in to single users knowledge and to head of each user there. To do this, the computer should rely on machine learning to defer to (average) users, which uses his language in a natural way. Through dynamic interfaces that integrate digital content into a human's live in seamless ways, a computer should even become adaptable to each individual user (see, e.g., [43]).

With an automatically built-in ontology, computers for example may become (more) responsive to humans. The aggregated FCM model, (together with any underlying submodels crawled and wrapped) includes fuzzy meaning of human world knowledge that can be used to bring together human and computers [44]. FCMs are qualitative alternative to dynamic techniques that allows observing the gross behavior quickly and without expert's help [41].

Let us consider concepts $C_1, C_2, \ldots, C_n$ in a simple aggregated FCM model, FCM^{new}. Suppose the graph is drawn using edge weight $e_{ij} \in \{0, 1, -1\}$. The adjacency matrix $E = (e_{ij})$ where is the weight of the directed edge C_iC_j (note that all matrices are always square matrices with diagonal entries as zero). If C_i is a concepts of a FCM, then an instantaneous state vector $A = (a_1, a_2, \ldots, a_n)$ where $a_i \in \{0, 1\}$ denotes an on-off position of the concepts at an instant. Hence, for $i = 1, 2, \ldots, n$:

$$a_i = \begin{cases} 0, & if\ a_i\ is\ off \\ 1, & if\ a_i\ is\ on \end{cases}$$

Let $\overrightarrow{C_1C_2}$, $\overrightarrow{C_2C_3}$, $\overrightarrow{C_3C_4}$, ..., $\overrightarrow{C_iC_j}$ be the edges of the FCM ($i \neq j$), then the edges constitute a directed cycle. A FCM is cyclic if it possesses a directed cycle, and acyclic otherwise; a FCM with cycles is said to have feedback and is called dynamic [33]. Now, $\overline{C_1C_2}$, $\overline{C_2C_3}$, ... $\overrightarrow{C_nC_{n-1}}$ is a cycle; if C_i is on (i.e., causality flows through the edges of the cycle) and causes C_i, the dynamic system is said to go round and round (i.e., true for any C_i, with $i = 1, 2, \ldots, n$).

However, these FCMs (i.e., each single FCM_i as well as FCM^{new}) can be used as simple representation of knowledge. Users through a provided adaptive interface now can investigate this aggregated Web knowledge structures. Today, from their perspective, browsing and searching are the main interactions on the Web [44]. While browsers provide visual mechanisms for navigating the Web, in many cases search engines are the source where a Web navigation process starts. In future, a search engine should provide the possibilities of searching and browsing not only the retrieved Web documents, but also the underlying meaning. For instance, in addition to only browse from a found Web document via link to another document, a user's search is extended by the possibility to follow a link into visualized knowledge structures (i.e., FCMs; see Fig. 3). Therein the user navigates the netlike structures for some time, and then follows back a link to a different Web document, as [45] illustrate.

4.4 Knowledge-Based Reasoning Using Fuzzy Cognitive Maps

In the Semantic Web exist numerous formal reasoner for (more or less simple) description logic-based reasoning (see Sect. 2). In the vision of a social Semantic Web, these reasoners should support user in their reasoning (e.g., in a investigative Web search for online privacy and reputation; see Sect. 3). This support, however, exhibits an initial form of users cognitive augmentation.

Via FCMs it is possible to aggregate ontologies from collective knowledge systems. According to Gruber are this "*human-computer systems in which* [computers] *enable the collection and harvesting of large amounts of human-generated knowledge.*" [7]. In a cognition augmentation interaction process, FCMs can on one hand be used to illustrate coherencies, and on the other hand they can be used in an automatic reasoning. Here as well, there are first versions of fuzzy reasoning architectures that should help users in their reasoning process at a later time (see, e.g., [46, 47]).

For example, such a reasoner can ascertain equilibriums in the FCM. An equilibrium in this dynamical system is called the hidden pattern. If the equilibrium is a unique state vector, then it is called a fixed point, if the map settles down with a state vector repeating in the form $A_1 \rightarrow A_2 \rightarrow \cdots \rightarrow A_i \rightarrow A_1$ then the equilibrium is called a limited cycle. However, in the sense of human's cognitive augmentation we focus here more on the visualized knowledge aspects through FCMs. Compared to other systems, FCMs are relatively easy to use for representing structured knowledge, and the inference can be computed by numeric matrix operation instead of explicit

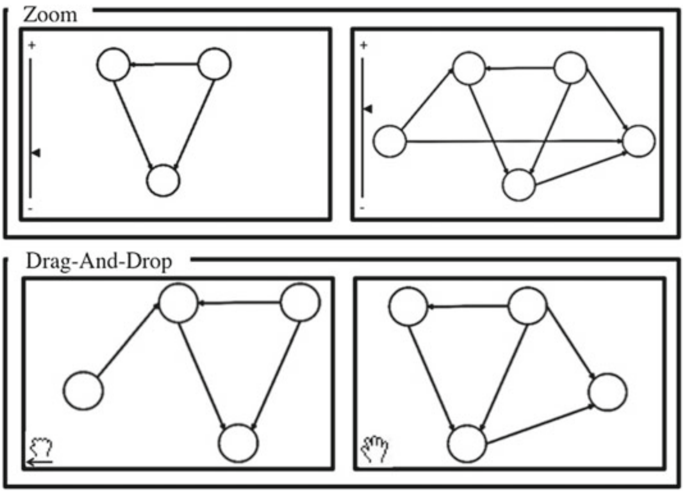

Fig. 5 Interactive knowledge representation

if-then rules [41]. FCMs are appropriate to explicit the knowledge and experience which has been aggregated.

In exploring the knowledge structures, additional functionalities (e.g., zoom, drag-and-drop, etc. [6]) to standard functionalities (i.e., clicking hyperlinks in browsing process; see previous subsection) are conceivable. Using such functions allows users to investigate efficiently online privacy and reputation related knowledge, information, and data (see Fig. 5). So it is for example possible that with the zoom function a special ontology $O_i (= FCM_i)$ can be zoomed in. After a closer investigation, a user can zoom out again to the aggregated ontology $O^{new} (= FCM^{new})$. In combination with a drag-and-drop function, this allows users a knowledge-based reasoning, which in future even can be supported by improved, user-adapted automatic reasoned [46, 47].

In conclusion, the next subsection illustrates the presented framework by means of a brief use case.

4.5 Tim Berners-Lee Use Case

Imagine that, to analyze his Web presence, Tim Berners-Lee wants to know all corresponding references. Hence, to spot them, a sound analysis should also include weak signs (e.g., not directly name-checked by an underlying websites), and, in addition, the found issues should be somehow summarized (e.g., into related topics). Yet, a challenge for a search for new and unobserved Web information is that the relationship between terms and topics is often unknown in advance. To scan all his (more or less related) mentions, Tim first searches for his name. After hitting the search button, on the left side of his browser window, immediately an ontology (i.e., the FCM^{new} including all aggregated FCM_i's) pops up (see Fig. 3). This FCM^{new} captures the vagueness of aligned human concepts [37] (i.e., stored in all the individual underlying ontologies FCM_i). Besides, on the right side of his browser, a list (e.g., ranked by relevance, trust, credibility, etc.) pops up that entails sorted Web hits (see also Fig. 3). This way Tim can browse the FCM^{new} (i.e., Popper's second and third world; see Sect. 3), and more importantly, also interactively discover underlying social media applications (i.e., Popper's first world) at one go.

The advantage is that Tim not only finds more relevant information concerning his search, but also more structured information (based on FCM^{new} and the respective hit list). With a conventional Boolean search, he would only find information positively containing his name. In contrast, our framework enables us, to find not only the search term but also related topics. Since the revealed browser window is interactive, Tim may also zoom in-and-out as well as drag-and-drop (see Fig. 5) and, that way, browse the FCM in a straightforward manner (e.g., as described in [6, 37]). That permits him to do an integrated analysis of his Web presence (e.g., his online privacy and reputation), and to reason about his very own situation (e.g., supported by automatic reasoners as presented in Sect. 2).

As last point, the next section first provides a short summary, followed by a conclusion and an outlook of further studies.

5 Conclusions and Outlook

First we have introduced the intended social Semantic Web that empowers its users to have collective Web knowledge at hand. It is composed of a human-centric social Web and the technic-centered Semantic Web. In the end, the Semantic Web becomes more social, or vice versa, social applications will be augmented with computer-understandable meaning of real-life concepts. In a social Semantic Web, controlling online privacy and reputation becomes increasingly important, and must be taken seriously. Investigative searches may reveal hidden knowledge of the underlying ontologies that can be used for managing online privacy and reputation efficiently. Based on FCMs, the Web aggregation, representation, and reasoning framework, allows an information integration, searchability, automation and querying. In addition to conventional ordinary Web information found, the netlike knowledge structures of the aggregated FCMs can also be searched and browsed. To support human reasoning, it is furthermore possible to zoom-in-and-out, as well as drag-and-drop these FCM knowledge structures.

Our interactive, visual, human-oriented approach to knowledge presentation should help an information seeker understand, or get to know, and (thus) express information needs, formulate queries straightforwardly, select from available information, understand results by browsing not only the retrieved Web documents but also the semantic relations of the document's content, and keep track of the progress of a search. The quality of the interface depends strongly on how Web users react to it. Its preferences may be given through different factors, such as speed of the underlying framework or familiarity and aesthetic realization of the inductive fuzzy cognitive maps, and so on. All these points are to be evaluated in a further step, using discount usability methods, as suggested by Nielson [48]. To this end, first prototypes for fuzzy Web knowledge aggregation, representation, and reasoning are at the early stages of development.

We realize that although progress has been made in ontology alignment, it still may appear to be virtually impossible. Indeed, for finding correspondences between concepts, it is necessary to approximate their meaning. The ultimate meaning of concepts is in the head of the people who developed those concepts and, originating from mathematical logic, we are unable to fully program computers to learn it par for par. However, the same remark leads to the conclusion that communication, even between people, is impossible [15]. Yet, we know that human beings achieve communication; they at least, succeed quite often in communicating and sometimes fail. Achieving this communication can be viewed as a continuous task of negotiating the relations between fuzzy concepts (i.e., arguing about alignments, building new ones, questioning them, etc.). Therefore, aligning ontologies is an on-going work and considering it in its dynamics can make further substantial progress in the field.

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Chapter 6
Decision Making by Rule-Based Fuzzy Cognitive Maps: An Approach to Implement Student-Centered Education

A. Peña-Ayala and J. H. Sossa-Azuela

Abstract In this chapter we outline a decisions-making approach (DMA) that is based on the representation and simulation of causal phenomena. It applies an extension of the traditional Fuzzy Cognitive Maps called *Rules-based Fuzzy Cognitive Maps* (RBFCM). This version depicts the qualitative flavor of the object to be modeled and is grounded on the well-sounded fuzzy logic. As a result of a case study in the educational field, we found empirical evidence of the RBFCM usefulness. Our DMA offers decision-making services to the sequencing module of an intelligent and adaptive web-based educational system (IAWBES). According to the student-centered education paradigm, an IAWBES elicits learners' traits to adapt lectures to enhance their apprenticeship. This RBFCM based DMA models the teaching-learning scenery, simulates the bias exerted by authored lectures on the student's learning, and picks the lecture option that offers the highest achievement. The results reveal that the experimental group reached higher learning than the control group.

1 Introduction

Our DMA is a cognitive computing approach that is inspired by the mental capabilities [12]. The DMA represents a decision-making framework to deal with uncertain and unreliable knowledge as a sample of cognitive reasoning [1].

A. Peña-Ayala (✉)
WOLNM, ESIME-Z, Instituto Politécnico Nacional, U. Prof. Adolfo López Mateos, s/n, GAM, Mexico, DF, México
e-mail: apenaa@ipn.mx

J. H. Sossa-Azuela
CIC IPN, U. Prof. Adolfo López Mateos, s/n, Gustavo A. Madero, 07738 Mexico, DF, Mexico
e-mail: hsossa@cic.ipn.mx

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Causality, our awareness of what produces a specific consequence in the world and why it matters, is the conceptual baseline to predict and explain some effects given particular conditions [14]. Both, cause and effect, represent instances of common sense (i.e. it concerns the knowledge that every person assumes her/his neighbors also posses, and the kind of reasoning that people daily perform to induce causal results) [6]. In our approach, both knowledge and reasoning are qualitatively characterized and deployed for decision making (i.e., they are stated by natural language terms and sentences to acquire, depict and reveal the meaning that individuals provide in their world and their every day experiences) [7].

According to the prior context, our DMA is designed and built as an approach for decision-making applicable cross-domains, such as education. Its description is organized as follows: A profile of the application context is shaped in Sect. 2 and its framework is sketched in Sect. 3. The processes to model the user and the lectures are set in Sect. 4; whereas, the knowledge base (KB) is outlined in Sect. 5. The teaching-learning model is represented in Sect. 6 and the mechanism for fuzzy-causal reasoning is explained in Sect. 7. A case study is given in Sect. 8; whilst the discussion and future work are stated in the conclusions.

2 Application Context

Student-centered education aims at tailoring educational curricula, lectures and evaluation to satisfy students' needs [21]. In this way, an AIWBES is able to intelligently adapt interfaces, content, tests, support, and assessments according students' likings and constraints with the purpose of enhancing their learning [16].

Such a paradigm is pursued when an IAWBES delivers suitable teaching-learning experiences to stimulate users' learning. Thus, the IAWBES should take into account several options to teach domain knowledge (DK). This strategy is deployed throughout the next tasks: The first organizes DK as a set of concepts to be taught. The second requests authoring content to teach DK from several viewpoints. Where, a viewpoint is designed as a learning object (LO) that applies a learning theory, privileges a user-system interaction style, and represents content to stimulate a sense. The third estimates the causal bias that each LO produces on student's learning. The fourth picks the LO that best biases the student's learning.

The third and four tasks concern the *sequencing* module of an IAWBES. Sequencing is responsible for planning, developing and controlling teaching-learning experiences. It decides what the user is going to do next. According to a learning goal, the sequencing chooses and delivers the most promising LO [5].

Evaluation and selection of LO are decision-making duties that are fulfilled by the DMA. The DMA shapes fuzzy-causal relationships between the LO attributes of the concept to be taught and the student's traits by a RBFCM. It estimates the bias that a LO exerts on the student's learning by means of fuzzy-causal reasoning. Once the LO have been evaluated, the DMA picks the most promising LO.

With the purpose of revealing the DMA attributes, several related works are introduced here. The first corresponds to the Natural Language Tutoring System built by Chin et al [4]. It applies an Elicit/Tell tutorial decision to predict the next step the student could follow. In comparison, our DMA also uses natural language to assert fuzzy-causal relationships that later are set like *If-then* fuzzy rules. But, the DMA predicts the student's learning achieved through a LO.

Concerning the work made by Goel et al., they apply fuzzy logic for student modeling [8]. The approach uses two rule-based fuzzy inference systems to predict the degree of error a student makes in the next attempt to solve a problem. In contrast, our DMA anticipates the level of knowledge acquired by a student as a result of dealing with a particular teaching-learning experience.

Sobecki and Fijałkowski designed an approach to schedule courses, where students express their preferences [19]. The system tailors the sequence of courses to be taken. In comparison, our DMA elicits the student's strengths and weaknesses, and depicts the candidates LO to teach a concept. Based on these attributes a simulation is carried out to evaluate the learning effect exerted by each LO.

3 Sequencing Framework

The DMA is part of a sequencing framework. It is designed to acquire user and content traits, administrate student and content models, and deliver educational services. The framework is deployed as a multi-agent system (MAS) [2], where agents perform roles such as: (1) *interface* to act as requester and responder for addressing messages to whom it concerns; (2) *management* to provide support functions to input, management and access the KB; (3) *mapping* to sketch a RBFCM to shape the causal model to be analyzed, such kind of cognitive map (CM) depicts concepts of several domains and the cause-effect relationships; (4) *engine* triggers a simulation of fuzzy-causal effects to depict causal behavior and outcomes.

The sequencing framework interacts with users through functional and educational systems, as the IAWBES. Its agents collaborate to accomplish several tasks by the reception and delivery of messages. In this environment, our DMA plays the *requester* and *responder* roles. As a requester, the DMA demands information and services to functional systems to acquire, represent and access features of the object to be modeled. As a responder, educational systems request evaluation and decision-making tasks to the DMA (e.g., estimate the learning impact that a LO produces on the user' learning; choose the most promising LO to be delivered).

The framework holds the 22 tasks sketched in Fig. 1, where messages and queries to KB repositories (e.g., RBFCM, ontology and working memory) are respectively drawn by wide and narrow arrows. The framework holds two workflows. The first is devoted to knowledge acquisition, representation and management. The second is responsible for decision-making to evaluate LO and choose the most promising LO to teach a concept. The sequence of tasks is introduced next:

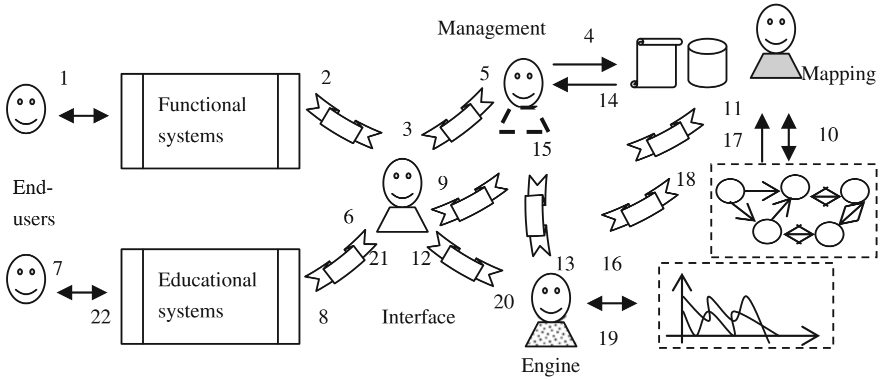

Fig. 1 The sequencing framework is pictured as an environment where users interact with functional and educational systems to request the sequencing of LO to teach a lecture

1. User provides student and content features to functional systems.
2. Functional systems forward features to interface agent.
3. Interface agent forwards data to management agent.
4. Management agent stores data and updates the KB.
5. Management agent commits and informs the achievement to interface agent.
6. Interface agent says *DMA is ready* to support educational systems as AIWBES.
7. Student interacts with AIWBES to learn a given DK topic.
8. AIWBES requests the LO of the next lecture to the interface agent.
9. Interface agent asks mapping agent to shape a RBFCM for each candidate LO.
10. Mapping agent automatically tailors a RBFCM for each LO to be evaluated.
11. Mapping agent shapes the RBFCM and informs to interface agent.
12. Interface agent asks engine agent to evaluate candidates LO and pick the best.
13. Engine agent requests KB data of the LO and student to management agent.
14. Management agent retrieves requested data from KB.
15. Management agent forwards the requested KB data to engine agent.
16. Engine agent requests a RBFCM of each LO to be evaluated to mapping agent.
17. Mapping agent retrieves the requested RBFCM.
18. Mapping agent forwards the RBFCM to engine agent.
19. Engine agent evaluates each RBFCM by fuzzy-causal inference and stores the learning level reached by the student through the examined LO.
20. Engine agent compares the learning level produced by each LO and chooses the LO that produces the highest.
21. Engine agent informs the *id* of the LO that produces the highest apprenticeship to interface agent.
22. Interface agent forwards the decision to the requester AIWBES.
23. The sequencing module of an AIWBES interprets the decision and performs the corresponding action during its interaction with end-user.

4 User and Content Characterization

In order to deliver student-centered education, the modeling of the student and the content is essential. According to the sequencing framework, the functional systems are responsible for collecting key properties of the student and the content. The features represent the raw input for student and content modeling. This is the reason why functional systems implement psychological models, pedagogical criteria, and guidelines for web graphic design to produce a student model, a content model, and an ontology. The repositories form the KB. Functional systems provide the user-system interface to capture personal data and infer behaviors [11].

The case study shown in this work shapes a student model composed of the next four domains: cognitive skills, personality traits, learning preferences and DK. The content model embraces attributes to depict DK concepts and candidate LO. The tools used to collect knowledge for both models are the following [15]:

- Taxonomy of Learning Objectives (TLO) reveals seven levels of DK mastered by a student. They are identified in ascending order: ignoring, remembering, understanding, applying, analyzing, evaluating, and creating [20].
- Minnesota Multiphasic Personality Inventory (MMPI) has forty three traits organized into three scales: (1) basic: depression, paranoia, introversion…; (2) supplementary: anxiety, repression…; (3) content: fears, anger… [10].
- Wechsler Adult Intelligent Scale (WAIS) measures eleven skills for estimating the intelligence quotient (IQ), such as: (1) verbal: information, comprehension, numerical reasoning…; (2) performance: observation, visual-logical… [3].
- Gardner's Multiple Intelligence Model (GMIM) estimates eight learning preferences (e.g., intrapersonal, interpersonal, verbal linguistic, kinesthetic…) [13].
- Guidelines to use Learning Technologies with Multimedia (GULTM), they depict traits of the concept to be taught (e.g., abstract, abundant, complex…) and the LO option (e.g., dynamic, static, constructive, declarative…) [9].

5 Knowledge Base Management

During the interaction between user (e.g., student, pedagogue…) and the five functional systems, the features of the learner and content are collected. Such attributes are represented like *concepts*, *relations*, and *measure-values*. The data is stored in the KB through steps 1–5 of the workflow pictured in Fig. 1. A description of the KB organization and a code sample, based on [17], are given next:

The KB is organized and managed to provide input and access to the next five repositories: student model, content model, ontology, a RBFCM of each candidate LO, and working-memory. Most of the repositories store raw data as eXtended Markup Language (XML) documents.

The semantic definition of concepts, relationships and values held by those repositories is stated in the ontology. The semantics are encoded by means of the structure and items of the Web Ontology Language (OWL). A sample of such OWL ontology is presented at the end of this section and explained as follows:

The content model consists of two repositories: (1) *meta-taxonomy* shapes the hierarchy of classes and properties to depict LO; (2) *taxonomy* describes the features of a LO (e.g. the definition of the concept hypothesis is set in lines 00–07).

The student model holds four XML repositories: (1) *record* sets personal data of the learner; (2) *assessment* records the behavior, responses and results fulfilled by the student during the teaching-learning experiences; (3) *knowledge* depicts the background and the acquired DK gained by the student as a result of the lectures taught by the AIWBES; (4) *profile* structures the main features of the personality, cognitive and learning preferences domains (e.g., see lines 20–25). The profile contains ten files more (e.g., five for personality, four for cognitive and one for preferences), which offer fine grain knowledge of the domains.

The RBFCM repository sketches the topology of a RBFCM by the *id* that identifies the items (e.g., cause and effect concepts, fuzzy rules-base) of the causal relationships. The working-memory repository stores the linguistic terms that instantiate the *level* and *variation* values attached to the state of concepts at each time t_i.

The ontology holds four kinds of OWL sentences: (1) *class* defines a class and its inheritance relationships with ancestor classes; (2–3) *datatypeProperty* and *functional-Property* set properties and links between they and classes; (4) *instance* defines a specific class object, whose properties have instantiated values.

```
00: <!---Statement hypothesis concept in taxonomy repository-->
01: <profile id_term="LO_profile" id_LO ="9">
02: <domain_knowledge id_term="dk">
03: <DK_concept_instance id_concept="hypothesis">
04: <Concept_criteria id_criteria="concept_level">
05: <attribute_instance id_instance="dynamic">
06: <fuzzy_term_level>normal</fuzzy_term_level>
07: <membersip_degree>1.0</membersip_degree>
:::

20: <!---Statement of anger concept in profile repository-->
21: <profile id_term="student_profile" id_student="8">
22: <personality_skills id_term="personality">
23: <instance id_concept="anger">
24: <fuzzy_term_level>too low</fuzzy_term_level>
25: <membersip_degree>1.0</ membersip_degree>
:::
```

6 Cognitive Mapping

Making-decision tasks, evaluation of LO and selection of the best LO, are achieved by cognitive mapping and fuzzy-causal reasoning simulation. The first process is explained in this section and the second is stated in the next section.

The application domain is conceptualized like a teaching-learning cycle, where a LO is the *cause* (i.e., the stimulus), the student's mental faculties the *effect-cause* (i.e., they are stimulated and also used to learn), and the student's apprenticeship the final *effect* (e.g. a specific DK concept to be learned by the student).

Such a conceptual model is sketched as a CM, whose topology is split into three tiers of concepts (e.g., like a three-layer artificial neural network). The first tier contains concepts that depict the LO to be evaluated; the second tier holds concepts that shape the student; the third tier reveals the concept to be taught.

According the steps 7–11 of the workflow pictured in Fig. 1, the mapping agent receives the *id* of the candidate LO, the *id* of the learner, and the *id* of the concept to be taught as parameters wrapped in a message. Next, it tailors the RBFCM structure that corresponds to the LO to be evaluated. The cognitive mapping process sets the topology of the RBFCM according to the concepts and relationships stated in the repositories of the student model, content model and ontology. A sample of the topology sketched for the CM is explained as follows:

Concepts (i.e., the features that shape the student and the content models) hold a *state* that is qualitatively measured. The state is instantiated by a *level* (L), or a *variation* (V), or both values. The *L* value shows how intense is the concept's presence or reveals the difference between the current value and a reference in a given time t_i. The *V* value gives a sense (e.g., *increase*, *decrease*) and a qualitative degree of change of the concept's presence (e.g. *little*, *much*…) after a period t_{i+1}.

The state of concepts that describe a LO are only instantiated by levels because the content is static during the lecture. Whereas, the state of concepts that depict the learner and the concept to be taught are qualified by L and V values due to they hold an initial value that could be altered during the development of the lecture.

Concerning the CM tiers, the first layer shapes the LO by two types of concepts: (1) *general* concepts are features of the concept to be taught; (2) *specific* concepts depict a LO. The second level reveals student's concepts of her learning preferences, personality and cognitive. The third level is the concept to be taught.

The relationships sketch the bias exerted by the L or the V value of a cause concept's state on the L-state or V-state of an effect concept. In a RBFCM there are three sorts of relationships that are identified and explained next:

1. *Unidirectional* shows the bias exerted by a cause concept on an effect one (e.g., first layer concepts only exert concepts of the second tier by L-V relationships).
2. *Feedback* shows the reciprocal bias that an effect concept exerts on a cause concept (e.g., second level concepts bias each other and also exert the concept of the third level by V-V and L-V relationships; whilst, the concept of the third tier also exerts second level concepts by V-V and L-V relationships).
3. *Self-feedback* reveals the evolution of the concept's L-state as a result of its prior L-state value and its current V-state value by L+V-L relationships (e.g., a concept of the second or the third level is able to bias itself).

A small sample of the universe of concepts and relationships is chosen to explain how a RBFCM is set. Thus, Fig.2 draws a CM with 26 nodes, whose node's number corresponds to the *id* of the series of concepts presented next:

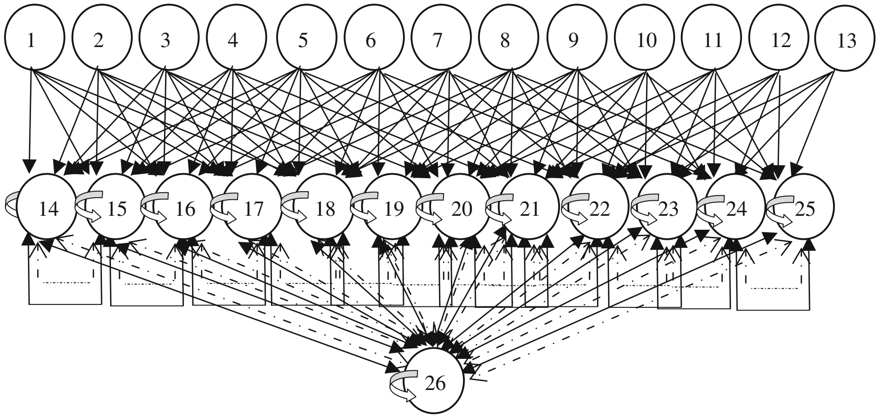

Fig. 2 A small version of the RBFCM stated in Sect. 6 that is used in the case study; where nodes depict concepts, its label is the *id* of the concept, *arrowhead* shows the target of the bias, *continue line* reveals a L-V relationship, *doted line* is a V-V and *double-line* states L+V-L

The first layer holds five general concepts (e.g., (1) *abstract*; (2) *abundant*; (3) *complex*; (4) *practical*; (5) *technical*) and eight specific concepts (e.g., (6) *dynamic*; (7) *static*; (8) *constructive*; (9) *declarative*; (10) *linguistic*; (11) *non-linguistic*; (12) *sonorous*; (13) *visual*). The second level contains four concepts for each domain: personality (e.g., (14) *hysteria*; (15) *psychasthenia*; (16) *introversion*; (17) *depression*), cognitive (e.g., (18) *causal reasoning*; (19) IQ; (20) *auditory memory*; (21) *visual memory*), learning preferences (e.g., (22) *auditory*; (23) *logical*; (24) *linguistic*; (25) *visual*). The third level only holds the concept to be learned, whose *id* is 26.

The topology of a RBFCM is drawn by: (1) 156 L-V relationships (i.e., 13 * 12) to depict the unidirectional bias that first level concepts exert on concepts of the second tier; (2) 12 L-V and 12 V-V relationships (i.e., 12 * 1 + 12 * 1) to reveal the influence that second tier concepts produce on the concept of third layer; (3) 12 L-V and 12 V-V relationships (i.e., 1* 12 + 1 * 12) as the feedback that concept of third tier exerts on second tier concepts (i.e., the effect that the learning in progress exerts on the performance of the student's mental traits); (4) 132 L-V and 132 V-V feedback relationships (i.e., 12 * 11 + 12 * 11) between concepts of the second level; (5) 12 L+V-L and 1 L+V-L self-feedback relationships for the 12 and 1 concepts of the second and third tiers respectively; due to the self-feedback a new L value is computed for the L-state of the concepts to represent its evolution.

The topology of the RBFCM has: 3 tiers, 26 concepts, and 481 relationships, where all the relationships are defined by their respective fuzzy rules-base. The theoretical and mathematical baseline for tailoring a RBFCM and make reasoning with RBFCM as a tool for modeling system dynamics is clearly outlined in [18].

7 Sequencing Engine

Sequencing is a decision-making process devoted to evaluate action courses of candidate LO with the aim at choosing the one that maximizes the student's learning. According to steps 12–22 of the workflow, we depict how the DMA evaluates the candidates LO authored to teach a concept and how it picks the best LO: Firstly, an ad-hoc UOD is given to the state of concepts as follows:

1. UOD with six levels {*so low*, *low*, *medium*, *high*, *so high*} is joined to the L-state of concepts that shape the LO and the learner.
2. UOD with seven levels {*ignoring*, *remembering*,*understanding*, *applying*, *analyzing*, *evaluating*, *creating*} is set for the L-state of the concept to be taught.
3. UOD with eleven variations {decreases: *so much*, *much*, *regular*, *little*, and *so little*, *holds*, increases: *so little*, *little*, *regular*, *much*, *so much*} is attached to the concepts' V-state that describes the student and concept to be taught.

Next, the L and the V states of the concepts are initialized with L, V, or both values that were measured and stored in the KB along framework's steps 1–11.

Thereafter, the simulation of causal effects starts during discrete increments of time $t_1 \ldots t_n$. At each time t_i, the causal effects on the state of the *effect* concepts are estimated. The simulation ends when a stable status is reached (i.e. the state of each concept does not change or a cyclic pattern of values appears every period t_{i+j}) or a chaotic situation is faced. Thus, at any time t_1, two sorts of inductions, *causal inference* (CI) and *fuzzy inference* (FI), are computed. Both inductions are mathematically stated in [21]; whilst, in this case study they are used as follows:

1. The levels attached to the L-state of concepts in the first tier exert the V-state of concepts in the second tier as a variation estimated by CI.
2. The variations revealed as the V-state of concepts at second and third tiers bias the V-state of concepts in second and third tiers as a variation computed by CI.
3. The levels assigned to the L-state of concepts in second and third tiers exert the V-state of concepts in second and third tiers as a variation made by CI.
4. The L and the V values that respectively instantiate the current L-state at t_i and the new V-state at t_{i+1} of a concept c, which belongs to the second or third layers, bias its own L-state to produce a new L value at t_{i+1} by means of FI.

The state of concepts in the first level never changes; but, the L and the V values attached to the state of concepts in second and third levels could change along the simulation. It means, for example, the former L and V values (i.e., those used for initializing the concept's state at t_0) given to the state of the concept to be taught could be altered. For instance, Fig.3 shows the evolution of the L attached to the L-state of the concept to be taught. At t_0, the student masters the *understanding* TEO-level. During the evaluation, three LO options are considered. Thus, the simulation of the causal bias is progressively fulfilled through discrete increments of time $t_{1 \ldots n-1,n}$. As a result, one option produces a neutral effect and the other two exert a positive bias; but, just one reaches the *evaluating* TEO-level.

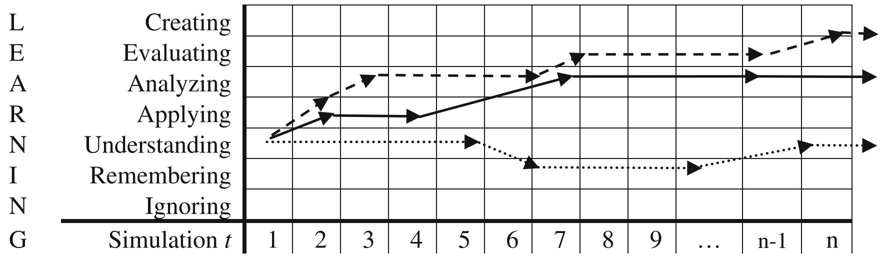

Fig. 3 Fuzzy-causal simulation of the bias that *three* LO exert on the concept to taught

Concerning the question: which is the best LO? The decision is made by choosing the LO whose simulation produces the highest L and the greatest positive V estimated at t_n as the final L-state and V-state of the concept to be taught (e.g., the LO drawn by an interrupted line in Fig. 3 is expected to be the most profitable).

8 Case Study

The making-decisions support given by our DMA was tested in the educational arena as that responsible for evaluating the candidates LO and deciding which of them is the most profitable LO to teach the learner. Thus, according to the sequencing framework sketched in Fig. 1, it receives messages sent by an educational system before delivering a lecture to the student. The application of the approach is illustrated as follows.

In order to promote the development of research projects, our institution launched a campaign for encouraging graduates to enhance their current DK about the "Scientific Method". After a web-based promotion, several hundred people were programmed to participate in the free e-training. However, just 200 graduates enrolled by filing an e-form with personal data, which was stored in the record repository.

The applicants answered psychological and DK tests in the next order: preferences, personality, cognitive, and DK by interacting with functional systems. The collected data was stored in student model repositories, one per subject. But, along the process 75 % of the universe gradually deserted and only 50 people successfully fulfilled the four tests. Thus, the size of the population (N) is 50.

As a training stage, an e-course about Philosophy of the Science was delivered to the population. Moreover, an e-course about ten *basic DK concepts* (e.g., *hypothesis*, *law*…) was authored. The content is made up of four candidates LO to teach a concept. They represent a viewpoint to stimulate learning as follows: One LO stimulates objectivism learning another applies constructivism learning, a third provides sonorous linguist content, and the last sends visual stimuli.

A sample (n) was organized with the first 18 persons who achieved the training. The sample was randomly split into two comparative groups of nine people: *control*

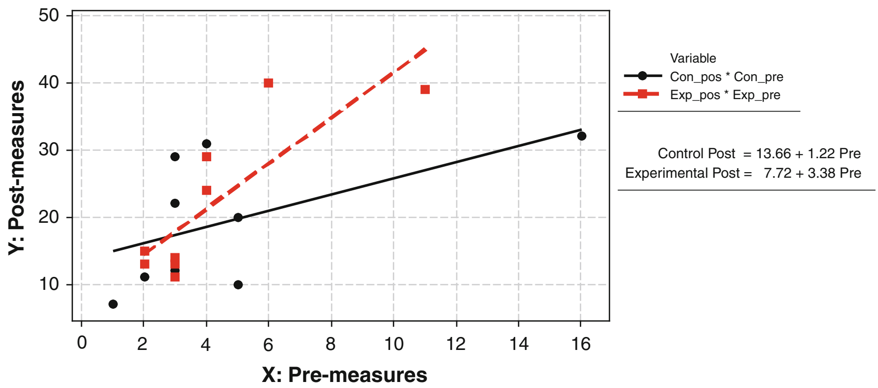

Fig. 4 Dispersion diagram of Pre and Post measures for Control and Experimental groups

(*C*) and *experimental* (*E*). Furthermore, a pre-measure of their prior knowledge (PK) about the ten basic DK concepts was applied to the *n* participants. A functional system measured the mastered TEO-level held by the subjects through the UOD that holds the seven levels of the TEO. An integer was attached to the linguistic terms (e.g., 0 *ignoring*, 1 *remembering*, 2 *understanding* ...) to estimate a PK sum between [0, 60]. Thus, the sum range for a group is [0, 540].

Later on, the stimuli were provided to *n* subjects by delivering just one LO for each basic concept. The AIWBES delivered LO, randomly chosen, to the C group, and LO, selected by the DMA, to the *E* members.

Once the members of both groups achieved the e-course, a post-measure was made. It is a re-test oriented to estimate the current knowledge (CK) of the ten basic concepts. Therefore, the difference between CK and PK represents the learning acquired (LA) by the subject and the whole group, *C* and *E*.

Based on the assessment, a statistical process was carried out. As a sample of the outcomes, Fig. 4 and Table 1 outline several descriptive and co-relational parameters concerning the PK, CK, and LA. What is more, Table 1 depicts three concepts of the student model, where the IQ is the most important.

As regards the analysis of the results, the statistical data reveals *C* group held more PK, 44 % *high* IQ, and greater intercept of the linear regression than the ones estimated for *E* group. However the CK, LA, linear regression slop, and Person's coefficient fulfilled by *E* group are higher than the ones achieved for *C* group. Furthermore, the statistical significance accomplished for *E* group is quite reliable, whereas the one of *C* group is too low.

The interpretation of the statistical parameters produced several findings, such as: Although *C* group had an advantage at the beginning of the case study, the *E* group overcame the deficit and reached higher learning. Another finding is: In spite of the IQ advantage of *C* group members over their peers of *E* group, the IQ was not a decisive factor to accomplish the highest learning. Therefore, the circumstantial

Table 1 Main statistical measures outcome by comparative groups during the test

Criterion	Experimental group	Control group
Pre-measure	PK: Sum 38; mean 4.22	PK: Sum 42; mean 4.67
Post-measure	CK: Sum 198; mean 22	CK: Sum 174; mean 19.33
Learning gained	LG: Sum 160; mean 17.78	LG: Sum 132; mean 14.67
Logical preference	44 % quite high, 44 % high, 11 medium	44.4 % quite high, 55 % high
Depression trait	11 % high, 22 % medium, 66 % low	22 % high, 22 % medium, 55 % low
IQ skill	11 % high, 22 % medium, 66 % low	44 % high, 22% medium, 33 % low
Pearson's coefficient	$r = 0.828$	$r = 0.554$
Statistical significance	$P = 0.0059$	$p = 0.122$
Linear regression	Post $= a$ 7.72 $+ b$ 3.28 Pre-measure	Post $= a$ 13.7 $+ b$ 1.22 Pre-measure

reason is: The kind of stimulus. In this sense, the support given by our DMA was decisive [18].

9 Conclusions

Modeling making-decisions is a challenge. It claims the use of a suitable representation of the object of study, the appropriate characterization of the decision factors, and the reliable definition of criteria. CM is a tool that embraces a model and an inference engine, whose research is growing and application is spreading to different fields.

In this chapter RBFCM are introduced as a tool for decision-making to exploit features such as: mixing fuzzy logic and causality principles. RBFCM provide gray-levels to measure the state of concepts involved in the model, preserve the qualitative description of causal relationships between concepts, and facilitate the definition of decision rules through a rules-base. These kinds of fuzzy-rules make use of a well-sounded inference mechanism to produce reliable results.

The main issue of the RBFCM is the overload of computation, because of the scan of the rules-base to trigger the rule that corresponds to the V and L values attached to the cause concept's state. But, their benefits overcome such an issue.

In this work, the RBFCM are part of the DMA to support the sequencing of content. This functionality is essential to deliver student-centered education by IAWBES. In the case-study the DMA was the responsible for the evaluation of candidates LO and the selection of the most profitable LO. Based on its decisions, the IAWBES provided the most promising LO to learners. As the case study demonstrated, learners benefited by our DMA reached higher acquisition of DK than those who lacked such a support.

The implementation of intelligent and adaptive behavior in educational systems by means of the RBFCM-based DMA is just an instance of useful outcomes. Another is the development of user modeling grounded on fuzzy logic. One more corresponds to the sequencing implementation according to a mixture of fuzzy and causal knowledge and reasoning.

As part of future directions, we consider exploring mechanisms for machine-learning acquisition of RBFCM features and adding engines to deal with non-monotonic and probabilistic reasoning. Moreover, the dynamic evolution of the input stimuli and the application to other fields are objects for future exploration.

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Chapter 7
Extended Evolutionary Learning of Fuzzy Cognitive Maps for the Prediction of Multivariate Time-Series

Wojciech Froelich and Elpiniki I. Papageorgiou

Abstract Fuzzy cognitive maps (FCMs) is a knowledge representation tool that can be exploited for predicting multivariate time-series. FCM model represents dependencies among data variables as a directed, weighted graph of fuzzy sets (concepts). This way, FCM can be easily interpreted or constructed by experts in contrary to black box knowledge representation methods. Since FCM is a parametric model, it can be trained using historical data. So far, the genetic algorithm has been used to solely optimize the weights of FCM leaving the rest of FCM parameters to be adjusted by experts. Previous studies have shown that the genetic algorithm can be also used not only for optimizing the weights but also for optimization of FCM transformation functions. The main idea presented in this chapter is to further extend FCM evolutionary learning process. Special focus is given on fuzzyfication and transformation function optimization, applied in each concept seperately, in order to improve the efficacy of time-series prediction. The proposed extended evolutionary optimization process was evaluated in a number of real medical data gathered from the internal care unit (ICU). Comparing this approach with other known genetic-based learning algorithms, less prediction errors were observed for this dataset.

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W. Froelich (✉)
Institute of Computer Science, University of Silesia, ul.Bedzinska 39, Sosnowiec, Poland
e-mail: wojciech.froelich@us.edu.pl

E. I. Papageorgiou
Department of Computer Engineering, Technological Educational Institute of Central Greece, 3rd Km Old National Road Lamia-Athens, 35100 Lamia, Greece
e-mail: epapageorgiou@teilam.gr

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1 Introduction

The prediction of multivariate time-series is an important issue that emerges in numerous application domains. Many diverse models have been developed for prediction task, e.g. multivariate autoregressive models, artificial neural networks, dynamic Bayesian networks, rule-based fuzzy systems and some others. An alternative prediction model [19, 23] that recently attracted the interest of researchers is fuzzy cognitive maps. FCMs have been proposed as a tool for modeling causal relationships that occur among real-world factors. Similarly as most of other predictive models, FCMs can be constructed by domain experts. Numerous approaches of FCMs that refer to multivariate time-series prediction have been applied in several domains such as medicine [3, 11, 16], geographic information systems [10], economics [7], agriculture management [12].

FCM could be seen as a parametric predictive model that can be learned from raw historical data. The learning objective is to construct an FCM that will be able to predict multivariate time-series effectively. There are three categories for FCM learning, i.e. adaptive (mainly based on Hebb-rule), population-based and hybrid that combines adaptive and population-based approaches [14]. The most known algorithms for adaptive learning approaches are: DHL [8], BDA [5], AHL [13], NHL [18], whereas the corresponding algorithms for population-based approaches are: RCGA (real coded genetic algorithm) [20], PSO based algorithm (applies particle swarm optimization method) [17], simulated annealing optimization based algorithm [4], differential evolution based algorithm [6]. A survey of learning methods for FCMs can be found in [21].

The population-based algorithms are the most efficient as far as the produced prediction errors are concerned. Literature have shown that RCGA algorithm outperforms other learning algorithms concerning prediction task [2]. Recently, our previous study [15], has demonstrated that the evolutionary algorithm can be used to optimize the gain of transformation function used in FCM. This way, the predictive performance of FCM was achieved in a positive way. In this chapter, in order to further decrease prediction errors, three extensions of previous FCM's evolutionary learning algorithm are proposed:

1. gain optimization for every concept individually, instead of using the same value of gain of logistic transformation function for all concepts,
2. optimization of fuzzyfication function, instead of ad-hoc adjusted fuzzyfication of data,
3. prediction errors calculation through a modified formula due to the incorporation of fuzzyfication function into the process of FCM training. This formula can be applied for each fuzzyfication function.

The reminder of this chapter is organized as follows. Section 2 presents the theory of fuzzy cognitive maps followed by Sect. 3 which proposes the three extensions of the evolutionary algorithm that are the main objective of this work. Section 4 reports the results of experiments that validate the proposed approach, whereas Sect. 5 outlines the conclusions of this chapter.

2 Fuzzy Cognitive Maps—Theoretical Background

Next sections depict the fuzzyfication of data and the way they are used in FCM for multivariate time-series prediction.

2.1 Fuzzyfication of Data

Let $V = \{v_1, v_2, \ldots, v_n\}$ be the set of real valued variables that constitute the observed problem environment. Let $C = \{c_1, c_2, \ldots, c_n\}$ be a superset of fuzzy sets c_i, where $n = card(C)$ denotes the cardinality of C. At time step $t \in [0, 1, ...t_e]$, $t_e \in \aleph$ is constant parameter that limits the considered time period. Every value of $v_i(t)$ is mapped by the fuzzyfication function μ_i to the corresponding fuzzy set c_i. In fact, the value of $c_i(t) = \mu(v_i(t))$ denotes the degree in which $v_i(t)$ belongs to the fuzzy set c_i at the time of observation t. As it is known from fuzzy sets theory, the construction of fuzzyficaton functions μ_i is a complex problem usually left to domain experts. However, in most practical cases, fuzzyfication function μ_i is constructed by assuming a simple linear normalization (1):

$$c_i(t) = \frac{v_i(t) - \min(v_i)}{\max(v_i) - \min(v_i)}. \tag{1}$$

This way, for all concepts, the vector $C(t)$ is constructed in order to describe the state of data at time t. Multivariate time-series are represented by the sequence of state vectors $C(1), C(2), \ldots, C(t_e)$.

Let assume that $C(t_s)$ is currently observed and $C(t_s + 1)$ is the first unknown vector that must be predicted by FCM. Assuming h $\in \aleph$ as a parameter determining the prediction horizon, the considered prediction problem is formulated by (2):

$$C(t_s + h) \approx FCM(C(t_s)), \tag{2}$$

where the sign $\approx$ denotes approximated equality. In case that the fuzzyfication function is linear, the predicted concept states are calculated as follows: $v_i(t_s + h) = \mu^{-1}(c_i(t_s + h))$.

2.2 Formal Model of FCM

FCM is usually defined as an ordered pair $\langle C, W\rangle$, where C is a vector of concepts and W is the connection matrix [9]. Every concept is denoted as $c_i = q_i \cup \neg q_i$, where q_i is a fuzzy set and $\neg q_i$ is its complement. The matrix W stores the weights $w_{ij} \in [-1, 1]$ that are assigned to the pairs of concepts. The value $w_{ij} = 1$ represents full positive and $w_{ij} = -1$ full negative impact of the ith concept on the jth effect concept respectively. The intermediate values of weights relate to partial causality.

As already mentioned, FCM model is employed for the prediction of the unknown state vector. The prediction is carried out by using the reasoning Eq. (3):

$$c_j(t+1) = f(\sum_{i=1, i \neq j}^{n} w_{ij} c_i(t)), \tag{3}$$

where: $n = card(C)$ is the cardinality of set C, $f(x)$ is the transformation function and x stands for its argument. Diverse types of transformation functions can be used [22], e.g.: bivalent, trivalent or most commonly used logistic (4):

$$f(x) = \frac{1}{1 + e^{-gx}}, \tag{4}$$

where $g > 0$ is the parameter that determines the gain of transformation, for example $g = 5$ [20]. Depending on the value of g, the transformation function amplifies or inhibits the weighted sum of concept states. It also restricts the accumulated impact of concepts into the interval [0, 1]. A rescaled reasoning Eq. (5), that overcomes the spurious concept states was proposed in [11]:

$$a_j(t+1) = f(\sum_{i=1, i \neq j}^{n} (2a_i(t) - 1) w_{ij}). \tag{5}$$

In case where $h > 1$, the (3) or (5) has to be called iteratively. The iterative calling of reasoning equation leads alternatively to three types of behavior of the state vector $C(t)$ [21]: (1) fixed-point attractor (the state vector becomes fixed after some simulation steps); (2) limit cycle (the state vector keeps cycling); or (3) chaotic attractor (the state vector changes in a chaotic way).

FCM can be learned from historical time-series data. The learning approaches for FCMs are concentrated on learning or adjusting matrix W, aiming to minimize prediction errors. The most effective learning algorithm RCGA [20] creates the population of chromosomes (genotypes); each of them is a vector of weights of a candidate FCM. The populations of genotypes are iteratively evaluated by decoding them to FCMs and then by calculating fitness function (6) [23]:

$$fitness(FCM) = \frac{\alpha}{\beta e + 1}, \tag{6}$$

where α, β are constant parameters and e is the prediction error [20] calculated by Eq. (7):

$$e = \frac{1}{(K-1) \cdot n} \cdot \sum_{t=1}^{K-1} \sum_{i=1}^{n} |c_i(t) - c'_i(t)|^q, \tag{7}$$

where: $t \in <0, 1, 2, ..., K-1>$, K is the length of the learning sequence, q is the parameter equal to 1 [22] or 2 [23], $c_i(t)$ is the real value of concept and $c_i'(t)$ is its predicted value.

3 Extended Optimization of FCM

The causal impact of concept c_i on concept c_j is measured quantitatively by the weight w_{ij} which is restricted in $w_{ij} \in [-1, 1]$. The limited causal impacts represented by weights can be modified by the transformation function that is able to amplify or inhibit the accumulated impact caused by several concepts. This impact depends on the following three factors:

- shape of the fuzzyfication function,
- values of weights, i.e. matrix W,
- shape of the transformation function.

Thus, the proposed method of extended evolutionary learning for FCM is concentrated on the optimization of fuzzyfication and transformation functions respectively. In contrary to our previous approach [15], both functions are proposed to be optimized for each concept $c_i \in C$ of FCM.

3.1 Optimization of the Fuzzyfication Function

The main drawback of previously mentioned linear normalization of fuzzification function is its complete ignorance of data distribution within $[min(v_i), max(v_i)]$, where $min(v_i)$ and $max(v_i)$ denote the minimum and maximum of the domain interval of v_i, respectively. Notice that in case of practical applications, these values should be provided by experts. Their assignment is unreliable when they are solely based on available data, as new data are usually observed. On the other hand, the theoretical values of $min(v_i)$ and $max(v_i)$ determined by experts may not express the real values observed within data. In consequence, it leads to highly unbalanced distribution of the observed data within the interval $[min(v_i), max(v_i)]$. As justified in [15], such situation leads also to the increase of prediction errors generated by FCM. Another consequence of using simple normalization (1) is the significant influence of the possible outliers within data over the fuzzyfication process. Notice that even one outlier observed for v_i can shift the most of the fuzzyfied values c_i close to the bounds 0 or 1 of the targeted interval $[0, 1]$. Finally, notice that the normalization (1) is in fact a linear function with the directional coefficient determined solely by $min(v_i)$ and $max(v_i)$ values respectively. This way the real data distribution is for one more time completely neglected.

As it was shown [15], the shape of fuzzyfication function influences substantialy the process of FCM learning. The fuzzyfication function depends on data distribution and thus it should be fitted to them. A modified normalization function was proposed in [15] and given as follows (8):

$$c_i(t) = \frac{v_i(t) - l(v_i)}{u(v_i) - l(v_i)}, \tag{8}$$

where: $l(v_i) = mean(v_i) - \lambda_i \cdot stdDev(v_i)$, $u(v_i) = mean(v_i) + \lambda_i \cdot stdDev(v_i)$. After substituting $l(v_i)$and $u(v_i)$ in (8), the (9) is obtained:

$$c_i(t) = \frac{v_i(t) - mean(v_i) + \lambda_i \cdot stdDev(v_i)}{2 \cdot \lambda_i \cdot stdDev(v_i)}. \tag{9}$$

If the calculated $c_i(t) > 1$, then it must be truncated, i.e.: $c_i(t) = 1$. Similarly, if $c_i(t) < 0$, then $c_i(t) = 0$. The application of (9) make the outliers that lay beyond the interval $[min(v_i), max(v_i)]$ not influence the directional coefficient of the fuzzyfication function. The optimal shape of the fuzzyfication function (with respect to prediction errors) and the values of parameters λ_i depend on the distribution of source data. Therefore, the fuzzyfication function and its parameters λ_i were proposed to be adapted. The parameters λ_i for every i^{th} concept supplement the genotype used by the evolutionary process.

3.2 Optimization of the Transformation Function

The drawback of logistic transformation function, with the value of gain determined apriori, is its limited, constant amplification/inhibition capability. This imposes a restriction that limits the predictive capabilities of FCM [15]. In this chapter the value of gain g is supposed to be optimized and data dependent. In fact, the goal of the optimization of g is to adjust the transformation function to the characteristics of considered data. This work proposes that every single concept should use optimized transformation function seperately.

Due to mutual dependency among parameters, the parameters g_i are required to be optimized together with the matrix W to further supplement the genotype, including all g_i.

3.3 Modified Calculation of Prediction Errors

Due to inclusion of fuzzyfication functions into the learning process, the formula used for the calculation of prediction errors (7) needs to be modified. Thus, a new formula for the evaluation of prediction errors is proposed (10):

$$e = \frac{1}{(K-1)\cdot n} \cdot \sum_{t=1}^{K-1} \sum_{i=1}^{n} \frac{|v_i(t) - v_i'(t)|}{|max(v_i) - min(v_i)|}, \tag{10}$$

where $max(v_i), min(v_i)$ are given by the domain experts, $v_i(t)$ is the real value taken from the dataset, and $v_i'(t) = \mu^{-1}(c'(t))$ is the defuzzyfied value $c'(t)$ that was predicted by the FCM.

In fact (10) calculates prediction errors rate using directly the source data $v_i(t)$, and not their corresponding fuzzyfied values $c_i(t)$ as (7) did.

Also notice that the normalization in (10) plays a completely different role than the normalization over source data, as its role is to calculate errors of the corresponding observational variables. It does not influence the distribution of the fuzzyfied data and therefore does not influence also the dynamical behavior of the FCM. The calculation of prediction errors (10) is independent of the assumed fuzzyfication function, i.e. it enables the comparison of prediction errors obtained with different fuzzyfication functions.

3.4 Learning Algorithm

The main contrinution of this chapter is the extended content of the genotype used by the evolutionary learning algorithm. Actually, the genotype includes the following three vectors:

- the consecutive $n = card(C)$ raws of matrix W (excluding the elements on the diagonal) [20],
- the vector of n parameters λ_i of the corresponding to concepts fuzzyfication functions μ_i,
- the vector of n parameters g_i of the corresponding to concepts transformation functions $f_i(x)$.

For evolutionary learning of FCM, the procedure of standard genetic algorithm was used. The input of genetic algorithm is the initial random population of genotypes. Its output is the best genotype, evaluated by fitness function, after the convergence of the algorithm. The general flow of the algorithm consists on the following steps, where the details can be found in [20].

1. Initiate the first random population of genotypes,
2. Check the stop criterion. If it is satisfied, the algorithm stops.
3. Use the fitness function to evaluate every individual within the current population.
4. Select the individuals for reproduction, and move them to the new population.
5. Apply reproduction, i.e. generate offsprings using mutation and single-point crossover.
6. Supplement the new population with the offsprings and go to step 2.

The algorithm stops when the calculated value of fitness of the best individual is not increased more than the rounding 10^{-4}.

4 Experiments

For the validation of the proposed approach, the same data as in [15] were used. These data contain twenty (20) sequences of multivariate time-series. Every sequence corresponds to the disease history of a patient with confirmed pneumonia. These cases were acquired anonymously from a Greek hospital. Pneumonia is an infection of the lower respiratory tract that represents a major cause of morbidity and mortality worldwide. In this case study, all patients were in ICU and in a very bad health condition, and only few showed an improvement after two or three days. The patients were aged from to years old, and most of them were men. They were selected by the physicians from the hospital's ICU database. Laboratory examinations were necessary for the diagnosis and proper treatment of pneumonia. For every patient, three measurements per day were accomplished. Thus for every seven or eight hours (one record), attributes were measured. This means that for a period of three days, approximately nine sets/records of measured attributes, were gathered. The measurements refer to a number of the following observable variables:

- v_1—temperature,
- v_2—systolic blood pressure,
- v_3—diastolic blood pressure,
- v_4—heart rate,
- v_5—pH—the acid-base status of the organism,
- v_6—pO2—the partial pressure of oxygen in the arterial blood,
- v_7—pCO2—the partial pressure of carbon dioxide,
- v_8—bicarbonate-HCO3,
- v_9—base excess-BE,
- v_{10}—concentration of total hemoglobin CTHB,
- v_{11}—HCT—Hematocrit,
- v_{12}—sO2—oxygen saturation,
- v_{13}—Na—Sodium,
- v_{14}—K—Potassium,
- v_{15}—WBC—white blood cells.

Assuming that observation is available, a physician should predict the future state of the patient. On the basis of prediction, the physician prescribes a medical treatment, e.g. the prescription of a drug. To every observational variable a corresponding concept of the FCM were assigned. For each patient, the measurements were taken every seven or eight hours. First, the missing data were replaced using the linear interpolation method implemented within the statistical software R [1]. The detailed statistics of the considered data are given in [18]. For the evolutionary algorithm, the following parameters were assumed:

- the reasoning Eq. (5) was assumed for every FCM,
- the fitness function (6) was assumed with the parameters $\alpha = 1$, $\beta = 100$,
- cardinality of the initial population = 1,000,
- probability of mutation = 0.6, probability of crossover = 0.5,

Table 1 The statistics of the prediction errors

	Mean	StdDev
FCM-I	0.1672	0.0224
FCM-II	0.1182	0.0105
FCM-III	0.1061	0.0107

- rounding used for the intermediate calculations 10^{-8},
- rounding used for the final results 10^{-4},
- the domain interval for the parameters of fuzzyfication function $\lambda_i \in [3, 27]$, after the statistical analysis of data [15], the number of data points of μ_i within the interval $[l(v_i), u(v_i)]$ was: 95.58 % for $\lambda_i = 2$ and 100 % for $\lambda_i = 27$. For the values of λ_i besides the assumed interval, prediction errors were very high [15],
- the domain interval for the gain of transformation function $g_i \in [0.1, 20]$, as for the values of g_i beside such interval, the prediction errors were very high [15].

To compare prediction errors of different learning approaches three types of FCMs were considered for learning:

- FCM-I—learned using standard genetic algorithm with normalization (1), gain $g_i = 5$ [20],
- FCM-II—fuzzyfication assumed with $\lambda_i = 4$ for all concepts, optimization of gain g_i(the approach presented in [15]),
- FCM-III—learned with optimization of λ_i and g_i (this approach is presented in this chapter).

For the analysis of results, all FCMs were learned using the fitness function based on the modified calculation of errors (10). It is pinpointed that the previous numerical results in [15] are not comparable to these obtained in this study due to the modification of error function. Because of the small number of available sequences, the leave-one-out cross validation (LOOCV) method [1] was applied. For every learn-and-test trial, the set used for learning contained almost all available sequences except one testing sequence that was used in the testing process. This way, learn-and-test trials were performed. The mean and standard deviation of errors (10) were calculated with respect to patients, whereas the statistics are shown in Table 1.

The prediction errors obtained when using FCM-III were lower when compared with the results produced by the conventional FCM-I approach and the previously used FCM-II. Although there is an obvious decrease of mean for FCM-III in comparison with FCM-II, the standard deviations are comparable (there is a difference on the fourth decimal place). From the medical point of view, it was hard for physicians to give a certain threshold value of error where the prediction below that value is acceptable. In consequence, it was not possible to calculate the prediction rate with the percentage of the properly predicted values.

5 Final Remarks

This chapter presents how the conventional evolutionary approach to FCMs learning can be extended with the inclusion of fuzzyfication and transformation functions respectively. Due to the introduction of the fuzzyfication function into the learning process, a modified calculation of prediction errors has been proposed. This novelty tackles with the task of FCM learning using different fuzzyfication functions. Moreover, the individual optimisation of gain overcomes to a certain extend the limited domain intervals of FCM weigths. The conducted experiments showed that the proposed approach seems to improve the prediction capabilities of FCM.

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Chapter 8
Synthesis and Analysis of Multi-Step Learning Algorithms for Fuzzy Cognitive Maps

Alexander Yastrebov and Katarzyna Piotrowska

Abstract This chapter is devoted to the synthesis and some analysis of multi-step learning algorithms for fuzzy cognitive maps (FCM). Multi-step supervised learning based on gradient method and unsupervised learning type of differential Hebbian learning (DHL) algorithm were described. Comparative analysis of these methods to one-step algorithms, from the point of view of the influence on the work of the medical prediction system (average percentage prediction error) was performed. FCM learning and testing was based on historical data. Simulation research together with the analysis results were done on prepared software tool ISEMK (Intelligent Expert System based on Cognitive Maps). Selected results of this analysis were presented.

1 Introduction

The concept of multi-step pseudogradient algorithms (also known as methods with adequate memory) was introduced in optimization of statistic objects, and then analyzed in many works connected with the parametric adaptation (identification) of dynamic systems [33, 34]. Later, methods of similar kind were introduced in the algorithms area of supervised learning of artificial neuron networks type MLP (e.g. the backpropagation method with the momentum is a typical two-step algorithm of

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A. Yastrebov · K. Piotrowska (✉)
Department of Computer Science Applications, Kielce University of Technology, Kielce, Poland
e-mail: k.piotrowska@tu.kielce.pl

A. Yastrebov
e-mail: a.jastriebow@tu.kielce.pl

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supervised learning [5]). In this paper the algorithms of similar type were used in learning of some models of fuzzy cognitive maps (FCM).

The basis of the structure of FCM is a directed graph, which nodes denote concepts significant for the researched phenomenon. The concepts influence each other with an intensity described by the weights of connections between them, taking on the values from the range $[-1, 1]$ [11]. FCM can be initialized on the basis of expert knowledge [1, 8, 10, 20] or created automatically based on historical data [4, 6, 19, 24].

FCM are applied in the analysis of complex decision support systems, in the context of both, the current state monitoring and the next state predicting. Papers [6, 22, 23] are devoted to the prediction of time series. The article [32] describes the use of cognitive maps in decision monitoring of the condition of the vehicle. In [16, 25, 26] complex systems of process control are presented. FCM also work well in risk analysis [12], in network intrusion detection [20], in military [31] and socio–economic models of decision support systems [8]. Quite a large number of publications is devoted to the use of fuzzy cognitive maps in medical decision support systems, including radiotherapy treatment planning [18], treatment management of uncomplicated urinary tract infection [13], the evaluation of pneumonia severity [7], the prediction of pulmonary infection [15] and autistic disorder [9].

The crucial issue connected with the analysis of FCM is their ability to improve their operation on the light of experience (learning of the relations matrix). Adaptation of the relations matrix weight can be done by unsupervised learning based on the Hebbian method [3, 9, 11, 16, 26, 27] and supervised ones with the use of evolutionary computation [3, 4, 30] or gradient method [21, 32, 36].

This chapter is devoted to the synthesis and some analysis of multi-step algorithms of FCM weights adaptation, which are some kind of generalization of known one-step methods of learning, which wide review was shown in [14]. The analyzed map was initialized and learned based on historical data, and then used to predict the clinician's Parkinson's disease symptom. Part 2 briefly characterizes the structure and dynamic model of FCM. Part 3 presents the multi-step algorithms of supervised and unsupervised learning. Part 4 describes an intelligent expert system based on cognitive maps (ISEMK), enabling the synthesis and the analysis of FCM. Part 5 presents selected results of simulation research of the developed algorithms, done in ISEMK. Part 6 contains a summary of the thesis.

2 Fuzzy Cognitive Maps

The basis of the structure of FCM is a directed graph in the form:

$$< X, R >, \tag{1}$$

where $X = [X_1, \ldots, X_n]^T$ is the set of the concepts, $X_i(t)$ is the value of the i concept, $i = 1, 2, \ldots, n$, n is the number of concepts, $R = \{r_{j,i}\}$ is relations matrix, $r_{j,i}$ is the relation weight between the concept j and the concept i.

Dynamic models of FCM were presented in [32]. In this chapter a nonlinear dynamic model described by the Eq. (2) was used.

$$X_i(t+1) = F\left(X_i(t) + \sum_{j \neq i} r_{j,i} \times X_j(t)\right), \tag{2}$$

where t is discrete time, $t = 0, 1, 2, \ldots, T$, T is end time of simulation, $F(x)$ is stabilizing function, which can be chosen in the form:

$$F(x) = \frac{1}{1 + e^{-cx}}, \tag{3}$$

where $c > 0$ is a parameter.

3 Multi-Step Learning Algorithms for FCM

The idea of multi-step learning algorithms for fuzzy cognitive maps is presented below. The characteristic feature of these algorithms is the estimation of a current value of the relations matrix element on the basis of a few previous estimations, which can be achieved according to the equation:

$$r_{j,i}(t+1) = P_{[-1,1]}\left(\sum_{k=0}^{m_1} \alpha_k \times r_{j,i}(t-k) + \sum_{l=0}^{m_2} \beta_l \times \eta_l(t) \times \Delta J_{j,i}(t-l)\right), \tag{4}$$

where $\alpha_k, \beta_l, \eta_l$ are learning parameters which are determined using experimental trial and error method ($k = 1, \ldots, m_1$; $l = 1, \ldots, m_2$), m_1, m_2 are the number of the steps of the method, $\Delta J_{j,i}(t)$ is pseudogradient of selected function of the learning error, $P_{[-1,1]}(x)$ is an operator design for the set [-1,1], described by an exemplary relation:

$$P_{[-1,1]}(x) = \begin{cases} 1 & \text{for } x \geq 1 \\ x & \text{for } -1 < x < 1 \\ -1 & \text{for } x \leq -1 \end{cases}. \tag{5}$$

A special case of multi-step algorithm is one-step method, which consists of modifying the relations matrix on the basis of one previous estimation, according to the formula:

$$r_{j,i}(t+1) = P_{[-1,1]}\left(r_{j,i}(t) + \beta_0 \times \eta_0(t) \times \Delta J_{j,i}(t)\right). \tag{6}$$

Simulation analysis of multi-step learning algorithms for FCM was realized based on the gradient method [32, 35, 36] and the differential Hebbian learning (DHL) algorithm [2, 27].

3.1 Supervised Learning Using Gradient Method

Supervised learning of the type (4) is a modification of the weights in the direction of steepest descent of error function described by the formula:

$$J(t) = \frac{1}{n}\sum_{i=1}^{n}(X_i(t) - Z_i(t))^2, \tag{7}$$

where $X_i(t)$ is the value of the i concept, $Z_i(t)$ is the reference value of the i concept.

Gradient of the error function for the gradient method (4) describes the equation:

$$\Delta J_{j,i}(t) = (Z_i(t) - X_i(t)) \times y_{j,i}(t), \tag{8}$$

where $y_{j,i}(t)$ is sensitivity function, described as follows:

$$y_{j,i}(t+1) = \left(y_{j,i}(t) + X_j(t)\right) \times F'\left(X_i(t) + \sum_{j \neq i} r_{j,i} \times X_j(t)\right), \tag{9}$$

where $F'(x)$ is derivative of the stabilizing function. Learning parameters α_k, β_l, η_l have to satisfy the conditions (10)–(13) to obtain the convergence of the multi-step learning algorithm [33, 34].

$$\sum_{k=0}^{m_1}\alpha_k = 1, \tag{10}$$

$$0 < \eta_l(t) < 1, \tag{11}$$

$$\eta_l(t) = \frac{1}{\lambda_l + t}, \tag{12}$$

$$\beta_l \geq 0, \lambda_l > 0. \tag{13}$$

3.2 Unsupervised Learning Using DHL Algorithm

Unsupervised learning of the type (4) is a modification of the weights in the direction of steepest descent of error function described by the formula:

$$J(t) = \frac{1}{n}\sum_{i=1}^{n}(X_i(t) - X_i(t-1))^2. \tag{14}$$

Pseudogradient of the error function for the DHL algorithm (4) describes the equation [2, 27]:

$$\Delta J_{j,i}(t) = \begin{cases} \Delta X_j(t) \times \Delta X_i(t) - r_{j,i}(t) & \text{for} \Delta X_j(t) \neq 0 \\ 0 & \text{for} \Delta X_j(t) = 0 \end{cases}, \tag{15}$$

where $\Delta X_i(t)$ is the increment of the i concept. Learning parameters α_k, β_l, η_l have to satisfy the conditions (16)–(19) to obtain the convergence of the multi-step learning algorithm [2, 33, 34].

$$\sum_{k=0}^{m_1} \alpha_k = 1, \tag{16}$$

$$0 < \eta_l(t) < 1, \tag{17}$$

$$\eta_l(t) = 1 - \frac{t}{1.1 \times \lambda_l}, \tag{18}$$

$$\beta_l \geq 0, \lambda_l > 0. \tag{19}$$

Simulation analysis of the algorithm functioning was realized based on ISEMK software tool. The basic functionality of ISEMK is described below.

4 ISEMK System

ISEMK is a computer software, which is a universal tool for modeling phenomena based on FCM [17]. ISEMK application was designed using the Visual Studio by Microsoft. The system comprises three elementary blocks: the knowledge base, the inference machine, and an interface with a user. A cognitive map plays a crucial role as a knowledge base, as well as the inference machine. But the knowledge base is represented by a set of map concepts together with the relations matrix, and the inference is connected with the map functioning. ISEMK realizes:

- the structure of cognitive maps of the FCM type,
- the implementation of initial values of weights and map concepts based on expert knowledge and historical data loaded from .data files,
- reading and writing of FCM parameters from .xml files,
- dynamic monitoring of cognitive maps,
- supervised and unsupervised learning (weight adaptation) by multi-step algorithms with optimal chosen parameters (e.g. the memory length and so on),
- the analysis of designed learned FCM by testing of system operation based on historical data,
- exporting data of learning and FCM analysis to .xls files,
- proper visualizations of done research on devised computer software.

Figure 1 shows an exemplary visualization of multi-step algorithm of supervised learning based on the gradient method in the ISEMK system. Figure 2 represents an exemplary visualization of testing of learned map.

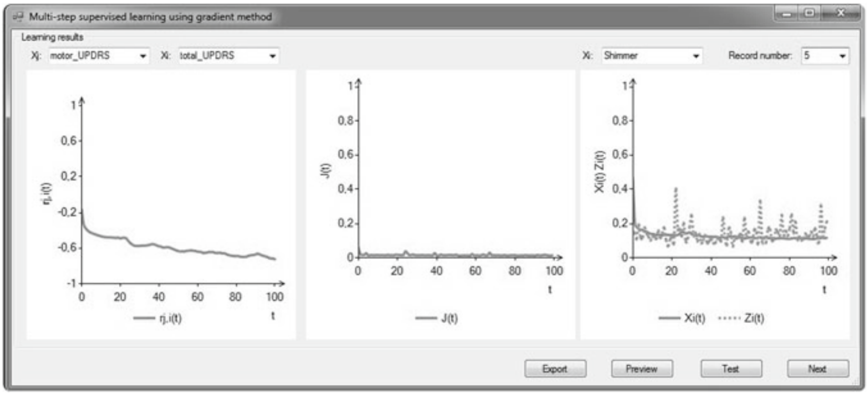

Fig. 1 Visualization of multi-step algorithm of supervised learning in the ISEMK system

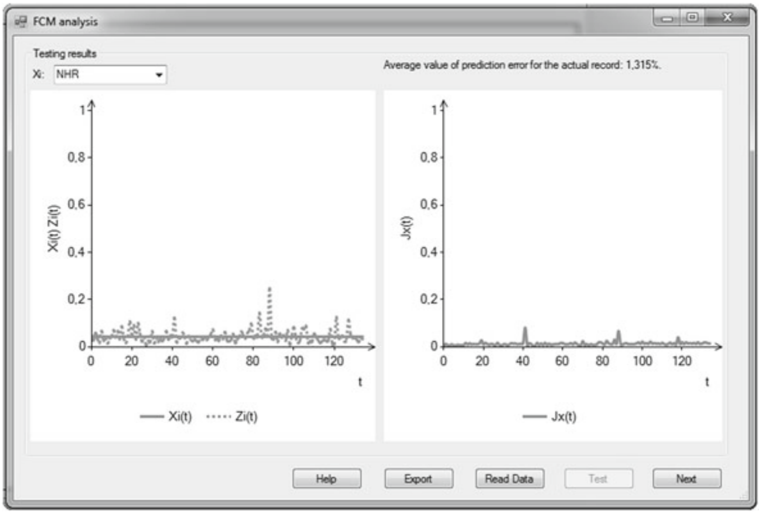

Fig. 2 Visualization of testing of learned map in the ISEMK system

5 Chosen Results of Analysis

The simulation research of multi-step algorithms of FCM learning was analyzed on the example of predicting the clinician's Parkinson's disease symptom. FCM initialization, multi-step learning and testing of learned system functioning was realized based on historical data taken from the UCI Machine Learning Repository [28]. The dataset is composed of a range of biomedical voice measurements and values of the Unified Parkinson's Disease Rating Scale (UPDRS) from 42 patients recruited to a six-month trial of a telemonitoring device for remote symptom progression monitoring. The dataset authors used a range of linear and nonlinear regression methods to

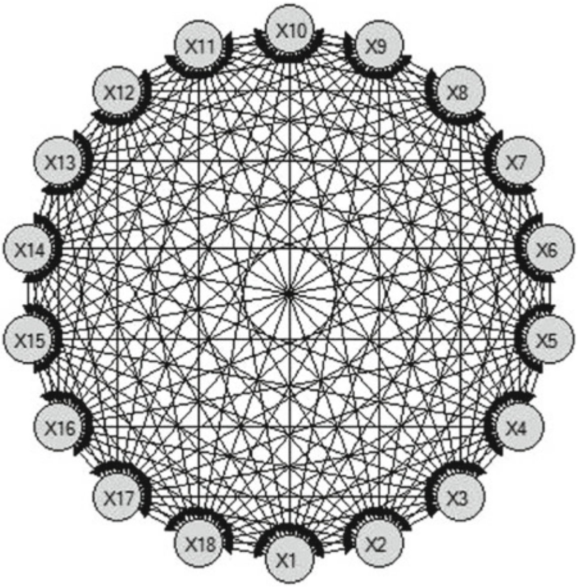

Fig. 3 Structure of the initialized map, where *X1*—motor_UPDRS, *X2*—total_UPDRS, *X3*—Jitter (%), *X4*—Jitter(Abs), *X5*—Jitter: RAP, *X6*—Jitter: PPQ5, *X7*—Jitter: DDP, *X8*—Shimmer, *X9*—Shimmer(dB), *X10*—Shimmer: APQ3, *X11*—Shimmer: APQ5, *X12*—Shimmer: APQ11, *X13*—Shimmer: DDA, *X14*–NHR, *X15*—HNR, *X16*—RPDE, *X17*—DFA, *X18*–PPE

predict the clinician's Parkinson's disease symptom [29]. In this analysis, data of 32 patients were used in the supervised learning process based on multi-step gradient method. Data of 10 others were applied in testing the operation of learned system.

On the basis of normalized numerical data for monitoring of Parkinson's disease, the fuzzy cognitive map with the structure presented in the Fig. 3 was implemented in ISEMK. The relations matrix was initialized with random values from the interval $[-0.2, 0.2]$.

Initialized map was learned with the multi-step gradient method and then, with the multi-step DHL algorithm. Figure 4 shows the exemplary results of the learning.

Table 1 presents the relations matrix obtained in the multi-step supervised learning based on gradient method for the following parameters: $m_1 = 0$, $m_2 = 1$, $\alpha_0 = 1$, $\alpha_1 = 0$, $\alpha_2 = 0$, $\beta_0 = 60$, $\beta_1 = 40$, $\beta_2 = 0$, $\lambda_{0,1,2} = 100$.

The results of the comparative analysis of multi-step algorithms of FCM weights adaptation to one-step algorithms, from the point of view of the influence on the work of the chosen medical prediction system are presented below. An average percentage prediction error, described by the formula (20) was compared [29].

$$J_X = \frac{1}{n_t} \sum_{k=1}^{n_t} \left(\frac{1}{T_t(k)} \sum_{t=0}^{T_t(k)} J(t) \right) \times 100\,\%, \tag{20}$$

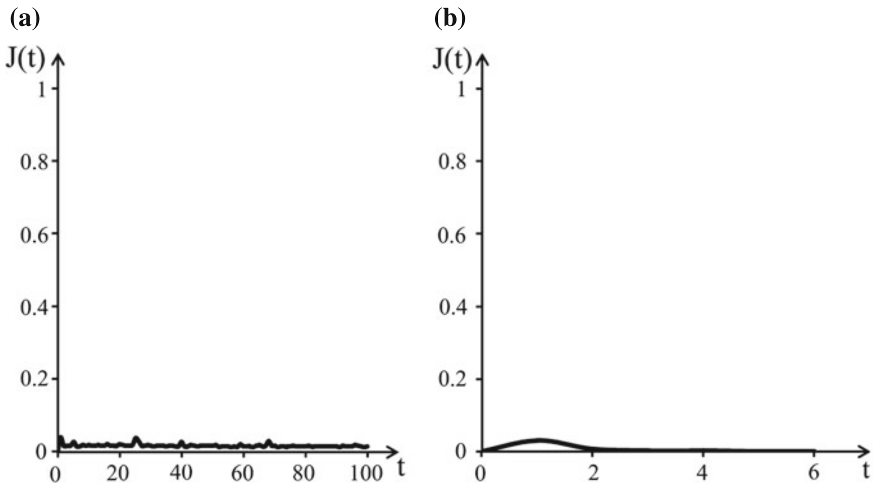

Fig. 4 Exemplary results of the learning of the analyzed map. **a** error function $J(t)$ for the multi-step gradient method, **b** error function $J(t)$ for the multi-step DHL algorithm

Table 1 Exemplary relations matrix for the map learned with the gradient method

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	X_{18}
X_1	0	−0.9	−0.9	−1	−0.9	−1	−0.9	−0.8	−0.7	−0.9	−0.8	−0.8	−0.7	−1	0	−0.3	−0.9	−0.6
X_2	−0.9	0	−0.9	−0.7	−1	−1	−1	−0.7	−0.7	−0.8	−0.8	−0.8	−0.9	−1	0.1	−0.5	−0.9	−0.4
X_3	−0.1	−0.1	0	−0.2	−0.5	−0.4	−0.5	−0.4	−0.6	−0.6	−0.4	−0.4	−0.4	−0.5	−0.2	0.1	−0.1	−0.2
X_4	−0.1	−0.1	−0.9	0	−0.9	−0.9	−0.9	−0.7	−0.6	−0.7	−0.6	−0.6	−0.7	−0.9	−0.1	−0.2	−0.2	−0.3
X_5	−0.2	−0.2	−0.3	−0.1	0	−0.5	−0.5	−0.5	−0.3	−0.4	−0.4	−0.4	−0.4	−0.5	−0.1	0	0	−0.1
X_6	−0.1	−0.1	−0.5	−0.2	−0.5	0	−0.5	−0.4	−0.3	−0.4	−0.5	−0.3	−0.4	−0.4	−0.2	−0.2	0	−0.2
X_7	−0.2	−0.2	−0.4	−0.1	−0.3	−0.6	0	−0.4	−0.3	−0.3	−0.4	−0.5	−0.4	−0.5	−0.1	0.2	0.1	−0.2
X_8	−0.2	−02	−0.8	−0.1	−0.6	−0.5	−0.5	0	−0.6	−0.5	−0.4	−0.3	−0.5	−0.8	−0.1	−0.1	0.1	−0.3
X_9	−0.1	−0.2	−0.6	−0.3	−0.6	−0.7	−0.5	−0.3	0	−0.6	−0.4	−0.5	−0.5	−0.6	−0.3	−0.1	−0.1	−0.3
X_{10}	−0.2	−0.2	−0.4	−0.1	−0.6	−0.4	−0.6	−0.4	−0.6	0	−0.4	−0.4	−0.5	−0.6	−0.2	0	0	−0.3
X_{11}	−0.2	−0.2	−0.5	0	−0.6	−0.5	−0.6	−0.4	−0.2	−0.5	0	−0.4	−0.5	−0.4	−0.1	−0.2	0.1	−0.2
X_{12}	−0.3	−0.1	−0.7	−0.1	−0.5	−0.6	−0.5	−0.5	−0.3	−0.5	−0.6	0	−0.5	−0.7	−0.3	−0.1	0	−0.2
X_{13}	−0.1	−0.1	−0.5	0.1	−0.4	−0.6	−0.5	−0.3	−0.2	−0.5	−0.4	−0.5	0	−0.6	0	0	0	−0.2
X_{14}	−0.3	−0.1	−0.5	−0.2	−0.6	−0.7	−0.6	−0.4	−0.4	−0.4	−0.4	−0.5	−0.5	0	0	−0.1	−0.2	−0.1
X_{15}	0	−0.1	−1	0	−1	−1	−1	−0.7	−0.6	−0.8	−0.8	−0.9	−0.8	−1	0	−0.2	0.2	−0.2
X_{16}	−0.9	−0.9	−1	−0.6	−0.9	−1	−1	−0.8	−0.8	−0.7	−0.7	−0.9	−0.9	−1	0	0	−0.4	−0.8
X_{17}	1	1	−0.8	−0.2	−1	−1	−1	−0.6	−0.5	−0.7	−0.7	−0.8	−0.6	−1	−0.3	0.1	0	−0.4
X_{18}	−0.5	−0.3	−0.6	−0.2	−0.9	−0.9	−0.6	−0.4	−0.7	−0.6	−0.5	−0.6	−0.6	−0.9	0	−0.4	−0.1	0

where n_t is the number of the test records, $T_t(k)$ is a computer time of testing for the k record, $J(t)$ is difference between the desired and obtained in learning process concepts values, expressed by the Eq. (7).

Table 2 Chosen results of analysis of the multi-step supervised algorithm based on gradient method

m_1	m_2	α_0	α_1	α_2	β_0	β_1	β_2	$\lambda_{0,1,2}$	J_X [%]
0	0	1	0	0	100	0	0	100	2.778
0	1	1	0	0	80	20	0	100	2.771
0	2	1	0	0	80	10	10	100	2.771
0	1	1	0	0	60	40	0	100	2.765
0	2	1	0	0	60	30	10	100	2.765
1	0	0.7	0.3	0	100	0	0	100	2.772
2	0	0.7	0.2	0.1	100	0	0	100	2.773
1	0	0.6	0.4	0	100	0	0	100	2.767
2	0	0.6	0.3	0.1	100	0	0	100	2.768
1	1	0.6	0.4	0	60	40	0	100	2.767
1	2	0.6	0.4	0	60	30	10	100	2.767
2	1	0.6	0.3	0.1	60	40	0	100	2.767
2	2	0.6	0.3	0.1	60	30	10	100	2.767

5.1 Simulation Analysis of Multi-Step Gradient Method

The initialized map was learned with the multi-step gradient method based on data of 32 patients. Prediction error (J_X) for the initialized map was 23.2 %. The learning process was realized for various learning parameters, respectively, for the number of steps: $m_1 \leq 2$ and $m_2 \leq 2$. Optimal in some sense parameters of learning were chosen based on minimization of the average percentage prediction error. Table 2 presents chosen results of the impact of steps number and learning parameters on the prediction error (J_X).

Prediction error $J_X = 2.778\,\%$ was obtained as a result of one-step algorithm ($m_1 = 0$, $m_2 = 0$). Increasing the number of steps of the gradient method led to reduced average percentage prediction error. The error minimum ($J_X = 2.765\ \%$) was obtained for the following parameters: $m_1 = 0$, $m_2 = 1$, $\alpha_0 = 1$, $\alpha_1 = 0$, $\alpha_2 = 0$, $\beta_0 = 60$, $\beta_1 = 40$, $\beta_2 = 0$, $\lambda_{0,1,2} = 100$ and $m_1 = 0$, $m_2 = 2$, $\alpha_0 = 1$, $\alpha_1 = 0$, $\alpha_2 = 0$, $\beta_0 = 60$, $\beta_1 = 30$, $\beta_2 = 10$, $\lambda_{0,1,2} = 100$.

5.2 Simulation Analysis of Multi-Step DHL Algorithm

To analyze the multi-step DHL algorithm the initial map from Sect. 5.1 was learned using gradient method for learning parameters: $m_1 = 0$, $m_2 = 2$, $\alpha_0 = 1$, $\alpha_1 = 0$, $\alpha_2 = 0$, $\beta_0 = 60$, $\beta_1 = 30$, $\beta_2 = 10$, $\lambda_{0,1,2} = 100$ ($J_X = 2.765\,\%$) and then using the multi-step DHL algorithm. Unsupervised learning was realized for various learning parameters, respectively, for the number of steps: $m_1 \leq 2$ and $m_2 \leq 2$. Table 3

Table 3 Chosen results of analysis of the multi-step unsupervised algorithm based on DHL method

m_1	m_2	α_0	α_1	α_2	β_0	β_1	β_2	$\lambda_{0,1,2}$	J_X [%]
0	0	1	0	0	0.07	0	0	100	2.507
0	1	1	0	0	0.06	0.01	0	100	2.502
0	2	1	0	0	0.05	0.01	0.01	100	2.497
0	1	1	0	0	0.04	0.03	0	100	2.496
0	2	1	0	0	0.04	0.02	0.01	100	2.494
1	0	0.7	0.3	0	0.07	0	0	100	2.507
2	0	0.7	0.2	0.1	0.07	0	0	100	2.493
1	0	0.6	0.4	0	0.07	0	0	100	2.507
2	0	0.6	0.3	0.1	0.07	0	0	100	2.493
1	1	0.6	0.4	0	0.06	0.01	0	100	2.502
1	2	0.6	0.4	0	0.05	0.01	0.01	100	2.497
2	1	0.6	0.3	0.1	0.06	0.01	0	100	2.491
2	2	0.6	0.3	0.1	0.05	0.01	0.01	100	2.489

presents chosen results of the impact of steps number and learning parameters on the prediction error (J_X).

Use of DHL algorithm resulted in the reduction in prediction error. $J_X = 2.507$ % was obtained as a result of one-step algorithm ($m_1 = 0$, $m_2 = 0$). Increasing the number of steps of the DHL algorithm led to reduced average percentage prediction error. The error minimum ($J_X = 2.489$ %) was obtained for the following parameters: $m_1 = 2$, $m_2 = 2$, $\alpha_0 = 0.6$, $\alpha_1 = 0.3$, $\alpha_2 = 0.1$, $\beta_0 = 0.05$, $\beta_1 = 0.01$, $\beta_2 = 0.01$, $\lambda_{0,1,2} = 100$.

It can be stated that the implementation of the multi-step technique enables reduction of prediction error J_X.

6 Conclusions

This chapter contains the description of multi-step algorithms of supervised and unsupervised learning. Simulation analysis of the gradient method and the DHL algorithm functioning was realized based on ISEMK software tool. Chosen results of analysis of multi-step learning of fuzzy cognitive maps were presented, which will be used to predict the clinician's Parkinson's disease symptom.The advantage of the application of multi-step algorithms is the improvement of the operations of the learned system by reduction of average percentage prediction error. There are plans of further development of multi-step algorithms as possible generalization of known one-step methods of FCM learning. In addition, it is planned to implement genetic algorithms in ISEMK for comparative analysis.

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Chapter 9
Designing and Training Relational Fuzzy Cognitive Maps

Grzegorz Słoń and Alexander Yastrebov

Abstract This chapter deals with certain aspects of the design of fuzzy cognitive maps, which operations are based not on a set of causal rules but on mathematically defined relationships between the model key concepts. In such a model, which can be called a relational fuzzy cognitive map, the key concepts are described by fuzzy numbers, and the relationships between concepts take the form of specially shaped fuzzy relations. As a result, the operation of the model is described mathematically by the system of special equations operating on fuzzy numbers and relations. This approach introduces formal and technical difficulties but on the other hand, it allows to apply certain automation of the process of creating and modifying the relational model of a fuzzy cognitive map. It also enables detachment from the rigidly defined linguistic values in relation to their abstract equivalents, which number can be easily changed depending on the current needs of the modeling process. The chapter describes the results of work up until today by authors of design of fuzzy relational models of cognitive maps.

1 Introduction

Cognitive maps can be treated as certain mathematical models used to formalize and analyze a complex problem or system. They will obtain a form of set of concepts mapping the variables, combined with determining cause and effect relations between

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G. Słoń (✉) · A. Yastrebov
Kielce University of Technology, al. Tysiaclecia P. P. 7, 25-314 Kielce, Poland
e-mail: g.slon@tu.kielce.pl

A. Yastrebov
e-mail: a.jastriebow@tu.kielce.pl

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them. Starting from the works [1, 11], cognitive maps have been analyzed in a form of a directed graph. In 1986 B. Kosko [5] introduced so called fuzzy cognitive maps (FCM), in which concepts took on values from range [0, 1], while relations were real numbers. However, in this approach, activities based on Zadeh's fuzzy sets were not actually realized in calculative aspect, which was, in a certain sense, contradictory to the name. Later, the approach based on maps of FCM type developed in two ways: the analysis of minus influences of concepts, accumulation of influences of several chosen concepts to one and the introduction of different models of map dynamics description. Wider introduction of fuzzyfication to models of cognitive maps leads to the description of concepts and relations in a form of linguistic variables with the application of production principles (type THEN–IF) and to introducing special operation of fuzzy accumulation of influences of concepts into one of them (so called Fuzzy Carry Accumulation). Moreover, a lot of works were devoted to synthesis and analysis of learning algorithms (supervised and unsupervised) of cognitive maps [7]. All of these activities were aimed at maximum generalization of the approach to modeling of cognitive maps, so that on one hand they could model uncertainty, imprecision of expert information on the problem, on the other hand: to accumulate knowledge by appropriate learning. Contrary to the above mentioned approaches, in this chapter Relational FCM models (RFCM) will be described and in a certain sense analyzed. The main purpose of introducing the RFCM is to use the algebra of fuzzy numbers for creating and optimizing the structure of fuzzy cognitive maps using automated algorithms. In the rule-based model (especially with a larger number of concepts) the design and modification of a set of rules can be very difficult, especially when changing number of concepts or the number of linguistic values that describe the concepts. These processes are related to limitations resulting from the structure of rules built on the basis of expert knowledge. In rule-based FCM model, instead causal rules, functionally defined fuzzy relations are applied, and sets of linguistic values are replaced by sets of sample points of so-called universum, which constitutes the base of membership functions for the fuzzy concepts as well as for the fuzzy relations. Thanks to that, processes of designing and learning can be automated with focus, for example, on minimizing the number of sampling points of the universum. As a result, one can obtain a model described (like the rule-based model) with membership functions sampled with a small frequency, but more convenient to operate. In such models, following elements play the most important role:

- proper fuzzyfication of concepts and relations between them,
- analysis of calculative activities in such maps, based on arithmetic of fuzzy numbers,
- the method of supervised training these RFCM, implemented on the base of some kind of the method of successive approximations.

Underneath a short characteristics of key elements of the process of creating RFCM is given, description of which will be the subject of this chapter.

2 Synthesis of the Relational Model of Fuzzy Cognitive Map

Design process of the model should be preceded by an analysis of operation of the modeled system in aspect of the assumed objectives of modeling. This step is very important, because it determines the selection of key factors, whose configuration can be different for different tasks of the system. From the viewpoint of practical applications it is convenient when variables with easily measurable values are key concepts. On the other hand, it should be stressed, that in principle concepts may also be purely abstract, which does not diminish their importance. The essence of proper selection of concepts is to limit the number of them to a minimum sufficient for proper mapping of the system work, which implies that it may be necessary to perform several tests to find the best set of them. A further important component of the process of creating a model is to collect a set of data for training and testing. This data shall be obtained by measuring or observing the work of a modeled system, and then used in the process of the supervised learning of the built model.

2.1 Normalization of Values of Concepts

The role of each key concept is as important as other. Nevertheless, physical concepts may have values that differ by several orders of magnitude (eg. due to the used system of units), what could cause distortion of their meaning. For objectivize the model work, the values of concepts need to be pre-normalized, what will lead them to the dimensionless range $[-1, 1]$. This can be achieved by various methods, eg. according to (1):

$$X_i(t) = \mathrm{Sgn}\left((X_i^*(t)\right) \cdot \frac{|X_i^*(t)| - \min(|X_i^*|)}{\max(|X_i^*|) - \min(|X_i^*|)} \tag{1}$$

where: $X_i^*(t)$—real value of the i-th concept at the t-th step of discrete time; $X_i(t)$—normalized value of the i-th concept at the t-th step of discrete time.

The approach proposed in (1) gives an additional advantage which is to keep the real signs of concepts, which may be useful in some applications.

2.2 Fuzzyfication of Values of Concepts

The values of the factors in the model occur in fuzzy form, what is similar to the forms known from many fuzzy environments. The membership functions in various forms are used, but, from the viewpoint of further calculation automatics, fuzzyfication of concepts is conveniently carried out basing on the Gauss-type membership functions (such a function also complies with the requirements for fuzzy number):

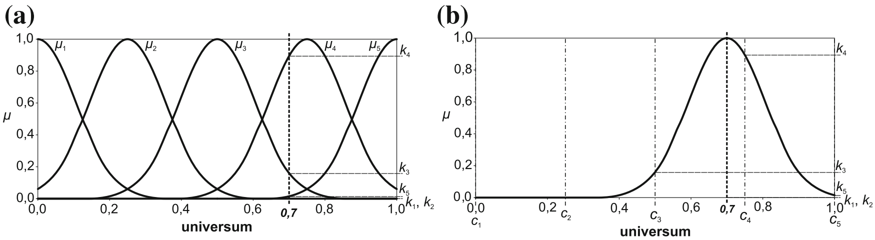

Fig. 1 Fuzzyfication of the number 0.7 with use of five (**a**), and one (**b**) membership functions of linguistic values. μ_1–μ_5—membership functions of consecutive linguistic values; k_1–k_5—levels of membership to consecutive linguistic values

$$\mu_{X_i}(x) = e^{-\left(\frac{x-\overline{X}_i}{\sigma_i}\right)^2} \tag{2}$$

where: $\overline{X}_i$—center of the membership function of the i-th fuzzy value; $i = 1, ..., n$; n—number of concepts; x— given sampling point of the universum; σ_i—fuzziness coefficient of the i-th concept value.

The center of $\overline{X}_i$ in (2) is normalized value of the i-th concept, while x is a sampling point of the universum, on which this value is fuzzyfied. The applied approach has discrete nature, and the sampling points of the universum correspond to the linguistic values, used in a method based on the cause and effect rules (of IF – THEN type). In such an approach, instead of overlapping k membership functions of k linguistic values, you can enter only one function, which values in k sampling points of the universum give the same effect. It is illustrated by Fig. 1:

Proper selection of the universum is a separate issue, which virtually not occurs in the rule-based method. The specificity of algebraic operations on fuzzy numbers means that, in addition to proper selection of concepts, the choice of parameters of the universum is another key element of creating a model. Generally, the smaller the number of sampling points of the universum (linguistic values), the shorter the computation time, on the other hand—the wider range of universum, the greater the accuracy of the model (it has to do with the symmetry of a membership function of a fuzzy value of the concept in relation the scope of the universum. This issue was discussed, among others, in [8]. The problem of the selection of parameters of the universum and fuzziness coefficients of individual concepts (σ_i) is solved in the model learning process.

Fuzzyfication is closely connected with defuzzyfication a concept value. Among the many existing methods, the most useful seems to be the weighted average method (3) because in a sense, it reflects the signal energy.

$$\overline{X}_i = \frac{\sum_{j=1}^{k} w_{ij} \cdot x_j}{\sum_{j=1}^{k} w_{ij}} \tag{3}$$

where: $\overline{X}_i$—defuzzyfied value of the i-th concept; x_j—the j-th sampling point of the universum; w_{ij}— degree of membership of the i-th concept to the j-th linguistic value (in the j-th sampling point) of the universum.

2.3 Building the Fuzzy Relations

The main difference between relational and rule-based fuzzy cognitive maps results from the introduction of fuzzy relations with arithmetically defined membership functions. These relations reflect the interactions between concepts and are defined on two-dimensional universum, and this universum has parameters (range, number of sampling points), which are identical with the universum for fuzzyfication of values of concepts.In the dynamic model, in addition to time-dependent, fuzzy relation determines the strength and direction of the impact of changes of one concept to another. It can be determined by the function of two arguments such as (4):

$$\mu_{R_{i,j}}(x_1, x_2) = e^{-\left(\frac{x_2 - r_{i,j}(x_1)}{\sigma_{i,j}}\right)^2} \tag{4}$$

where: $\mu_{R_{i,j}}$—membership function of fuzzy relation between concepts i and j; x_1, x_2—axes of the universum of fuzzy relation; $\sigma_{i,j}$—fuzziness coefficient of fuzzy relation between concepts i and j; $r_{i,j}$—power coefficient of fuzzy relation determined as a function of the universum.

In the basic model, the function $r_{i,j}$ from (4) is linear, and its graphical representation is presented in Fig. 2:

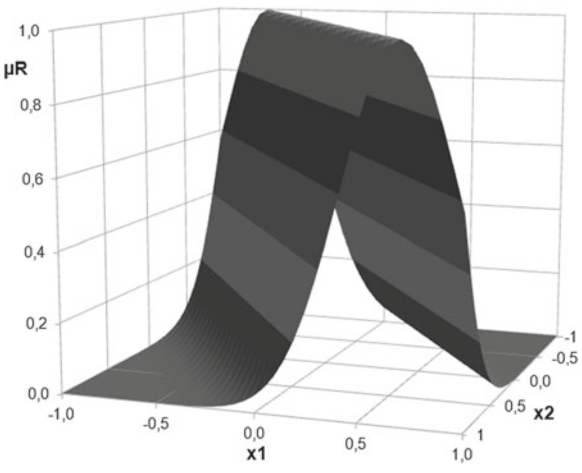

Fig. 2 Graphical representation of fuzzy relation on the universum $[-1, 1]$. $x1, x2$—the universum dimensions

2.4 Elements of Fuzzy Numbers Arithmetic

Fuzzy number is a fuzzy set with the specified characteristics [4]. Fuzzy arithmetic provides tools [4] to perform algebraic operations (such as addition, subtraction, etc.) on such sets. Thanks to its application one can move away from rule-based principles of creation and work of models of fuzzy cognitive maps and replace them with partially automated approach based on algebraic equations. Analyzed type of the model has a discrete nature (due to computer processing algorithms), and hence the discrete nature of such equations. In described solution three algebraic operations on fuzzy numbers and relations are used: addition and subtraction of fuzzy numbers and fuzzy composition of fuzzy number and fuzzy relation:

- fuzzy addition (operator $\oplus$):

$$\mu_{A\oplus B}(y) = \max_{\substack{y_1, y_2 \\ y=y_1+y_2}} \min\{\mu_A(y_1), \mu_B(y_2)\}, \tag{5}$$

- fuzzy subtraction (operator $\ominus$):

$$\mu_{A\ominus B}(y) = \max_{\substack{y_1, y_2 \\ y=y_1-y_2}} \min\{\mu_A(y_1), \mu_B(y_2)\}, \tag{6}$$

- fuzzy composition (operator $\circ$):

$$\mu_{A\circ R}(y) = \max_{x\in A} \{\min[\mu_A(x), \mu_R(x, y)]\}. \tag{7}$$

where: A, B—fuzzy numbers; $\mu_X(y)$—value of a membership function of the fuzzy concept in point y of the universum; R—fuzzy relation; $\mu_R(x, y)$—value of a membership function of the fuzzy relation in point (x, y) of the relation base.

Operations (5–7) concern the discrete models.

2.5 The Work of Dynamic Model of Relational Fuzzy Cognitive Map

Depending on the nature of the modeled system and the purpose of modeling, one can use the models of relational fuzzy cognitive maps of a static or dynamic character. Complex systems are usually characterized by multi-level interactions of concepts, connected each other by multiple feedbacks, and therefore it seems that dynamic models have more universal nature, taking into account the variability in the time of the signals flowing inside the cognitive map. Additionally, the model of relational fuzzy cognitive map may be either partially or fully fuzzy. Among the different models of this kind, for the needs of the considerations in this study, the fully fuzzy model (8), which operates on increments of values of concepts at time, was selected.

$$X_i(t+1) = X_i(t) \oplus \bigoplus_{j=1}^{n} \left(\Delta X_j(t) \circ R_{j,i} \right) \tag{8}$$

where: i—number of considered concept ($i = 1, ..., n$); t—discrete time; n—number of concepts; $X_i(t)$—value of considered concept in the t-th step of discrete time; $\oplus$— operator of fuzzy addition; $\ominus$—operator of fuzzy subtraction; $R_{j,i}$—individual fuzzy relation between concepts numbered j and i; $\circ$—operator of max-min fuzzy composition; $\Delta X_j(t) = X_j(t) \ominus X_j(t-1)$.

Application of the approach (8) is clear from the point of view of control theory. The model of relational fuzzy cognitive map is a dynamic system with multiple closed-loop feedbacks, so its activity is mainly dependent on changes of key parameters (in steady state, when these changes are zero, the values of the parameters are constant). Such an approach for the fuzzy systems has already been tested [2] and its correctness was proved.

In the model (8) the value of given concept in the next step of discrete time t is obtained by summing the value of this concept from the current discrete time step and the cumulative effects of changes of other concepts, connected with the reference concept through the fuzzy relations. It should be kept in mind that, regardless of the selected model, its structure (i.e. the nature of the concepts, their method of fuzzyfication and defuzzyfication, the parameters of the relations) has initially only an approximate nature, determined, for example, on the basis of expert knowledge. The working structure, which optimally mapping the modeled object, arises only in the process of the model learning.

Equation (8) defines the main rule for calculating (in successive steps of discrete time) individual fuzzy values of concepts. It is assumed, that one cycle of flowing of all signals through the model is made in one step of discrete time. Due to properties of the fuzzy arithmetic operations, after each cycle all values of concepts are defuzzyfied, then fuzzyfied according to general system rules and then introduced into the model to calculate the next cycle. The same mechanism is used to calculate the closeness coefficient (9) during the learning process.

2.6 Learning Procedure in a Relational Fuzzy Cognitive Map

Model learning mechanism is crucial for proper operation of the model. In intelligent models it is actually the only way to adapt the model parameters to the real parameters of the object. In the literature one can find many different approaches to the construction, operation and learning of classic fuzzy cognitive maps. Most of them (such as [1, 5, 7, 9, 11, 12]) operate on relations that are defined through sets of rules or powers of the connections presented in the form of real numbers. Arithmetic operations in such models (if any are made) have a nature of equations on real numbers, what determines the technical aspects of not only the work but also the model learning. By using calculations on numerical quantities, one can implement into cognitive maps the learning methods, which are known from other applications, such as genetic [9], evolutionary [12] or multi-step [6] algorithms, and in some applications—gradient methods of optimization [3]. Most of this type of learning methods is based on the functional processing of numerical values, which for a system based on fuzzy numbers and fuzzy relations is difficult and may introduce additional errors. Moreover, substitution of fuzzy relations by real numbers is a certain departure from the fuzziness idea and, in fact, makes the model to be crisp. Regardless, it must be remembered that the function which argument is a fuzzy variable determined on a specific universum, impacts de facto on this universum, changing usually both the range and parameters of sampling points of it. At the same time, from the viewpoint of the correct operation of the model, it is necessary to maintain constant parameters of the universum. There is therefore a certain contradiction, which can be overcome by introducing additional mechanisms for correcting the universum after every change. Such mechanisms in fact already exist in the model (when interpreting the results of fuzzy addition and subtraction), but their reproduction is not recommended, because every activation of them slightly deforms the final shape of the membership function of the processed fuzzy number. For the above reasons, at the current stage of research, authors are applying the method of supervised learning using the successive approximations algorithm [8] with floating step of the parameter changes, which is based on making small changes (according to special rules) of key parameters and investigation of differences between the work of RFCM and the modeled real system. General approach to this method (for Gauss-type (4) membership functions of the relations) is shown, in the form of pseudo code, in Fig. 3.

"Stop criterion" mentioned in Fig. 3 is met in one of two situations: closeness coefficient value is less than threshold or number of learning cycles is more than

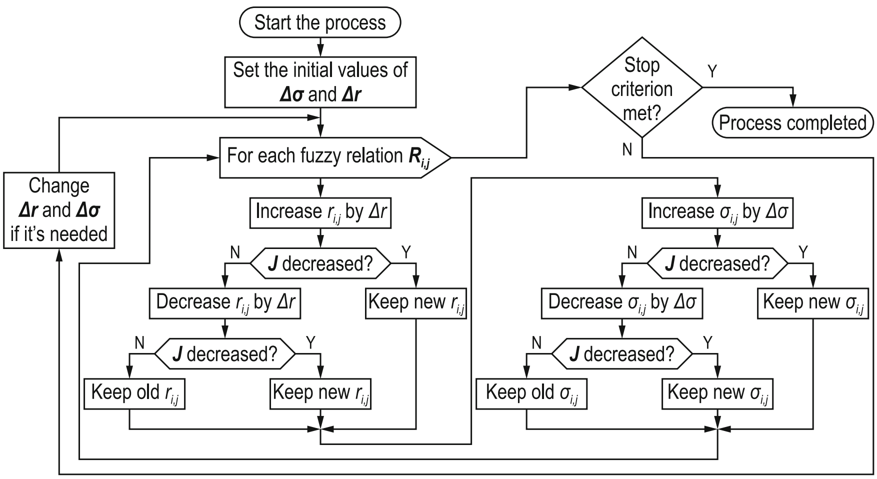

Fig. 3 General diagram of learning by successive approximations algorithm method for Gauss-type membership functions of the RFCM relations. J—closeness coefficient type (9)

limit. In fact every method of learning, which operates fully fuzzy quantities can be applied here because the main goal of this work is to show certain approach to the modeling with the use of the special kind of a cognitive map. The chosen method is quite convenient for multi-parameter variables, such as fuzzy relations (each of them is described with the use of at least three independent parameters, i.e.: power of the relation, fuzziness coefficient of the relation and number of sampling points of the universum). In dynamic models, the system usually requires some time (some steps of discrete time) for the internal stabilization after the external stimulation. Depending on the purpose of modeling, procedure of learning can adjust the parameters of the map to indicate the correct values in one, selected step of such a cycle, with no attention given to steps preceding (this method is faster) or in the whole cycle of the stabilization. For this second option, one possible criterion is to minimize the closeness coefficient, which is defined by Eq. (9):

$$J_i = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\overline{X}_i(t) - X_i^*(t)\right)^2} \tag{9}$$

where: J_i—closeness coefficient of the i-th concept; t—discrete time; T—stabilization time of dynamic model (expressed in steps of discrete time); $\overline{X}_i$—defuzzyfied value of the i-th concept of the relational fuzzy cognitive map; X_i^* —crisp value of the i-th concept of the reference data (from modeled object).

Equation (9) applies to research single concept. In general, the minimization can concern a factor containing the values of all concepts.

3 Exemplary Model

Presented above rules for creating, learning and operating relational model of the fuzzy cognitive map will be illustrated with an example of the fuzzy system, consisting of ten concepts influencing each other (shown in Fig. 4), which was built to analyze the behavior of the passenger rail system in Poland in years 2003—2011 (the reference statistical data was taken from [10]). For the modeling purposes the following parameters were selected: X_1—number of passengers carried during the year; X_2—transport work (in passenger-km); X_3—average distance of transport of a single passenger; X_4 —average number of passenger trains that run throughout the day; X_5—the average number of passengers in trains; X_6—number of passenger coaches; X_7—number of employees; X_8—revenue from operating activities; X_9—profit from operating activities; X_{10}—the GDP growth rate. The aim of the constructing the model is to enable the study of the impact of changes of value of a single concept on values of other concepts. The proposed approach will be considered valid, if the fully fuzzy system after completing the learning procedure, will work sufficiently similarly to the real reference system, which is basis for the learning.

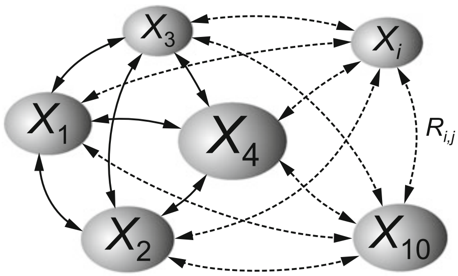

Fig. 4 Graphical representation of the relational fuzzy cognitive map used to build the model of the passenger rail system. X_1–X_{10}—fuzzy values of the successive concepts (X_i represents concepts numbered 5–9, which are omitted in the figure to improve its clarity)

In the first step, selected real data, taken from the official report [10], were normalized according to the rule (1). In the second step there was prepared the preliminary draft of the relational fuzzy cognitive map, which assumed the existence of fuzzy relations connecting each concept with all other and there was assumed initial, the same for all relations, parameters: power of the relation $r_{ij} = 0$ and fuzziness coefficient of the relation $\sigma_{ij} = 0.4$. σ_{ij} can take practically any non-zero value (they are typically in a range from -2 to 2). The value of 0.4 is some rounding of the most common averaging. It was assumed that values of concepts will be fuzzyfied in accordance with (2), and fuzzy relations— according to (4). Additionally, a joint fuzziness coefficient for concepts was assumed: $\sigma_i = 0.4$. Generally, each concept can take its own fuzziness coefficient, which can be determined on the basis of the expert knowledge, but numerous experiments have shown that all concepts can a common value of this coefficient, which can vary in the range from 0.3 to 0.6, where in the most convenient value is 0.4. For fuzzyfication needs, the universum of the range $[-2, 2]$ was used, in which 17 sampling points were placed uniformly. The range $[-2, 2]$ is wider than limits of the normalized concept values (they are from -1 to 1) due to properties of weighted average method, which is used for defuzzyfication purposes. This method is sensitive to the asymmetry of the concept membership function. Widening the uviversum range allows to reduce the significance of such asymmetries.

It was assumed that the model (8) will map all annual data of the variables, and closeness coefficients in accordance with (9) were used to optimize the parameters. The result is a relational fuzzy cognitive map, where relations have the following powers (Table 1) and fuzziness coefficients (Table 2):

It is worth to recall that the learning procedure modifies the parameters of the model solely on the basis of the observed behavior of the object in a given situation, without any knowledge of its actual internal structure (lack of such knowledge is indeed the essence of the described approach).

Relational model of fuzzy cognitive map obtained as a result of the learning algorithm work was stimulated by signals taken from the reference data. Achieved results for few selected concepts, combined with the real data of the studied object, are shown in Fig. 5.

Table 1 Powers of fuzzy relations obtained in a process of the relational fuzzy cognitive map learning (from common initial value 0.0)

r	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
X_1	0.00	0.26	−0.03	−0.33	0.06	0.23	57	−0.39	0.16	−0.40
X_2	0.14	0.00	0.28	−0.08	0.00	−0.24	0.48	0.05	−0.24	0.05
X_3	1.00	0.89	0.00	0.60	0.19	−0.19	0.14	0.21	0.42	0.57
X_4	0.21	0.35	0.18	0.00	0.23	−0.46	0.99	0.68	0.43	0.16
X_5	0.00	−0.26	−0.03	−0.27	0.00	−0.38	0.52	0.86	0.4	−0.46
X_6	−0.07	−0.33	−0.01	−0.39	0.00	0.00	−0.67	−0.25	0.15	−0.39
X_7	0.12	−0.14	−0.10	0.01	−0.14	0.02	0.00	0.61	0.61	−0.11
X_8	−0.04	−0.04	0.03	0.32	0.05	−0.22	0.36	0.00	−0.57	−0.08
X_9	−0.06	−0.03	0.02	−0.11	0.00	−0.05	−0.29	−0.42	0.00	−0.09
X_{10}	0.69	0.55	0.01	0.58	0.43	0.27	0.51	−0.30	−0.49	0.20

Table 2 Fuzziness coefficients of fuzzy relations obtained in a process of the relational fuzzy cognitive map learning (from common initial value 0.4)

σ	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
X_1	0.40	0.43	0.59	0.29	0.91	0.54	0.36	0.56	0.42	0.44
X_2	0.60	0.40	0.63	0.75	0.57	0.52	0.30	0.54	0.32	0.64
X_3	0.63	0.58	0.40	0.44	0.56	0.43	0.66	0.61	0.45	0.45
X_4	0.63	0.59	0.53	0.40	0.66	0.30	0.37	0.59	0.38	0.68
X_5	0.63	0.43	0.52	0.34	0.40	0.31	0.22	0.38	0.40	0.41
X_6	0.63	0.38	1.19	0.30	0.71	0.40	0.61	0.55	0.46	0.18
X_7	0.62	0.55	0.80	0.75	0.49	0.47	0.40	0.58	0.53	0.44
X_8	1.62	0.65	0.89	0.61	0.40	0.44	0.49	0.40	0.38	0.56
X_9	0.55	1.68	1.79	1.30	1.83	0.42	1.11	0.36	0.40	0.58
X_{10}	0.65	0.47	0.49	0.43	0.64	0.47	0.69	0.34	0.28	0.40

The main area of application of all types of cognitive maps is a study of the impact of one (or more) selected concept to the others. Under normal circumstances this is a very difficult task, because of all the concepts are changing simultaneously, so isolating the influence of only one of them may be impossible. In the next test, the model was programmed for the simulating the situation, in which all the concepts have zero values, and then one of them (the 7-th) changes its value from zero to 0.1 and keeps this value during whole test. The results are presented in Fig. 6.

As it is shown in Fig. 6, increase of X_7 causes an increase of X_4 and decrease of X_9. Similar results were obtained for other concepts but they are not included here for clarity of the drawing.

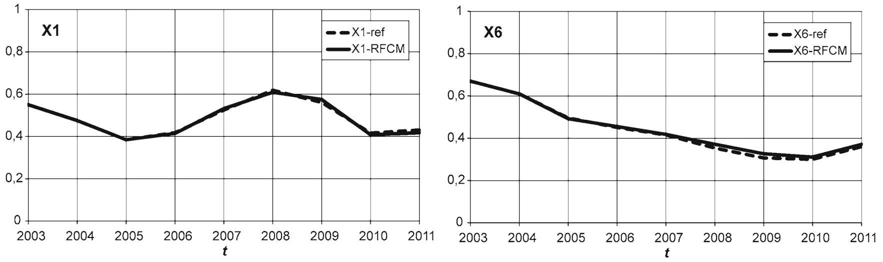

Fig. 5 Selected results of work of the relational fuzzy cognitive map after finishing the learning process, ref—the reference courses (in the real system), RFCM—courses of values of concepts in the model (after defuzzyfication)

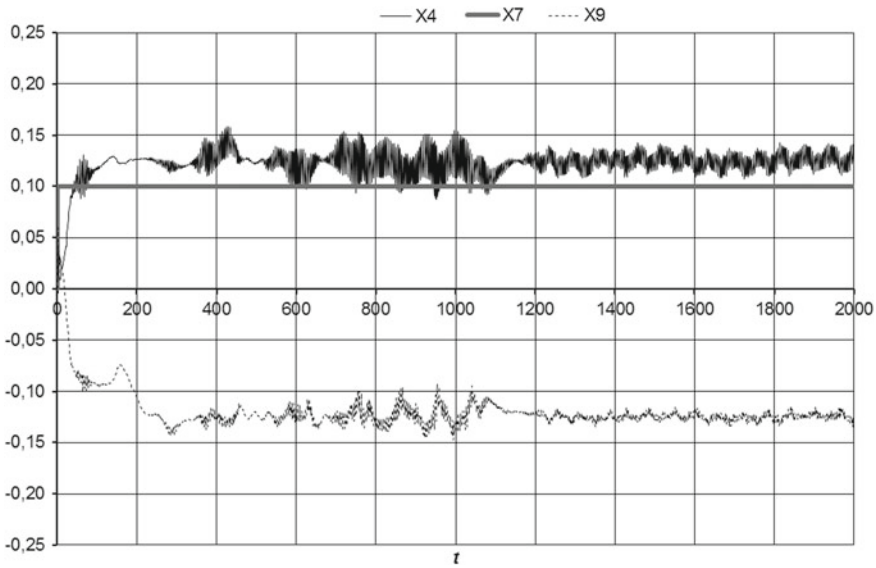

Fig. 6 Selected results of the testing the impact of increase of X_7 to other concepts

4 Conclusions

The arithmetic of fuzzy numbers is not a new field, but in principle it was not so far been used for constructing fuzzy cognitive maps. It is probably the result of the technical difficulties in the development and practical implementation of algorithms that use operations on fuzzy numbers and fuzzy relations. Their specificity causes that the load on the computer processing the model is highly dependent on the sampling density of the common universum (adoption of too short sampling step makes the model not effective in practical applications). Moreover, its quite difficult to find the proper method of designing the fuzzy relations that could be useful in automatic learning procedures and, at the same time, could sufficiently represent the object properties. The presented approach, based on the RFCM model with an appropriately defined fuzzy relations, allows to overcome both these problems. Of course it is still difficult to achieve the optimal levels of all parameters, but described method of the adaptation of key parameters of fuzzy relations can significantly ease this task.

Model of RFCM can be used either for time prediction of the concept values and, what is even more important, for studying the impact of selected concept change to behavior of other concepts, while maintaining all the features of the fuzzy structure on each stage of its work. Current research is focused on improving learning methods in order to use them to create more complex fuzzy relations.

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Chapter 10
Cooperative Autonomous Agents Based on Dynamical Fuzzy Cognitive Maps

Márcio Mendonça, Lúcia Valéria Ramos de Arruda and Flávio Neves-Jr

Abstract This work presents an architecture for cooperative autonomous agents based on dynamic fuzzy cognitive maps (DFCM) that are an evolution of fuzzy cognitive maps. This architecture is used to build an autonomous navigation system for mobile robotics that presents learning capacity, on line tuning, self-adaptation abilities and behaviors management. The developed navigation system adopts a multi-agent approach, inspired on the Brooks' subsumption architecture due to its hierarchical management functions, parallel processing and direct mapping from situation to action. In this paper, a DFCM is hierarchically developed, from low-level describing reactive actions to the highest level that comprises management actions. A multi-agent scheme to share experiences among robots is also implemented at the last hierarchy level based on pheromone exchange by ant colony algorithm. The proposed architecture is validated on a simple example of swarm robotics.

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M. Mendonça (✉)
Federal University of Technology—Paraná UTFPR, Av Alberto Carazzai 1640,
Cornélio Procópio, Brazil
e-mail: mendonca@utfpr.edu.br

L. V. R. Arruda · F. Neves-Jr
Federal University of Technology—Paraná UTFPR, Av Sete de Setembro,
Curitiba, PR3165, Brazil
e-mail: lvrarruda@utfpr.edu.br

F. Neves-Jr
e-mail: neves@utfpr.edu.br

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1 Introduction

In mobile robots, the use of computational intelligence techniques such as neural networks, fuzzy logic, evolutionary algorithms or agents is currently. Among these techniques, the intelligent agents can be highlighted. According to Wooldridge and Jennings [15] an "agent" is defined to be a computer system that is assigned to an environment and it is able to decide and take actions in this environment, without external interference, in order to complete the tasks delegated to it.

If the environment suffers sudden and unpredictable changes, an ability to learn is particularly important to the agent. Moreover, the coexistence with other agents in the same environment (that characterizes multi-agent systems) with the same or different tasks requires individual and/or group ability to cooperative solve conflicts and reach objectives.

In multi-agent systems, the term "collective intelligence" refers to sophisticated collective behaviors that can arise from a combination of many agents with relatively simple behavior and action, each operating autonomously. The development of robotic systems with collective intelligence is a new research area named as Swarm Robotics [13]. In fact, Swarm Robotics differs from more traditional multi-agent system due to their command structures and non-hierarchical and centralized control. However, swarm robotics systems as multi-agent systems are fully distributed, self-organized and inspired by the collective behavior of social insect colonies and other animals [2].

In this context, the present work develops an autonomous navigation system for mobile robotics that presents learning capacity, on line tuning and self-adaptation abilities and behaviors management. The navigation system must support the development of swarm robotics applications. For this, bio-inspired algorithms are used allowing agents to realize tasks. Subsumption architecture is also proposed to manage agent behaviors. The knowledge formalism to represent, model and implement the several agents' behaviors is based on dynamic fuzzy cognitive maps.

Fuzzy Cognitive Maps are signed and directed graph, in which the involved variables are fuzzy numbers. The graph nodes represent linguistic concepts modeled by fuzzy sets and they are linked with other concepts through fuzzy connections. Each of these connections has a numerical value (weight) taken from a fuzzy set, which models the relationship strength among concepts [8]. In addition, FCM can be considered a type of cognitive neuro-fuzzy network, which is initially developed by the acquisition of expert knowledge, but can be trained by several supervised and/or unsupervised techniques as reviewed in Ref. [11]. There are in the literature, several models based on fuzzy cognitive maps developed and adapted to a broad range of applications. A good survey of recent applications is given by Papageorgiou and Salmeron in Ref. [12].

The dynamic fuzzy cognitive map (DFCM), proposed here, is a causal model in which the causal relationships and the associated effects are both time varying. Moreover, the strengths of relationships are automatically self-adapted by a reinforcement learning algorithm as a result from environment interactions. In order to confer dynamic abilities to FCM, new types of concepts and relationships, beyond pure cause-effect ones, are developed. Moreover, some procedures are also necessary to confer adaptation skills to DFCM models. Such procedure functions are to add/remove concepts, to add/remove causal relationships, to magnify/reduce the level of system concepts and to magnify/reduce the strength of causal relationships.

In the proposed navigation system, the several DFCMs which correspond to behavioral modules of an agent are organized in a layered hierarchy of subsumption. The DFCMs placed in the lower layer present only purely causal relationships and/or fuzzy type relationships. These maps constitute a reactive knowledge that models continuous cause–effect behaviors. The intermediate level behaviors are driven by the aim to pursue planned goals (deliberative knowledge). In the higher layer, the functionalities to adaptation, communication with other agents and model evolution are inserted. The DFCM models in this layer can inhibit or suppress concepts and relationships and thus change the overall behavior of the model.

In order to validate our approach to swarm robotics applications, the proposed navigation system is applied to a simulated self-guided vehicle that must navigate and cooperate in dynamic and unpredictable environments.

This paper is organized as follows: Section 2 presents the proposed approach to develop dynamical fuzzy cognitive maps (DFCM). Section 3 develops the autonomous navigation system. Section 4 presents the simulation results and Sect. 5 concludes the work.

2 Dynamic Fuzzy Cognitive Maps

A dynamic fuzzy cognitive map can be considered a causal model in which the causal relationships and the associated effects are both time varying. For this, the herein proposed dynamic fuzzy cognitive map supports several types of concepts and relationships:

- Input/output data concept: this type of concept receives input (or deliveries output) data describing the system state. They are the concepts interfacing the real world.
- Level concept: this concept is perfectly represented by an absolute value that indicates the behavior of a dynamic model variable.
- Variation concept: its value represents a level variation of a model variable in given time. It can be computed by a first order difference equation.
- Decision concept: these concept values are the result from FCM inference and do not interact with other concepts. This concept is introduced into the graph by means of a selection relationship.
- Memory concept: this concept represents a memory about past decisions. There are two type of memory that can be modeled: temporal memory and data memory.
- Factor concept: this concept is necessary to magnify/reduce the level of the other model concepts. The use of a factor concept is determined by a conditional declaration.

- Causal relation: they represent cause and effect relationships between two concepts. The causal relations are calculated through a constant weighting matrix.
- Time varying causal relation: these relations establish a cause—effect connection among the FCM concepts that is driven by a time function. These relations can be also on line tuned by special procedures such as reinforcement learning algorithm. The resulting weighting matrix is a time varying matrix in which time is a variable explicitly considered.
- Fuzzy relation: this relation introduces a non-monotonic and fuzzy reasoning into the model. In this case, two or more concepts (antecedents) affect another concept (consequent) by means of a fuzzy function. The computed weighting matrix is a time varying matrix resulting from a fuzzy inference system.
- Selection relation: these relations indicate the occurrence of events and they also identify what cause–effect relationships are valid in a given time. They are conditional declaration expressed in term of if–then rules that are fired according to the modeled phenomena. These relations are naturally time-varying since that rules are valid only under special circumstances (events). The weighting matrix is resulting from fired rules. The selection relation represents in fact a mechanism that triggers (add or remove) concepts in the map.

The design of DFCM models even for small systems requires a large amount of concepts and relationships that need to be established which hinders a manual development of the model. To make this process easier and to allow a consistent analysis of the maps, a DFCM model must be developed incrementally, according to the kind of modeled cause–effect connections and organized into an ontology as proposed by Ref. [5]. A guide to incrementally design a DFCM model based on ontology is given in Table 1. Steps 1 and 2 correspond to classic FCM development [8]. Steps 3 and 4 are related to the inclusion in the graph of fuzzy and time varying relations that model cause-effect relationships. The use of a fuzzy relation allows modeling a relationship with more than a concept as antecedent and/or consequents and there-

Table 1 Steps for design (based on ontology [5]) DFCM models

Step 1:	Identification of elementary concepts, their roles (input, output, decision and level) and their interconnections, determining its causal nature (positive, negative, neutral)
Step 2:	Initial set-up of concepts and relationships. The initial state values of the map (nodes/edges) can be acquired from experts, historical data analysis and / or system simulation
Step 3:	Determination of ontological influence among concepts. Design of the different ontological views of the system
Step 4:	To each view of the system, design of fuzzy rule bases and time varying functions computing the values for the weights of the DFCM fuzzy and/or time-varying relations
Step 5:	Information processing, adaptation and optimization of the DFCM model, adjusting its responses to the desired output. If necessary, training method (reinforce learning, hebbian learning, evolutionary learning, etc) can be used for dynamic refinement of the model
Step 6:	Design of management level corresponding to the development of the rule base that are associated to factor concepts and selection relations, and, implementation of algorithm to on-line learning such as reinforcement learning rules
Step 7:	Development of methods or algorithms for share information (this step is optional)
Step 8:	Final test and validation of the DFCM model

fore a non-monotonic inference engine is represented. This inference constitutes an ontological influence as defined by Ref. [5] and it allows developing different paths linking the same set of concepts. Each different path constitutes an ontological view of the system. Step 5 corresponds to a tuning/adaptation model step that is very similar to learning in neural networks. This step is quite common in recent models using FCM [11]. In step 6, the rule bases associated with the strategic decision level are included. In step 7, methods or algorithms for sharing information acquired on line are considered if required by the application. Finally, step 8 corresponds to the model validation step that is usual in data driven modeling.

DFCM models in general can be quite complex, then a knowledge organization is required to represent, model and implement the several behaviors into the cognitive map.

These several behaviors correspond to different views of the modeled system. For this, we propose the use of an architecture similar to Brooks' subsumption architecture [3–7]. The subsumption architecture can shortly be summarized as a composition of hierarchical control loops, where each loop maps a perception to action behavior or cause-effect behavior. If these simple control loops are fitted with timers, they become finite state machines [10]. These state machines can be combined in incremental and hierarchical layers, working bottom-up toward increasingly complex systems. The lower layers are independent of higher layers and each layer forms a complete operational system. Another interesting feature of the Brook's architecture is that many behaviors can be simultaneously triggered; hence the need for a choice mechanism to select which state machine should actually be triggered [7].

As a subsumption hierarchy, our DFCM model is organized in layers related to the nature of modeled knowledge. Initially, small maps presenting only purely causal relationships and/or fuzzy type relationships are placed in the lower layer. These maps constitute a reactive knowledge that models continuous cause–effect behaviors. Then, the next layer includes sub-maps containing fuzzy rule bases, time varying causal relation and others relationships that are related to programmed tasks and planned goals (deliberative knowledge). Finally, the third layer is inserted and tested. The maps in this layer can inhibit or suppress concepts and relationships and thus change the overall behavior of the model. They are characterized by the presence of selection relations and factor concepts. The decision-making associated to these higher maps can be classified in three groups:

- low-level decisions used to magnify/reduce the strength of a causal relationships and/or the level of concepts;
- management decisions used to add or to remove concepts and/or causal relationships;
- drastic decisions used to completely change the current DFCM model, that is, the decision changes the cognitive model [1].

Summed to this hierarchical organization and management skill, the parallel processing is also a characteristic of subsumption architectures. Thus actions or decision-making can coexist. However, when the actions of a higher strategic level hierarchy are running, the others (lowers) are inhibited [3].

3 Autonomous Navigation System Based on Dynamic Fuzzy Cognitive Maps

The development of the DFCM model for autonomous navigation is guided by the general ontology presented in Table 1, however we use only some of the relationships and concepts presented. This model starts by the comprehension of agent behaviors and actions in several situations. These behaviors and actions are listed at Table 2 according to the navigation strategy and development plan.

Initially the three reactive behaviors (Table 2) needs to navigation are mapped. They are related to the environment description such as presence of obstacles and position of the obstacles in relation (left, right or front side) to the path followed by the robot.

These concepts form the set of elementary concepts of the ontology. Three actions describing the robot movements are also listed in Table 2: turn left, turn right and move on. The three inputs take values from measurements of three sensors placed on the left, right and front side of the robot. The resulting cognitive map is shown in Fig. 1a in which the input data concepts SR, SF and SL are connected by arcs to the decision concepts that represent the action of acceleration (positive connection) and braking (negative connection). Thus three motion decisions are originally modeled by three output concepts (OL, OR and OUTFront in Fig. 1): if the sensors accuse an obstacle on the left side, the robot must turn to the right side, and on the other hand if the sensors accuse an obstacle on the right side, the robot turns left. The decision to change direction implies a robot smooth deceleration. The third decision relates to an obstacles free environment. In this case, the robot follows a straight line in a smoothly acceleration. As recommended in step 2, the initial values of the weights corresponding to pure causal relationships W1 to W7 were obtained by simulations with a heuristic method based on simulated annealing [6]. In this case, all arcs are initialized to 0.5 (positive or negative depending on their causality), in the following, new values are incremented or decremented in a systematic and random way, until the model reaches the desired dynamic behavior.

This model also uses a temporary memory to induce a motion tendency during the evolving trajectory, and to prevent zig-zag movements. Thus, two memory type concepts (OL(-1) and OR(-1)) associated to previous turn right/left movements are added to the DFCM model.

The output concepts become OUTLeft, OUTRigth and OUTFront as shown in Fig. 1a. These concepts are added to elementary set and the fuzzy cognitive map in the lower level is given in Fig. 1a. This is a movement map allowing the robot locomotion as a reactive behavior.

In the next step, the reactive behavior in the fourth line of Table 2 is included. The subsequent robot action is resulting from a decision (to turn left or right?) that is modeled by means of fuzzy relations (WS1, WS2 and WS3) considering the robot actual position and sensing (OR and OL concepts). The resulting DFCM model is given in Fig. 1b and confers navigation skills to the robot. For example, the robot

Table 2 Behaviors/situations/actions executed by the agent

Behavior	Situation	Action
Reactive/navigation	Presence of obstacles at the robot right side	Turn left
Reactive/navigation	Presence of obstacles at the robot left side	Turn right
Reactive/navigation	Obstacles free path	Move on (accelerate/decelerate)
Reactive/navigation	Presence of obstacles at the robot front side	Turn right or turn left
Deliberative/navigation	Imminent collision (a sudden obstacle appearance)	Reverse course and resume
Deliberative/planning	Exploring the environment	Walk straight
Deliberative/planning	Mapping the environment	Identify obstacles
Deliberative/planning	Task	Collect targets
Intelligent/adaptation	Adaptation/tuning	Use a RL procedure to dynamic adaptation of the model
Intelligent/cooperation	Cooperation/tuning	Use navigation experience of others agents to model evolution
Intelligent/learning	Memory/tuning	Use the itself navigation memory to model evolution

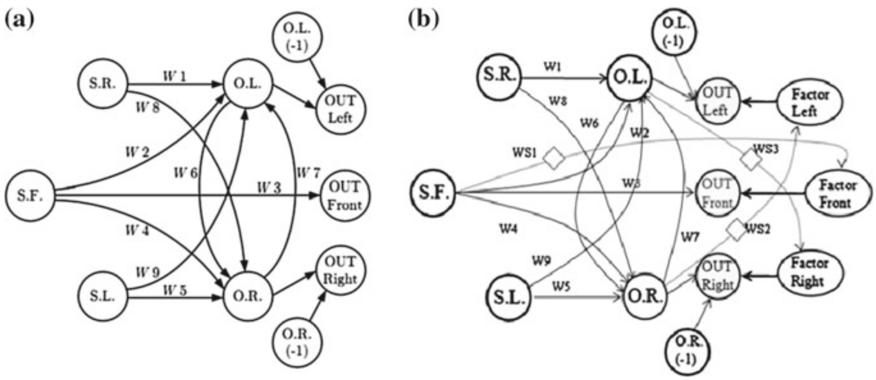


Fig. 1 Reactive behavior map to navigation (*lower layer*) **a** movement map, **b** movement decision map

can strongly accelerate if there is no obstacle ahead, or slightly correct the trajectory when it detects obstacles along the way.

The next layer to be added on the navigation system is related to deliberative knowledge. The planned actions and tasks such as move to the final position, collect target and prevent collision are modeled (see Table 2). The DFCM model mapping these behaviors/actions is shown in Fig. 2. At this figure, two decision concepts (DXR and DXL) and two selection relationships (WS4 and WS5) are related to collect target.

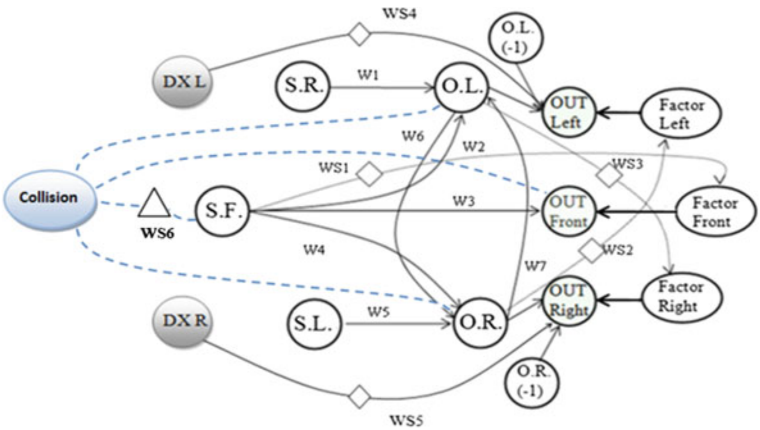


Fig. 2 DFCM model with two layers (deliberative/reactive behaviors)

Hence, the robot can reach the targets whose coordinates are previously assigned in the environment. The concepts DXL and DXR measure in navigation time the distances between the robot current position and the target coordinates.

Also in Fig. 2, the safety functionality need to prevent collision is shown. When a collision event is detected, a sequence of control actions is carried out as follows: the mobile robot brakes hard and makes a reverse movement, and then it slightly corrects the trajectory and continues the navigation. This behavior is modeled by a decision concept (Collision) and a selection relationship (WS6). This relationship triggers a task to avoid collision when the frontal sensor accuses a very high reading. The value of frontal sensor threshold is computed in order to guarantee that the robot can implement the above described hard maneuver. When a new safety path is attained, the robot returns to its initial navigation strategy, which has been interrupted by the occurrence of an imminent collision. The dashed lines connected to OL and OR concepts in Fig. 2 suggest that the initial control strategy of turning left, right or straight walk is resumed.

Finally the intelligent skills to adaptation, tuning, learning from experience and cooperation are added by means a navigation memory concept as shown in Fig. 3. The values of the arcs connecting this concept to the output concepts (OUTLeft, OUTRigth and OUTFront) are computed by a strategic controller. This controller analyses the actual robot state and takes a decision about the next movement based on the subsumption hierarchy of task given in Fig. 4 and the non-deterministic finite state machine shown in Fig. 5.

From Fig. 4, the adopted priority to the robot actions (blue blocks) is: obstacle avoidance, finding targets and exploring the environment. The others model actions (white blocks) are related to robot behavior managements and they are always running in a parallel way. In other words, the tuning algorithms and model adaptation and evolution act according to established premises (by the rules of the RL algorithm) independently of the decision/actions related to simple reactive behaviors. In order to

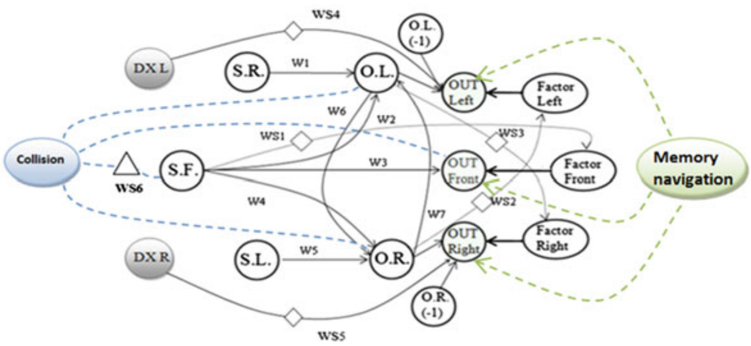


Fig. 3 Final DFCM model with three layers

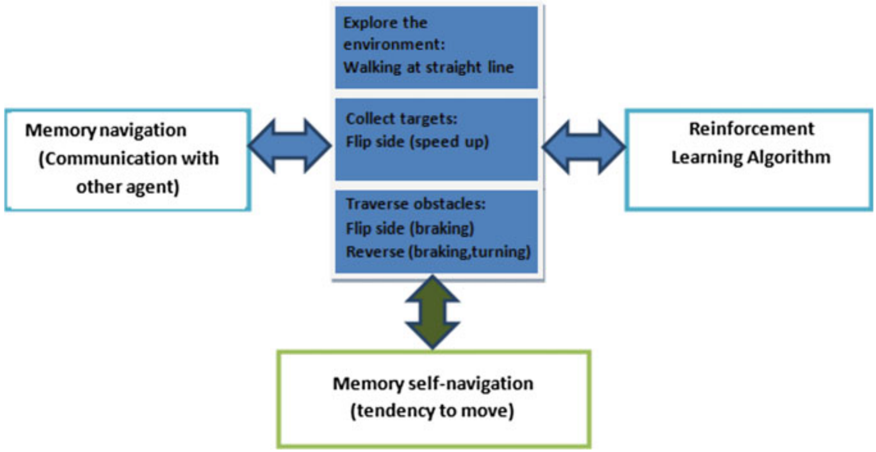
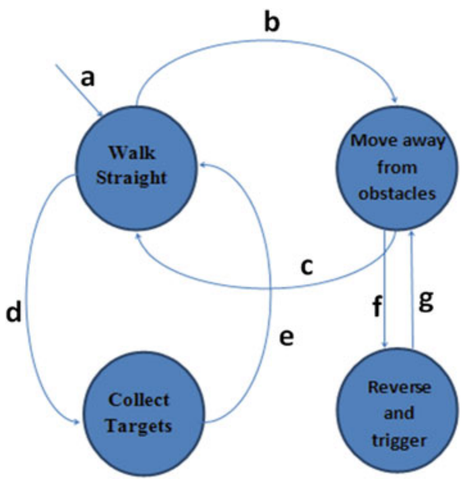


Fig. 4 Subsumption hierarchy

dynamic evolve the model, the temporal automata given in Fig. 5 governs the control strategy. In this case, the graph nodes are the control actions and the edges represent the events that are triggered by rules. The edge values are taken from an alphabet as following:

a. Initial stage the agent walk straight to explore the environment.
b. Obstacle detection: move away from the obstacle.
c. Free path: return to initial state.
d. Target detection (no obstacle): actions to move to target and collect it.
e. Collected target: return to initial state.
f. Collision detection: reverse control action.
g. Safe position detection: return to initial state.

Fig. 5 Control strategy



Each control action associated to the automata states requires the reconfiguration of the DFCM model in Fig. 3. That is, the concepts and/or relationships can be added or removed, or updated only.

In the DFCM model from Fig. 3, a reinforcement learning (RL) algorithm similar to Q-learning [14] is used for the dynamic tuning of DFCM weights (W1–W7). The actions of reward and punishment implemented in the RL algorithm are obtained from heuristic rules that describe the environment. The goal is fine tune causal relationships in order to provide a better model fit for possible changes in the dynamics of the robot and/or environment, such as a possible wear of parts and/or change of tack in the floor. The dynamical update of DFCM weights is carried out by the following equation:

$$W_i(k) \leftarrow W_i(k-1) + \alpha \times [r + \gamma \times W_{\mathrm{lim}} - W_i(k-1)] \tag{1}$$

where α is the learning factor, γ is the discount factor, r is the value of reward or punishment, and W_{lim} is the desired maximum (minimum) value for causal relationship weights in this state. These limits values are computed with a rule based formed by six heuristic rules, such as the following rule for weight W3:

- **IF** the intensity of the front sensor is greater than medium threshold THEN W_{lim} used to compute W3 is the maximum W_{fmax}.

Further details of the rule base and the implemented reinforcement learning algorithm can be found in Ref. [9].

Finally, the cooperation among the several agents is based on the pheromone used by ant colony algorithm in search of food [4]. Each agent directly shares its acquired information. However, the shared information impact over each agent action is no more than 5 % of the own actions. In other words, the next agent's actions are based on the perception of its sensors and on the group or only agent memories (experiences). For example, to an agent, the outputs of its actuators weigh up to a maximum of 5 %

of the earlier actions. This weighting of 5 % was obtained empirically with different weights of 1–15 %.

4 Simulation Results

A simulation environment with 2-D animation was developed to test and validate the navigation system. In the simulation environment, the trail with three or more brilliant colors symbolizes the mobile robot. The signs "+" symbolize the static obstacles, the sign "*" represents a dynamic obstacle, the symbol "o" represents obstacles that arise during navigation (unexpected obstacle), and finally the "▲" represents the targets to be collected by the robot. These symbols are shown in Fig. 6. In simulations with dynamic obstacles a blue track is also used to show the path taken by the obstacle.

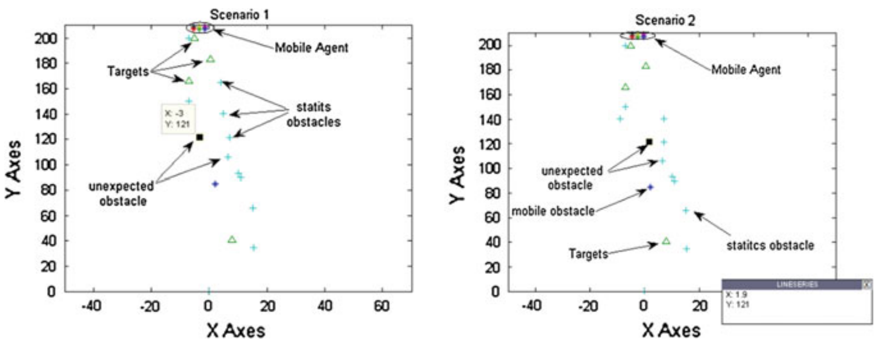


Fig. 6 Scenarios of experiments 1and 2

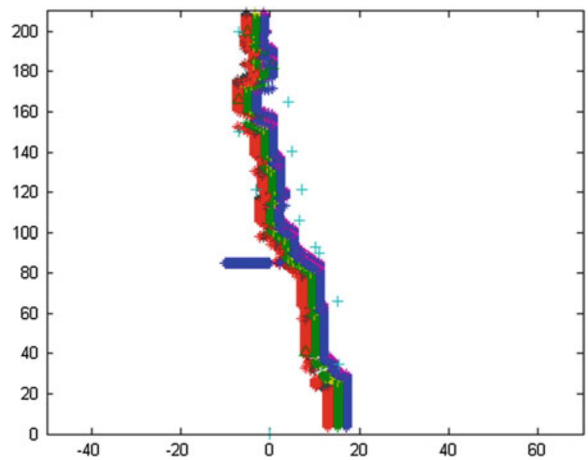


Fig. 7 Robot trajectory (Exp. 1)—Course 1

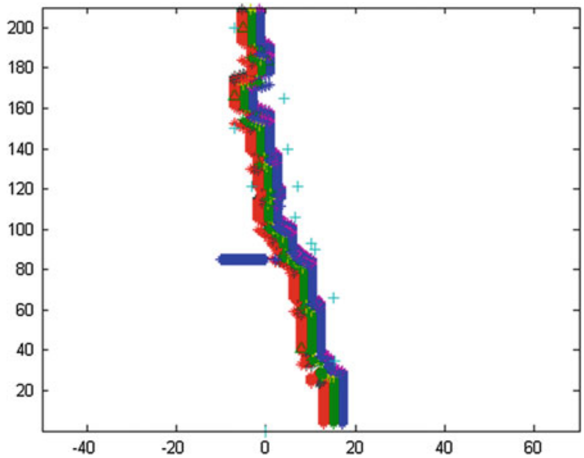


Fig. 8 Robot trajectory (Exp. 1)—Course 2

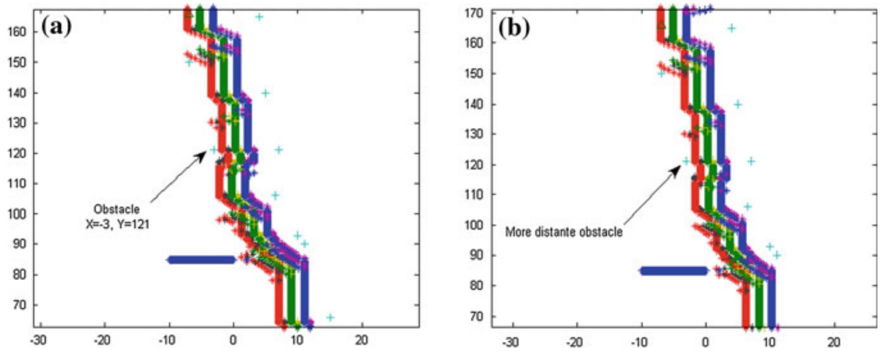


Fig. 9 Zoom of the robot trajectories in the first experiment **a** Course 1 **b** Course 2

The first experiment uses the scenario of Fig. 6 whose all fixed obstacles are known but there is a dynamic obstacle that moves around through the scenario, intercepting the trajectory of the robot. Moreover, there are several targets to be collected along robot path.

Figure 7 presents the resulting robot trajectory for a first course of the experiment 1. In the first course, the robot has no memory about tasks and paths. As can be seen in Fig. 7, the robot performs the actions correctly, i.e., the robots travels exploring the environment in a straight line, if it has no target to collect or obstacle to deflect. Finally, in case of unexpected obstacles, the robot is able to infer the imminent collision and to take decisions. As a result, a hard and quick maneuvering is implemented and after the trajectory is retaken. A second course is carried out with another robot (agent) that shares the experience from the robot in the first course. The trajectory developed

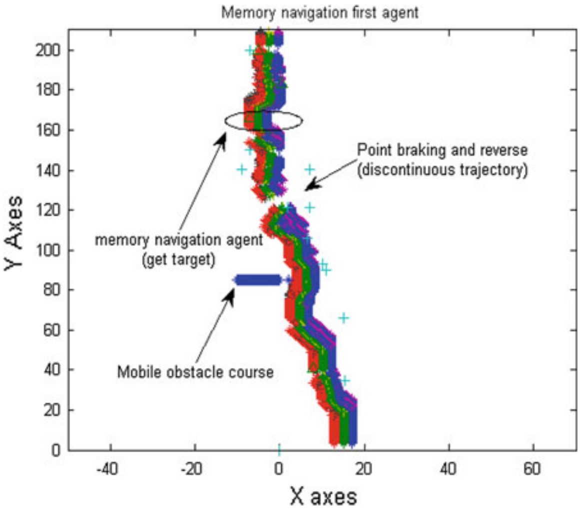


Fig. 10 Robot trajectory (Exp. 2)—Course 2

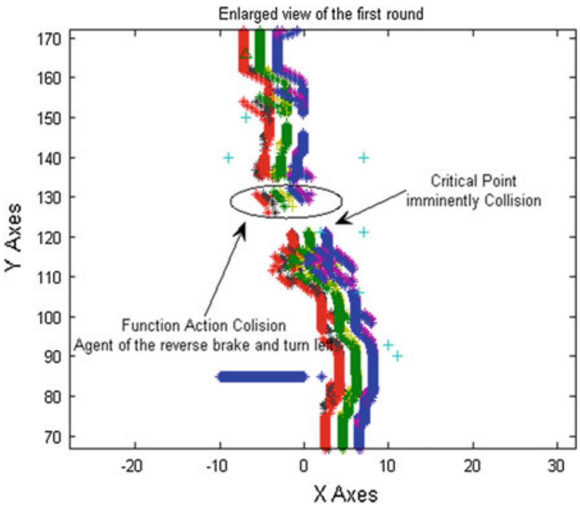


Fig. 11 Robot behavior at the critical point (Exp. 2)—Course 1

by the second robot is shown in Fig. 8. It is similar, but a little smoother than the trajectory developed in the first course.

Moreover, the second robot implements a fewer number of maneuvers to deviate from obstacles than the first one. This fact can be seen by comparing a zoom of both trajectories in Fig. 9. In resume, experiment 1 shows the autonomous robot capacity to recognize moving obstacles, to implement deviation maneuvers and to recover trajectory in different situations.

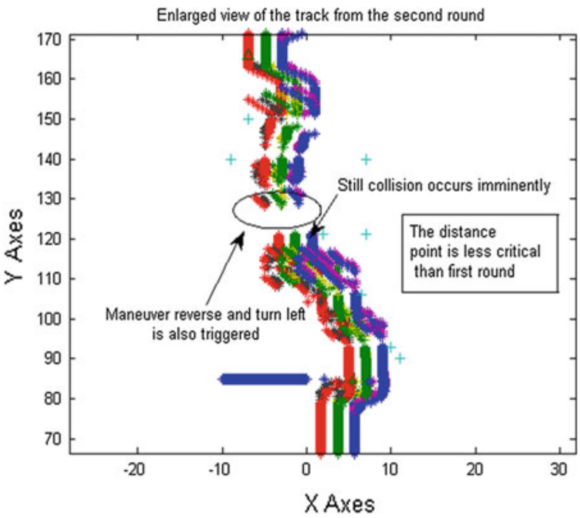


Fig. 12 Robot behavior at the critical point (Exp. 2)—Course 2

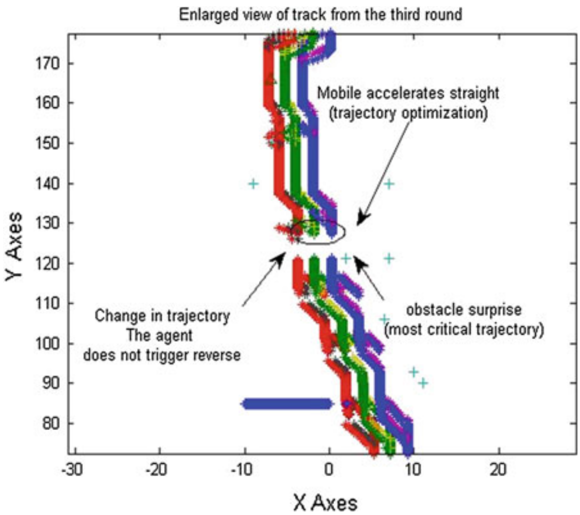


Fig. 13 Robot behavior at the critical point (Exp. 2)—Course 3

The second experiment also uses the similar scenario of Fig. 6. However in this experiment, an unexpected obstacle (second) appears in other position of trajectory. This sudden appearance forces a robot maneuver that can results in collision with other fixed obstacles around the position ($x = 1.9$, $y = 121$). The scenario complexity

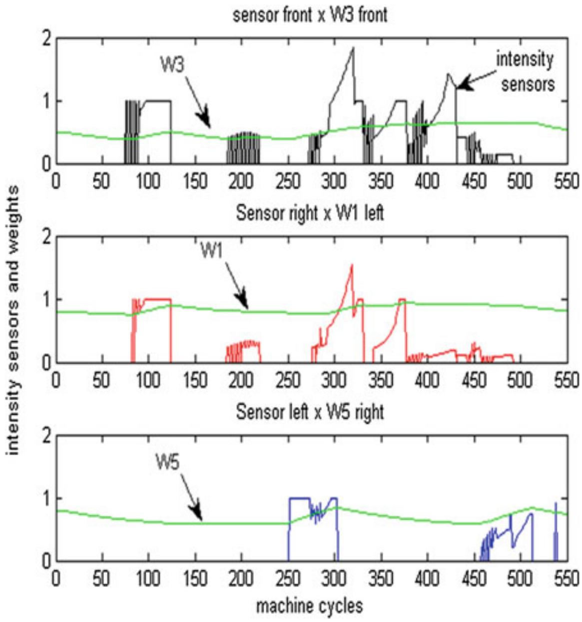


Fig. 14 Weights up-date by RL algorithm (Exp. 3)—Course 1

is high and only after three courses an agent implements a successful maneuver. At the end of each course, the robot shares its experience with the robot implementing the next course. The complete first course is shown in Fig. 10. A zoom of the collision during the first, second and third courses are shown in Figs. 11, 12 and 13, respectively. By analyzing these figures, we can see that in the second course, the robot also collides with the same obstacle of the first course, but it was almost avoided. In the third round, there is a model evolution and no collision is reported.

In order to illustrate the use of reinforcing learning algorithm, Figs. 14 and 15 show dynamic tuning weights of causal relationships (W1, W3 and W5) of the first and last scenarios (trajectories) according to the variations of the intensities of sensors. The used parameters are α =0.01; $\gamma = 1$; r = 0.1 for W_{max}, and r = −0.1 for W_{min}. The thresholds $W_{fmax} = 0.35$ and $W_{fmin} = 0.65$ define the range of variation for the causal weight W3 associated to frontal sensor. Similarly the right and left sensors have weights (W1 and W5) updated into the interval [0.6, 1]. In these figures, differences in intensities of the three sensors attest different trajectories assumed by the robot at the first and last experiments.

In conclusion, the experiments show that the navigation system fulfills its main goal which consists in guiding the robot to final end point, collecting the targets and avoiding collisions. The experiment also highlights the facility to share experiences among agents in a cooperative way.

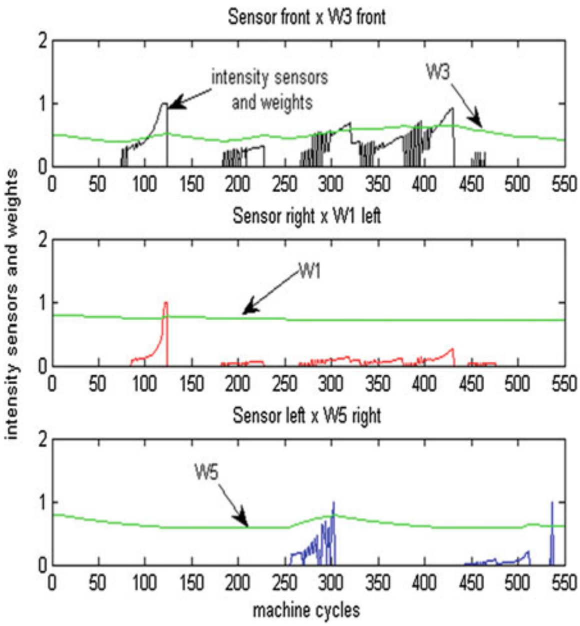


Fig. 15 Weights up-date by RL algorithm (Exp. 3)—Course 3

5 Conclusion

This work presents an architecture for cooperative autonomous agents based on dynamic fuzzy cognitive maps to swarm robotics application. The proposed subsumption architecture allows the decision-making in a dynamic environment by mapping three distinct layers that model different types of knowledge. These layers work together and contribute to the success of the application. An ontological guide is presented in order to support the development of DFCM models. Moreover, training methods are used for off-line calibration model and sharing experience among agents. A reinforcement learning algorithm is also used to on line tune the model.

The presented results indicate that the DFCM-subsumption model has shown a capacity of learning, adaptation and cooperation, that enabled the agent to be rational, i.e., during navigation the inferences have determined sequences of actions which had achieved their goals (exploring environment, obstacles deviation and targets collection) with good performance. The cooperation between agents is emphasized, in particular, in the third course of the second experiment when a reversal motion is not required in order to deviate from a critical obstacle in the environment.

Future studies may include the improvement of the third layer in order to allow the coexistence of several agents that can realize tasks in groups. New features must be also added in the lower layers such as robot power management. The comparison of the presented architecture with similar architectures based on other intelligent techniques (fuzzy systems, neural networks and neurofuzzy systems) could also be addressed. Finally, the implementation of the DFCM-subsumption architecture in real robotic platforms can be proposed.

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Chapter 11
FCM-GUI: A Graphical User Interface for Big Bang-Big Crunch Learning of FCM

Engin Yesil, Leon Urbas and Anday Demirsoy

Abstract Modeling of complex dynamic systems, for which establishing mathematical models is very complicated, requires new and modern methodologies that will exploit the existing expert knowledge, human experience and historical data. On one hand, Fuzzy Cognitive Maps (FCMs) are very suitable, simple, and powerful tools for simulation and analysis of these kinds of dynamic systems. On the other hand, human experts are subjective and can handle only relatively simple FCMs; therefore, there is a need of developing novel approaches for an automated generation of FCMs using historical data. Although, many novel learning algorithms are published in literature, there is no software existing that especially focuses on a learning method for FCMs. In order to fill this gap, and to help researchers and developers in social sciences, medicine and engineering, a graphical user interface (GUI) is designed. Since the interest of developing software or a GUI in Matlab is increasing within the last years, the proposed FCM-GUI is developed using Matlab. In this study, a new optimization algorithm, which is called Big Bang-Big Crunch (BB-BC), is proposed for an automated generation of FCMs from data. Two real-world examples; namely an ERM maintenance risk model and a synthetic model generated by the proposed FCI-GUI are used to emphasize the effectiveness and usefulness of the proposed methodology. The results of the studied examples show the efficiency of the developed FCM-GUI for design, simulation and learning of FCMs.

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E. Yesil(✉) and A. Demirsoy
Faculty of Electrical and Electronics Engineering, Control Engineering Department, Maslak, Istanbul Technical University, 34469, Istanbul, Turkey
e-mail: yesileng@itu.edu.tr

L. Urbas
Chair of Distributed Control Systems Engineering, Institute of Automation, Dresden University of Technology, 01062 Dresden, Germany
e-mail: leon.urbas@tu-dresden.de

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1 Introduction

Cognitive maps were introduced by Axelrod (1976) [1] to represent crisp cause-effect relationships which are perceived to exist among the elements of a given environment. Fuzzy cognitive maps (FCMs) were introduced by Bart Kosko in 1986 and since then FCMs have gained considerable research interest and are widely used to analyze causal complex systems. FCMs are fuzzy signed directed graphs with feedbacks, and they model the world as a collection of concepts and causal relations between concepts [2]. Their main advantages are flexibility and adaptability to a given domain [3].

Fuzzy Cognitive Maps consist of nodes (or concepts) and connections (or edges) that represent the causal relationships between the concepts. Each connection gets a weight (between 0 and 1) that depends on the strength of the causal relationship between the concepts in nodes. A relationship can be either positive (when growth in one concepts stimulates growth in the other one), negative (when growth in one concepts inhibits growth in the other one) or zero (no relation between the concepts). This graphical form can be represented in a mathematical form of a weight matrix that contains all the connections and a state vector made of the current weights of the concepts in the system.

In general, FCMs can be produced by an expert (or a group of experts) manually or generated by other sources of information computationally. These FCMs are named manual FCMs and automated FCMs, respectively. In most cases, the manual FCMs are produced when there is at least one expert who has expertise in the area under study. In some situations, a FCM could not be constructed manually if there is no expert to define a FCM, or when the experts' knowledge differs from each other and they even draw different FCM, or sometimes there are large amounts of concepts with connections between them, which could not be drawn without mistakes [4].

The above situation shows that in many cases developing a FCM manually becomes very difficult and experts' intervention cannot resolve the problem. Therefore, a systematic way should be found in order to bridge this gap. For these reasons, the development of computational methods for learning FCMs is necessary. Some methods for learning FCM model structure have been recently proposed. These methods, in general, are categorized in two main groups: Hebbian learning and global optimization methods. In literature, many different learning algorithms that are based on one of these approaches are introduced [5].

As mentioned in [6], there is a vast interest in FCMs and this interest on the part of researchers and industry is increasing, especially in the areas of control [7–9], business [10, 11], medicine [12–14], robotics [15, 16], environmental science [17, 18], and information technology [19, 20]. Parallel to this growth, today researchers develop new algorithms and their own software in a specific area of interest. The FCModeler tool [21] uses fuzzy methods for modeling networks and interprets the results using fuzzy cognitive maps. The front end of the FCModeler tool is a Java interface that reads and displays data from a database of links and nodes. The FCModeler tool is intended to capture the intuitions of biologists, help test hypotheses, and provide a modeling framework for assessing the large amounts of data captured. An easy to use tool, called FCMapper, is presented in [22]. FCMapper is based on Excel and VBA and it is freely available for noncommercial use on the internet. It can be used to calculate all indices, perform the dynamic simulations and transform the matrix coded FCMs into files that can be displayed and further analyzed with network-analysis software. In addition, a FCM applet called FuzCogMap is proposed in [23]. Another FCM tool is offered in [24], which allows different types of dynamic relationship. This tool is developed in Spanish and requires an expert knowledge about the problem to determine the type of dynamic relationships among the concepts. Java language is used for the tool; thus, the user should program the specific relationships of the problem modeled. A Matlab Simulink platform where FCM was encoded is presented in [25]. This platform, which simplifies the FCM design process and subsequent inference derivation is linked to Java Codes and used to simulate trading patterns in the UK electricity market. Another FCM tool [26] is created using the available interface features that MATLAB provides. The software tool incorporates Excel for facilitating the storing and retrieving of data from files. The friendly graphical interface helps the user to easily insert, save, retrieve and display data. In [27], a GUI based tool using MATLAB is developed for assessing software risks. Lately, FCM_uUTI tool [28] for uUTI (uncomplicated urinary tract infection) treatment management is explored proposing a graphical user interface (GUI) and presenting its evaluation results. Also, Matlab is preferred for the implementation of this tool.

Although above mentioned tools for the evaluation of FCMs are given and many novel learning algorithms are published in literature, there is no software existing that especially focuses on a learning method for FCMs. In order to fill this gap, and help researchers and developers in social sciences, medicine and engineering, a graphical user interface (GUI) is designed. Since the interest of developing software or a GUI in Matlab is increasing within the last years, the proposed FCM-GUI is developed using Matlab. The user will be able to design their FCMs using expert knowledge and simulate these FCMs for different scenarios without developing new codes. If the user needs an automated FCM using the existing historical data, then he/she can use the proposed BB-BC learning method provided in the proposed FCM-GUI.

2 Fuzzy Cognitive Maps (FCMs)

A fuzzy cognitive map F is a 4-tuple (N, W, C, f) [29] where
1. $N = \{N_1, N_2, \ldots, N_n\}$ is the set of n concepts forming the nodes of a graph.
2. W: $(N_i, N_j) \rightarrow w_{ij}$ is a function of $N \times N$ to K associating w_{ij} to a pair of concepts (N_i, N_j), with w_{ij} denoting a weight of directed edge from N_i to N_j, if $i \neq j$ and w_{ij} equal to zero if $i = j$. Thus $W(N \times N) = (w_{ij}) \in K^{n \times n}$ is a connection matrix.
3. C: $N_i \rightarrow C_i$ is a function that at each concept N_i associates the sequence of its activation degrees such as for $t \in N, C_i(t) \in L$ given its activation degree at the

moment t. $C(0) \in L^n$ indicates the initial vector and specifies initial values of all concept nodes and $C(t) \in L^n$ is a state vector at certain iteration t.
4. f: $R \rightarrow L$ is a transformation function, which includes recurring relationship on $t \geq 0$ between $C(t + 1)$ and $C(t)$.

The calculation rule that was initially introduced to calculate the value of each concept is based only on the influence of the interconnected concepts [2, 7, 30]

$$C_j(t+1) = f\left(\sum_{\substack{i=1 \\ i \neq j}}^{n} C_i(t) w_{ij}\right) \tag{1}$$

where n is the number of concepts, $C_j(t+1)$ is the value of concept C_j at time step t+1, $C_i(t)$ is the value of concept C_i at time step t, and w_{ij} is the weight of the causal interconnection from concept ith toward concept jth.

The transformation function is used to confine (clip) the weighted sum to a certain range, which is the set to [0, 1] or [-1 1]. The normalization hinders quantitative analysis, but allows for comparisons between nodes, which can be defined as active, inactive, or active to a certain degree. Four most commonly used transformation functions are shown below:

1. bivalent

$$f(x) = \begin{cases} 0, & x \leq 0, \\ 1, & x \geq 0. \end{cases} \tag{2}$$

2. trivalent

$$f(x) = \begin{cases} -1, & x \leq -0.5, \\ 0, & -0.5 < x < 0.5, \\ 1, & x \geq 0.5. \end{cases} \tag{3}$$

3. sigmoid (logistic)

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \tag{4}$$

4. hyperbolic tangent

$$f(x) = \tanh(\lambda x) = \frac{e^{\lambda x} - e^{-\lambda x}}{e^{\lambda x} + e^{-\lambda x}} \tag{5}$$

where λ is a parameter used to determine proper shape of the function. Both functions use λ as a constant for function slope (degree of fuzzification). The FCM designer

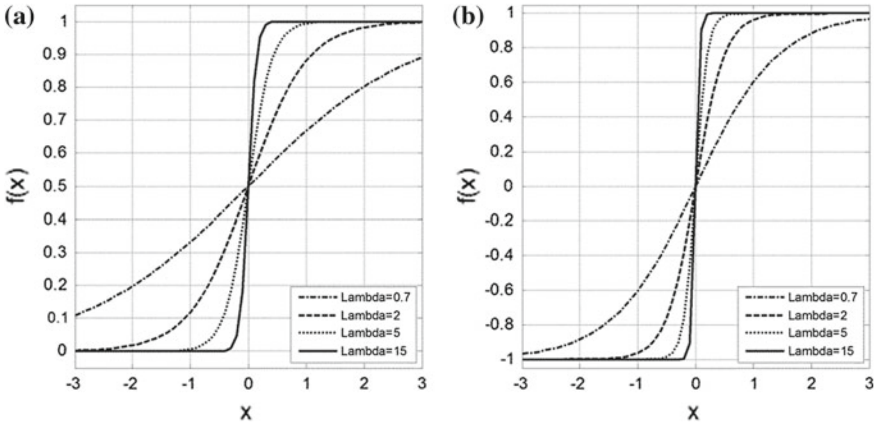

Fig. 1 The effect of transformation function parameter (λ): **a** sigmoid (logistic) function, **b** hyperbolic tangent function

has to specify the lambda value. For large values of lambda (e.g., $\lambda \geq 10$) the sigmoid approximates a discrete function that maps its results to interval (0,1); for smaller values of lambda (e.g., $\lambda \leq 1$) the sigmoid approximates a linear function; while values of lambda closer to 5 provide a good degree of fuzzification in the [0,1] interval [31]. The effect of transformation function parameter (λ) is illustrated in Fig. 1.

3 A Brief Overview of Big Bang-Big Crunch Algorithm

In this study, the Big Bang-Big Crunch (BB-BC) optimization [5, 32] method is recommend for learning of FCMs as an alternative to the existing optimization based learning methods. This global optimization method is preferred due to its low computational cost, a high convergence speed and the usage of only a few parameters which should be set by the designer for learning FCMs. The BB-BC optimization method is a natural evolutionary algorithm similar to the genetic algorithms, the ant colony optimization, the particle swarm optimizer and the harmony search [33]. It is reported in [32] to be capable of quick convergence even in long, narrow parabolic shaped flat valleys or in the existence of several local minima [5]. Recently, the BB-BC algorithm has found applications in many areas especially where the optimization problem must be solved in relatively small sampling times such as in fuzzy model inversion [34, 35], fuzzy model adaptation [36, 37]. Moreover, in the optimization of highly nonlinear engineering problems such as controller design [38, 39], design of space trusses [40], and size reduction of space trusses [41], airport gate assignment problem [42], this algorithm has been preferred because of its fast convergence speed and simplicity.

The Big Bang-Big Crunch (BB-BC) optimization method consists of two main steps: The first step is the Big Bang phase where candidate solutions are randomly distributed over the search space and the next step is the Big Crunch phase where a contraction procedure calculates a center of mass for the population.

The initial Big Bang population is randomly generated over the entire search space similar to any other evolutionary search algorithm. All subsequent Big Bang phases are randomly distributed around the center of mass or the best fit individual in a similar fashion. In [18], the working principle of the Big Bang phase is explained as energy dissipation or the transformation from an ordered state (a convergent solution) to a disordered or chaotic state (new set of candidate solutions).

After the Big Bang phase, a contraction procedure is applied during the Big Crunch. In this phase, the contraction operator takes the current positions of each candidate solution in the population and its associated cost function value and computes a center of mass according to Eq. 6,

$$x_{COM} = \frac{\sum_{i=1}^{N} \frac{1}{J_i} x_i}{\sum_{i=1}^{N} \frac{1}{J_i}} \tag{6}$$

where x_{COM} is the position vector of the center of mass, x_i is the position vector of the i_{th} candidate, J_i is the cost function value of the i^{th} candidate, and N is the population size. The new generation for the next iteration Big Bang phase is normally distributed around x_{COM}. The new candidates around the center of mass are calculated by adding or subtracting a normal random number whose value decreases as the iterations elapse. This can be formalized as

$$x^{new} = x_{COM} + \frac{r\,\alpha(x_{max} - x_{min})}{k} \tag{7}$$

where r is a normal random number, α is a parameter limiting the size of the search space, x_{max} and x_{min} are the upper and lower limits, and k is the iteration step. Since normally distributed numbers can be exceeding ± 1, it is necessary to limit the population to the prescribed search space boundaries. This narrowing down restricts the candidate solutions into the search space boundaries. The BB-BC algorithm is presented in the following Table 1.

Instead of the center of mass, other points like the best fit individual (elitist strategy) can also be chosen as the starting point in the Big Crunch phase. The positions of new candidate solutions at the beginning of each Big Bang are normally distributed around a new point located between the center of mass and the best solution,

$$x^{new} = \beta\,.x_{COM} + (1-\beta).x_{BEST} + \frac{r\,\alpha(x_{max} - x_{min})}{k} \tag{8}$$

where β is the parameter controlling the influence of the global best solution x_{BEST} on the location of new candidate solutions [40]. This modification of generating the new solution can be viewed as to be an elitist strategy, where the best solution influences the direction of the search.

The proposed BB-BC learning method develops a candidate FCM from input data as given in Fig. 2. The input data are given as time series and that consist of a sequence of state vectors which describe a given system at consecutive iteration. The number of these successive iterations of the given historical date is called as the data length. Given a system consisting of N concepts, the FCM model can be described fully by its weight (connection) matrix. The proposed FCM learning method uses the BB-BC algorithm and given input data to determine the weight matrix that represents FCM mathematically. In other words, the learning goal is to generate the same state vector sequence using the candidate FCM for the same initial vector as it is defined in the input data. Thereby, the candidate FCM generalizes the relations between the concepts, and it allows performing simulations from different initial state vectors in order to represent conclusions about the modeled system.

One of the most important considerations for BB-BC, similar to the other global optimization methods, is the design of a cost function, which is appropriate for a given problem. In literature many different cost functions are proposed. In this study

Table 1 Big Bang-Big crunch algorithm

Step 1:	An initial generation of N candidates is generated randomly in the search space.
Step 2:	The cost function values of all the candidate solutions are computed.
Step 3:	The center of mass is calculated.
Step 4:	New candidates are calculated around the new point calculated in Step 3 by adding or subtracting a random number whose value decreases as the iterations elapse.
Step 5:	Return to Step 2 until stopping criteria has been met.

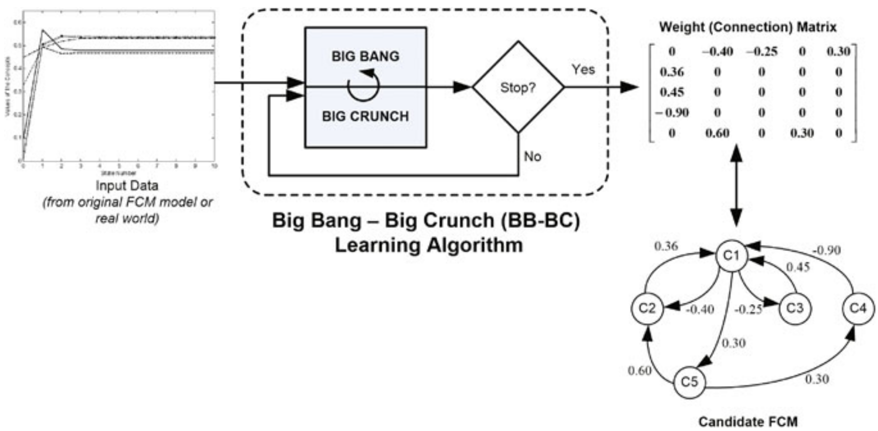

Fig. 2 Illustration of proposed BB-BC learning methodology

the following cost function is found to be appropriate [43]:

$$J = \frac{1}{(K-1)N} \sum\nolimits_{t=1}^{K} \sum\nolimits_{n=1}^{N} (C_n(t) - \hat{C}_n(t))^2 \tag{9}$$

where $C_n(t)$ is the given system response, $\hat{C}_n(t)$ is the candidate FCM response of the nth concept for the initial state vector, K is the data length, and N is the number of concepts. In order to normalize and visualize the cost function given in Eq. 9 the following fitness function which has the value [0 1] is proposed:

$$H = \frac{1}{\theta .J + 1} \tag{10}$$

where parameter θ is a positive scaling constant.

4 FCM-GUI: Big Bang—Big Crunch Learning for FCM

In this section, the FCM graphic user interface (GUI) developed for designing, simulating FCMs and also generating automated FCMs by using the Big Bang—Big Crunch optimization method is presented. The GUI is developed in English in order to reach a higher number of users, especially students and researchers from all around the world. Furthermore, MATLAB environment is preferred since it is widely used by researchers from engineering, medicine, information technologies and social science disciplines. Subsequently, the generated Matlab code is divided into as meaningful small functions as possible to increase readability and extensibility. In addition, the developed MATLAB code will be distributed as open source software; as a result, the users can develop and use the tool corresponding to their needs. This first version of the developed FCM-GUI consists of two main windows: The first window is called "Design and Simulation" that allows users to design and work on the user defined FCM, which represents expert knowledge or the randomly produced stable FMC and then simulate these FCMs to study different scenarios. The second window allows users to generate a FCM from a historical data by using the proposed BB-BC algorithm. The first line of the developed BB-BC learning specifies the calling syntax for the function BBBC as follows:

```
function[value]=BBBC(ConceptNumber,CostData,Populati-
onCount, DataLength, InitialStateVector,Q, FunctionToUse,
IterationCount, MAX, MIN, A,Lambda,handles, bEffect)
```

The outputs and the input arguments of this learning function are summarized in Table 2.

Table 2 Variables of Matlab Code developed for BB-BC learning

Concept-Number:	Number of concepts
Cost-Data:	Data of concept values (concept number x data length)
Population count:	Number of population of each iteration in BB-BC
Data length:	Number of iteration used in calculation of concept values
Initial state vector:	Initial state vector (1 x number of concepts)
Q:	Fitness function parameter (theta)
Function-To-Use:	Name of the transformation function to used (e.g. : 'Sigmoid')
Iteration count:	Number of iteration of BB-BC
MAX:	A matrix points to maximum values of searched concepts. It takes value from range of weights table (concept number x concept number)
MIN:	A matrix points to minimum values of searched concepts. It takes value from range of weights table (concept number x concept number)
A:	Limiting parameter (Alpha)
Lambda:	Lambda value
Handles:	UI handle of MATLAB GUI system. It is used to write values to GUI or read values from it.
bEffect:	Big Bang Big Crunch parameter (Beta).

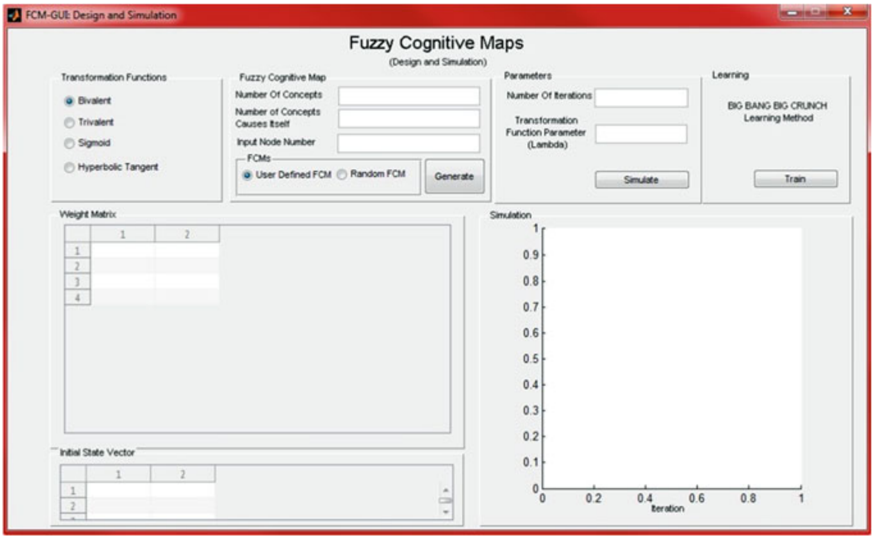

Fig. 3 FCM-GUI: design and simulation

4.1 Design and Simulation Window

As mentioned previously, the developed FCM-GUI has two windows and the main one is called "Design and Simulation" which is shown in Fig. 3. Mainly, users can design their FCMs using their know-how and change the weights that represent the relations between the concepts to see the effect for a given initial condition represented by initial state vector. In addition to these features, a random FCM generator bottom is added to the GUI for the researchers who study new learning methods. These researchers can generate FCMs that have a fix point attractor using the approach proposed in [44].

As seen in Fig. 3, the first window of FCM-GUI consists of some group boxes. Each group box has its own assignment and, in respect to this, contains relevant controls. These group boxes are placed in the screen by a logic frame and should be used in an order to increase usability.

Firstly, users should select the function type that will be used in the FCM calculation. When previous literature is examined, it is seen that four main transformation functions called bivalent, trivalent, sigmoid and hyperbolic tangent are commonly used; therefore, they are presented to the user as options in this box. It is significant to set this selection in the beginning since random map generation can only be applied with sigmoid and hyperbolic tangent functions. After this selection, the user should focus on the Fuzzy Cognitive Map group box. In here, concept number, number of concepts causes itself and the number of input nodes meaning nodes that influence but are not influenced by other nodes [44] should be determined. If the user generates a user defined FCM then he/she must select the "User Defined FCM" radio button and give only the number of concepts. Otherwise, if the user prefers to have a FCM generated by the FCM-GUI, the "Random FCM" radio box must be selected and then the "Generate" button should be clicked. After this operation, two major tables called "Weight Matrix" and "Initial State Vector" will appear on the window. In case that the "User Defined FCM" option was selected, "Weight Matrix" will be initially filled with zeros and can be editable by the user. When the radio button for "Random FCM" option is selected a random FCM will be generated by using the formulation stated in [44], and the weight matrix will be shown to the user.

After the design procedure of FCMs, the user must use the "Parameters" box to select iteration number and the transformation function parameter (lambda) in case that sigmoid defined in Eq. 4 or hyperbolic tangent defined in Eq. 5 is preferred. After all, the user can click the "Simulation" button to study the behavior of each concept for the given initial states in the figure. For the evaluation of the new values of each concept the formulation given in Eq. 1 is used.

The last box on the first window is the "Big Bang-Big Crunch Learning Method". When the "Train" button is clicked, the second window for generating an automated FCM using historical date will appear.

4.2 Big Bang-Big Crunch Learning Window

As previously stated, due to the nature of FCMs the data points are normalized to the unit interval [0, 1] or [−1, 1] and they correspond to the degree of presence of a given concept at a particular iteration. Given a system consisting of N concepts, the FCM model can be described fully by its weight (connection) matrix. The aim of the

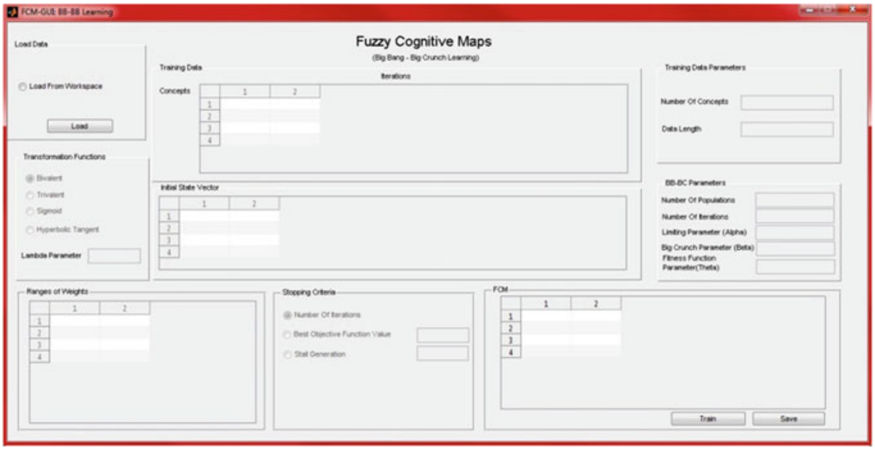

Fig. 4 FCM-GUI: Big Bang-Big Crunch learning

learning method is to establish the weight matrix that consists of N^2 variables assuming that these values are in the interval of $[-1, 1]$. The proposed FCM-GUI uses the BB-BC algorithm and given input data to determine these values. In other words, the learning goal is to generate the same state vector sequence using the candidate FCM for the same initial vector as it is defined in the input data. Thereby, the candidate FCM generalizes the relations between the concepts, and it allows performing simulations from different initial state vectors in order to represent conclusions about the modeled system.

In Fig. 4, the "Big Bang-Big Crunch Learning" window, which can be used for automated FCM is shown. In case that the user is lacking an expert for building a FCM model but possesses the data about the variations of the concepts, he/she can use the proposed user-friendly BB-BC learning tool.

As the first "Design and Simulation" window the "Big Bang-Big Crunch Learning" window consists of group boxes as well. As a start, the user needs the historical data to generate a FCM with BB-BC learning algorithm, and for this purpose the "Data Loading" section must be used. When the user presses the "Load" button, the relevant data will be shown in the "Training Data" matrix. The columns of the matrix represent the iteration number (time) and the rows will be the concepts. After loading the data, training data parameters, relevant to the historical data, the number of concepts, data length and the initial state vector will be automatically shown on the FCM-GUI window. As the consequent step, the user must define the "Transformation Function" using the radio buttons and also the transformation function lambda parameter if sigmoid or hyperbolic tangent is selected.

In order to use the Big Bang-Big Crunch learning method, basic BB-BC parameters must be determined from the "BB-BC Parameters" section. These parameters are "Number of Populations," Number of Iterations," "Limiting Parameter (Alpha)" defined in Eq. 7, “Big Crunch Parameter (Beta)” defined in Eq. 8, “Fitness Function Parameter (Theta)” defined in Eq. 10,.

After defining learning parameters, a table filled with question marks as “?” appears in the “Ranges of Weights” box. This will represent that the connection between the concepts are unknown and the BB-BC learning algorithm will search the optimal weight within the possible maximum interval as $[-1, 1]$. If there is no expert or any information to define the possible causal relationship between the concepts, then the user should leave the table with question marks. In case that some certain information about the concept values of the FCM are known then these information can be defined in the “Ranges of Weights” matrix. Therefore, the algorithm will be faster since it will avoid doing unnecessary searches. If a weight value between the certain concepts is known as greater than zero, then “+” sign must be entered in the corresponding cell of the table. Similarly, if it is known as less than zero then “-” sign must be written. Zero (0) must be entered, if it is known that there is no causal relationship between the concepts. One (1) must be entered when the causal relationship between the concepts is positive maximum, or similarly, minus one (-1) must be entered to the corresponding cell if the causal relationship between the concepts is negative maximum. As another option, the user may know exactly the relationship between the concepts then this exact value must be entered to the corresponding cell. In case that the weights between certain concepts are given as a constant as zero (0), positive one (1), negative one (-1), or a constant in the interval of $[-1, 1]$, the proposed BB-BC learning algorithm will not search the corresponding weight. In addition, sometimes the user may have information about the causality between the concepts as an interval. In this case, the user must give this information as $[w_{low}\ w_{max}]$, where w_{low} and w_{max} represents the lower and upper value respectively. In such a case, the BB-BC learning method will search the corresponding weight within the defined interval.

The last important condition for the BB-BC learning of FCM is the “Stopping Criteria.” It is defined in the developed FCM-GUI as following:

1. The algorithm terminates if the number of BB-BC generations exceeds the specific number.
2. The algorithm terminates if the predefined fitness function value is reached with the best candidate FCM.
3. The algorithm terminates if the best candidate FCM was not improved after a period.

The user has the option to choose one of the above mentioned stopping criteria using the radio buttons in “Stopping Criteria” box. The above mentioned options are also given in the GUI in the same order with the following names: “Number of Iterations,” “Best Objective Function Value,” “Stall Generation.”

After all of these steps, when the user clicks the “Train” button, the learning procedure starts till the stopping criteria is fulfilled. Then the best candidate FCM representing the historical data will be given in the “FCM” box in the learning window. In addition, two popup figure windows will open to compare the original and the candidate FCM behavior and, also, the second figure will show the learning convergence given in Eq. 10.

5 Simulations

In this study, many systems are studied; however, here two of these systems with different characteristics are discussed to show the ability of the proposed FM-GUI for design, simulation and BB-BC learning.

5.1 ERP Maintenance Risks Model

As it is well-known the successful performance of software, and indeed Enterprise Resource Planning (ERP), depends on proper system maintenance. For this reason the companies should follow a maintenance process that drives the ERP system toward success; but in general terms, ERP maintenance managers do not know what conditions they should target to successfully maintain their ERP systems. In order to address this requirement, in [45] a FCM-based ERP maintenance risks model is studied and a FCM is built with the help of many experts.

In this study, as a first example the FCM [45] that is representing how existing risks in the implementation of maintenance request impacted on ERP performance is used. The constructed FCM depicted in Fig. 5 contains the following thirteen concepts:

C1: Continuous organizational changes
C2: Requirements incomplete and/or unclear
C3: Instability in maintenance team members
C4: Lack group spirit and attitude in maintenance team members
C5: Inadequate mix of team skills
C6: Quality of original programming
C7: Methodology and maintenance process are not defined
C8: Maintenance tasks are excessively hard
C9: Project milestones cannot be defined
C10: Use of inadequate technology for system testing
C11: Wrongly-fit system with pre-existing applications
C12: Lack active participation by external parties
C13: ERP

The first 12 concepts are the risks and the thirteenth concept is the ERP maintenance. The activation function given in Eq. (3) is chosen because the values of the nodes can fall within the range $[-1, 1]$, in addition 5 being the value assigned to λ [45]. The connection matrix of the FCM built by the experts [45] is as follows:

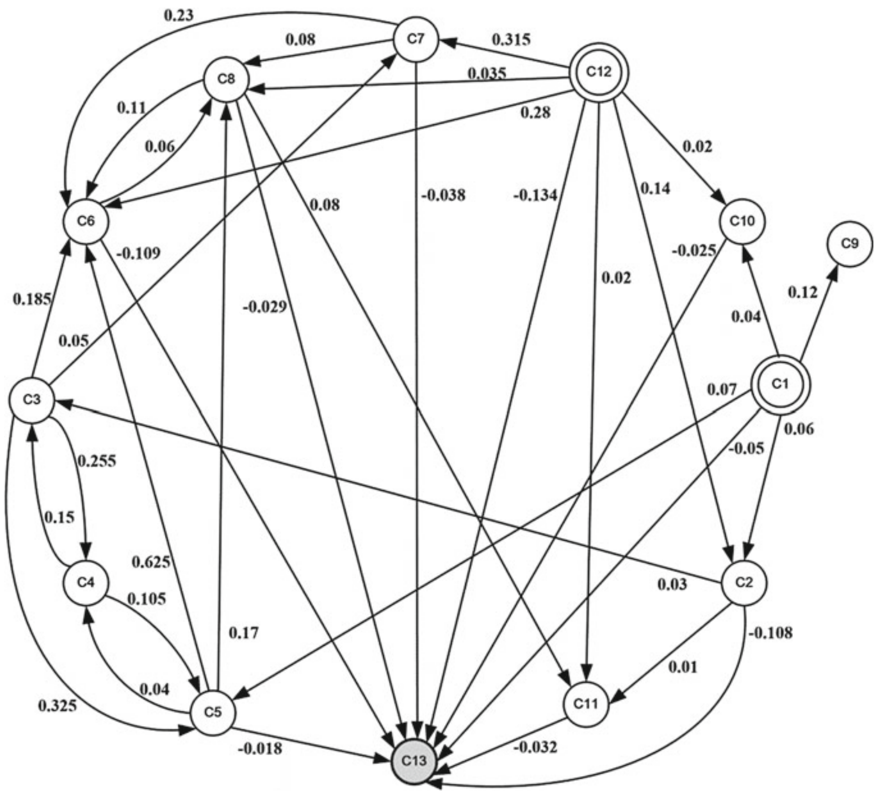

Fig. 5 Illustration of ERP maintenance risks model

$$
W = \begin{bmatrix}
0 & 0.06 & 0 & 0 & 0.07 & 0 & 0 & 0 & 0.12 & 0.04 & 0 & 0 & -0.05 \\
0 & 0 & 0 & 0 & 0 & 0.03 & 0 & 0 & 0 & 0 & 0.01 & 0 & -0.108 \\
0 & 0 & 0 & 0.255 & 0.325 & 0.185 & 0.05 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0.15 & 0 & 0.105 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0.04 & 0 & 0.625 & 0 & 0.17 & 0 & 0 & 0 & 0 & -0.018 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.06 & 0 & 0 & 0 & 0 & -0.109 \\
0 & 0 & 0 & 0 & 0 & 0.23 & 0 & 0.08 & 0 & 0 & 0 & 0 & -0.038 \\
0 & 0 & 0 & 0 & 0 & 0.11 & 0 & 0 & 0 & 0 & 0 & 0 & -0.029 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.08 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.025 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.032 \\
0 & 0.14 & 0 & 0 & 0 & 0.28 & 0.315 & 0.035 & 0 & 0.02 & 0.02 & 0 & -0.134 \\
0 & 0 & 0 & 0 & 0.105 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix} \tag{11}
$$

As it is seen from (11) and also from Fig. 5, the input nodes of FCM are concept 1 (C1) that is "continuous organizational changes" and concept 12 (C12) that is "lack

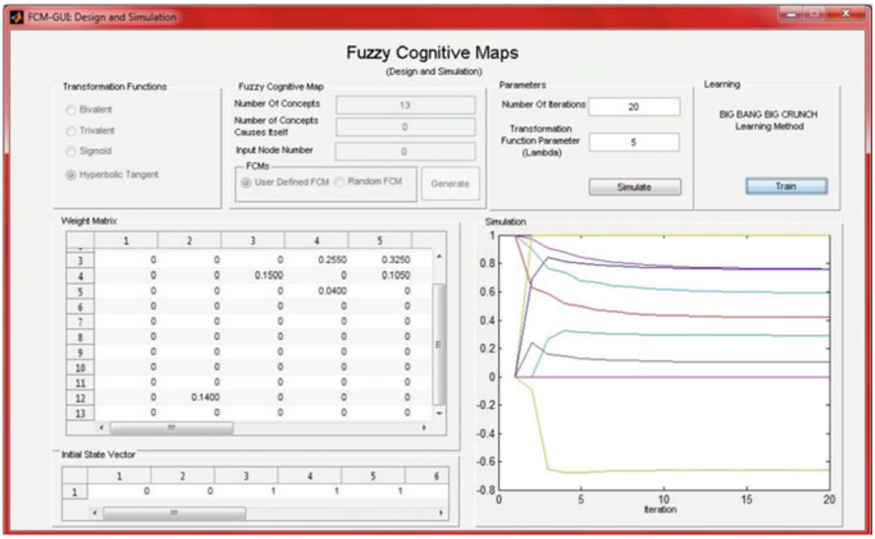

Fig. 6 FCM-GUI “Design and Simulation” for the first example

active participation by external parties" since the first and the twelfth columns of the weight matrix (W) are zero vectors. In fact, the initial concept values of these risks (input nodes) disturb the ERP performance most.

The FCM is designed using FCM-GUI “Design and Simulation” window as given in Fig. 6. The aim of this example is to show the design and simulation capability of the FCM-GUI; therefore, “User Defined FCM” radio button is clicked to design a FCM. As stated above, the number of concepts is selected as 5 and the weight matrix is filled as given in Eq. 11. The initial state vector C(0) is chosen for this study as follows:

C(0) = [0 0 1 1 1 0 0 0 0 0 0 0 0]

The values of the FCM concepts for 20 iterations for the given initial state vector are obtained on the FCM-GUI window as seen in Fig. 6.

In order to show the effectiveness of the proposed BB-BC learning of FCM, the concept data generated from the ERP maintenance risk FCM is used as the training set. For this reason, the data is loaded from the Matlab workspace, and the changes of the thirteen concept values appeared on the “Training Data” table as given in Fig. 7. In addition, the parameters about the data and the initial state vector come into view automatically on the screen.

As the next step, the ranges of the weights that are chosen by the expert are entered to the table in FCM-GUI as follows:

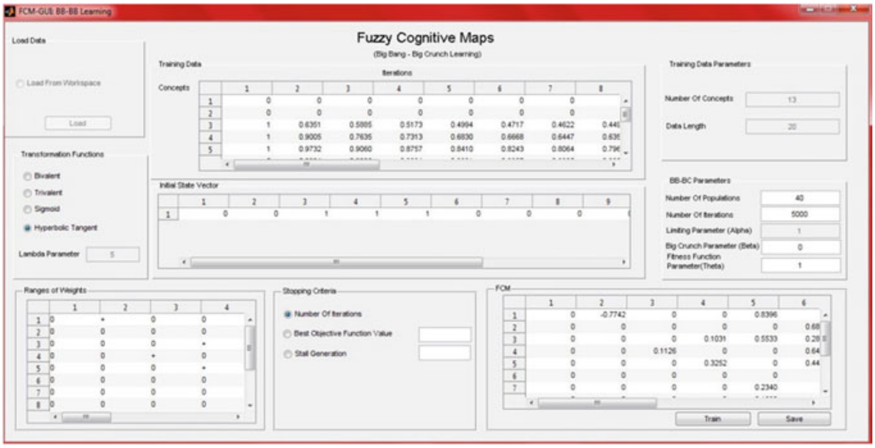

Fig. 7 FCM-GUI "Big Bang-Big Crunch Learning" for the first example

$$
\begin{bmatrix}
0 & + & 0 & 0 & + & 0 & 0 & 0 & [0, 0.12] & + & 0 & 0 & [-0.05, 0] \\
0 & 0 & 0 & 0 & 0 & + & 0 & 0 & 0 & 0 & ? & 0 & ? \\
0 & 0 & 0 & + & + & ? & + & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & + & 0 & + & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & + & 0 & + & 0 & [0, 0.25] & 0 & 0 & 0 & 0 & [-0.05, 0] \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & [0, 0.06] & 0 & 0 & 0 & 0 & - \\
0 & 0 & 0 & 0 & 0 & ? & 0 & [0, 0.08] & 0 & 0 & 0 & 0 & ? \\
0 & 0 & 0 & 0 & 0 & + & 0 & 0 & 0 & 0 & + & 0 & ? \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & ? \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & ? \\
0 & + & 0 & 0 & 0 & ? & ? & [0, 0.035] & 0 & + & + & 0 & [-0.02, 0] \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\tag{12}
$$

After the parameters of the BB-BC learning are entered as illustrated in Fig. 7, the stopping criteria is chosen as "Number of Iteration", which is set as 5000 for this example. Then "Train" button is clicked to start BB-BC learning. Because of the simplicity of the proposed learning BB-BC, the learning procedure took a relatively short period of time and the candidate FCM generated using the historical data appeared on the FCM-GUI window is as follows:

$$W_1^* = \begin{bmatrix} 0 & 0.1986 & 0 & 0 & 0.2771 & 0 & 0 & 0 & 0.9579 & 0.002 & 0 & 0 & -0.0372 \\ 0 & 0 & 0 & 0 & 0 & 0.8573 & 0 & 0 & 0 & 0 & -0.4935 & 0 & 0.0482 \\ 0 & 0 & 0 & 0.2498 & 0.4689 & -0.1008 & 0.05 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.15 & 0 & 0.0067 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.0428 & 0 & 0.6222 & 0 & 0.2473 & 0 & 0 & 0 & 0 & -0.0064 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.002 & 0 & 0 & 0 & 0 & -0.158 \\ 0 & 0 & 0 & 0 & 0 & 0.4651 & 0 & 0.0086 & 0 & 0 & 0 & 0 & -0.0162 \\ 0 & 0 & 0 & 0 & 0 & 0.1773 & 0 & 0 & 0 & 0 & 0.0796 & 0 & -0.0037 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0018 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0287 \\ 0 & 0.2698 & 0 & 0 & 0 & -0.1452 & 0.034 & 0.034 & 0 & 0.3507 & 0.9897 & 0 & -0.1286 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (13)$$

Also, additional pop-up figures open for additional information such as: The original historical data, the change of concepts generated from the candidate, the change of fitness value (H) using Eq. 10. The aim of these figures is to help researchers to report the learning procedure using the copy-paste utility of the Matlab Figure. As an example, the Fitness Value (H) Matlab figure is given in Fig. 8.

5.2 Randomly Generated FCM

In the first example, a FCM taken from real-world and constructed by experts is used. It becomes quite apparent that these FCMs are usually relatively small and the FCM density is low [29]. Small size is a result of the manual development of such maps where expert knowledge has to be relied on. It should be noted that mutual relationships among a large number of concepts are hard to comprehend, analyze, and describe, which results in substantial difficulties in the construction of the corresponding maps. Therefore, as the second example system a synthetic FCM model is constructed randomly using the "FCM-GUI: Design and Simulation window" by clicking the "Random FCM" radio button. The randomly generated FCM has 10 concepts; consequently, the connection matrix has 100 parameters in order to show the effectiveness of BB-BC learning method even the size of the FCM is high.

The weight (connection) matrix of the randomly generated FCM is obtained as given in Eq. (14). For the randomly generated FCM example, the transformation function is picked as sigmoid for the second example with $\lambda = 5$. As it is seen from Eq. (14) the FCM has no input node. The initial state vector C(0) is chosen for this study as follows:

C(0) = [0.64, 0.28, 0.89, 0.04, 0.33, 0.65, 0.58, 0.81, 0.35, 0.06]

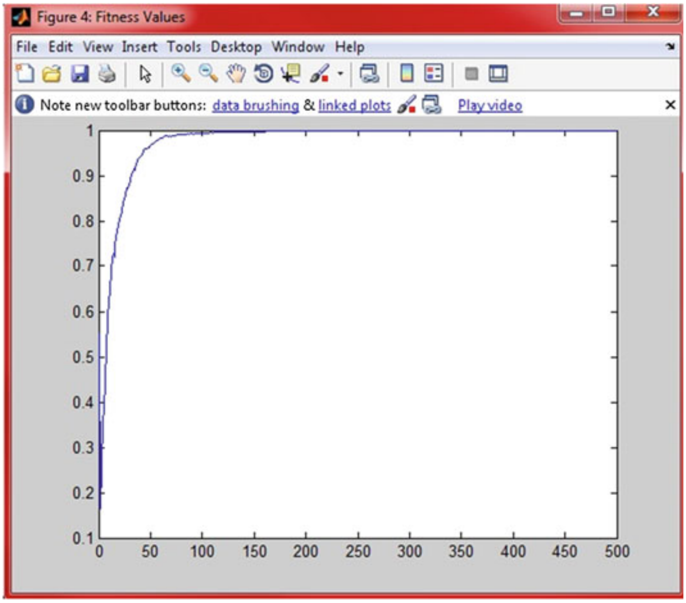

Fig. 8 FCM-GUI: Fitness value (H) change by iteration for the first example

$$W_2 = \begin{bmatrix} 0 & -0.7 & 0.3 & -0.82 & 0.73 & 0.37 & 0.15 & -0.92 & -0.64 & -0.67 \\ -0.86 & 0 & 0.53 & -0.06 & 0.15 & 0 & 0.46 & 0 & -0.25 & 0.88 \\ 0.95 & 0 & 0 & 0.63 & 0 & 0 & -0.58 & -0.56 & 0 & -0.61 \\ -0.58 & 0.84 & 0.82 & 0 & -0.77 & -0.54 & 0.12 & -0.14 & 0 & 0 \\ -0.12 & 0 & -0.71 & 0 & 0 & -0.49 & 0.03 & 0.63 & -0.78 & 0.06 \\ 0.2 & 0.6 & -0.21 & 0.04 & 0 & 0 & -0.47 & -0.65 & 0 & 0.26 \\ -0.49 & -0.21 & 0 & 0.32 & -0.31 & -0.81 & 0 & 0.43 & 0.36 & 0 \\ -0.85 & 0.48 & -0.48 & -0.27 & 0 & -0.42 & -0.12 & 0 & -0.84 & 0.28 \\ 0.98 & -0.68 & -0.56 & 0.38 & 1 & -0.5 & -0.2 & 0.23 & 0 & 0 \\ -0.39 & 0.81 & 0.9 & 0 & 0.57 & 0.78 & -0.74 & 0 & 0.43 & 0 \end{bmatrix} \tag{14}$$

Then the FCM is simulated to generate data to be using for BB-BC learning. After the values of the FCM concepts for 25 successive iterations for the given initial state vector is obtained, "BB-BC Learning" window of the FCM-GUI is opened.

The data is loaded from the workspace and the transfer function as selected as sigmoid. The "Ranges of Weights" table is used to enter the diagonal weights of the table which are zero (0) and the rest is kept with question marks (?); meaning, the BB-BC learning method should search the connection weights in the largest possible interval [−1, 1]. Therefore, 90 parameters are left to BB-BC algorithm to be determined. After starting the learning procedure for 5000 iterations and only 20 populations, a candidate FCM is obtained. Since the proposed BB-BC learning algorithm is a stochastic method, 10 simulations are performed. In Fig. 9, the results

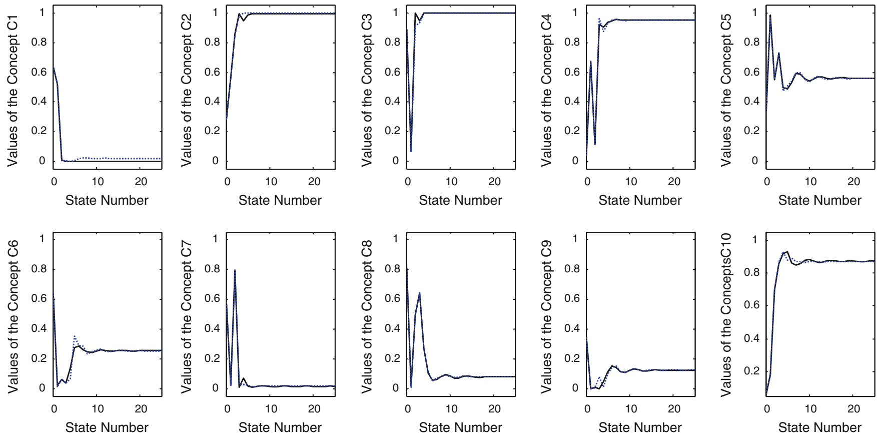

Fig. 9 Comparison of the input data and the data obtained from candidate FCM (*solid*: original FCM, *dashed*: best candidate FCM)

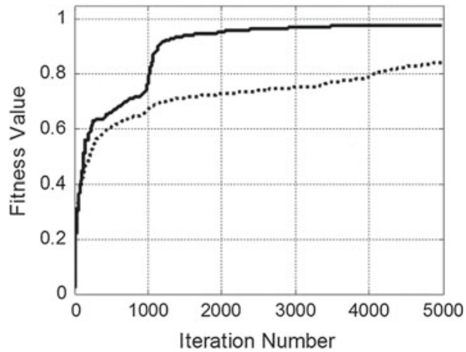

Fig. 10 Fitness functions of the second example (*solid*: best fitness, *dashed*: average fitness)

obtained at the end of the learning phase are plotted for the comparison of the best candidate FCM and original FCM using the pop-up figures of the developed FCM-GUI.

In order to report the learning performance of the BB-BC learning of FCM, the fitness function with theta parameter as 100 is illustrated in Fig. 10.

6 Conclusions

Fuzzy Cognitive Maps (FCMs) are very suitable, simple, and powerful tools for simulation and analysis of complex dynamic systems. In this study, in order to help researchers and developers in social sciences, medicine and engineering, a graphical user interface (GUI) designed in Matlab environment is presented. In the developed

FCM-GUI, a new optimization algorithm, which is called Big Bang-Big Crunch (BB-BC), is proposed for an automated generation of FCMs from data due to its low computational cost and a high convergence speed. The developed Matlab codes are open source software; as a result, the users can develop and use the tool corresponding to their needs. To emphasize the effectiveness and usefulness of the proposed methodology a ERM maintenance risks model and a synthetic model generated by the proposed FCI-GUI are used. The results of the studied examples show the efficiency of the developed FCM-GUI for design, simulation and learning of FCMs. For future work, existing FCM learning methods are planned to add to the proposed FCM-GUI in order to strengthen its usability.

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Chapter 12
JFCM : A Java Library for Fuzzy Cognitive Maps

Dimitri De Franciscis

Abstract *Java Fuzzy Cognitive Maps* (JFCM) [1] is an open source library written by Dimitri De Franciscis [2] that implements fuzzy cognitive maps using the Java™ programming language. In this chapter we will introduce the library and its main features, along with many code examples and experiments that show how to effectively use it in your projects.

1 FCM Tools

1.1 Other Cognitive Mapping Tools

The most important inspiration for the project came from Bart Kosko's *Fuzzy Thinking: The New Science of Fuzzy Logic* [3] as well as other sources ([4]). Many useful ideas came also from these projects:

- *FCMapper*, from FCMapper.net community [5];
- *Fuzzy Cognitive Maps applet* [6] by Guillermo Ochoa de Aspuru;
- various libraries written for Matlab or other specialised environments.

FCMappers.net is *"a network of scientists interested in fuzzy cognitive mapping and its connection to network analysis and systems modelling"* (source: FCMappers website). They realized a complex tool called FCMapper, based on Microsoft Excel, that can be used to model fuzzy cognitive maps, execute simulations and analyse results. As it is completely based on Excel and VBA (*Visual Basic for Applications*) macros, its source code can be examined, modified and enhanced. It has also some

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D. De Franciscis (✉)
Megadix, Freelance Java/CMS/Database consultant, Milano, Italy
e-mail: dimitri@megadix.it

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advanced features like export to NET-file, a file format used to view and analyse graph with *Pajek* [7] or *Visone* [8]. This tool is under active development, and new versions are released regularly. Its use is free for non-commercial projects.

Fuzzy Cognitive Maps applet by Guillermo Ochoa de Aspuru instead is written in Java and is meant to be executed as an application embedded in an internet page. It features a somewhat basic user interface and can be used to create maps and run simulations. Although useful from a didactic point of view, this tool has some serious drawbacks:

- is very old, as it has not been updated since 2002, thus it suffers from many compatibility problems;
- it can be run only from a Java-enabled browser or *appletviewer*;
- it is distributed under GPL license, so it cannot be used for free in commercial products.

1.2 The Need for JFCM

JFCM library was born as a simple programming exercise and a proof-of-concept, but it slowly became popular:

- it's a simple, standalone library written in Java, so it can run on many operating systems, unchanged;
- it has very few dependencies on other libraries;
- it is released under LGPL license, which permits inclusion in commercial projects.

Intended users of JFCM are:

- **students** willing to learn FCMs;
- **researchers** who can experiment new learning algorithms and FCM variants;
- **application developers** who need a simple, tested and extensible library;
- **companies** developing applications based on FCM technology.

The library is quite small and simple, but nevertheless can be used to build a wide range of cognitive maps. It has been developed following an object-oriented approach, so if the standard components are not sufficient for your purpose it's very easy to create your own, as we'll see later.

2 Library Overview

2.1 Main Classes

JFCM implementation of fuzzy cognitive maps is very similar to recurrent neural networks:

- **connections** between concepts are links with one input and one output;

- **concepts** accumulate inputs from incoming connections and use an activation (or transfer) function to calculate output;
- **real values** (*java.lang.Double*) are used for input/output and calculations.

All the relevant classes and interfaces that comprise the model reside in *org.megadix.jfcm* package and sub-packages:

- *org.megadix.jfcm*: main classes and interfaces;
- *org.megadix.jfcm.act*: implementations of *ConceptActivator* interface;
- *org.megadix.jfcm.conn*: implementations of *FcmConnection*;
- *org.megadix.jfcm.utils*: utilities.

Before diving into Java code examples, let's see how things work in JFCM. The main entry point for most users is class ***CognitiveMap***, which has methods to build, execute and inspect cognitive maps. CognitiveMap class acts like a container for the other classes of the model:

- ***Concept***: represents a single concept in a cognitive map;
- ***FcmConnection***: connects two concepts.

> Concept and FcmConnection are stored in Java maps (*java.util.Map*) inside a CognitiveMap, using their *name* attribute as *key*. This means that, to avoid clashes, you should always **choose unique names for concepts and connections**. Just think about the *name* attribute as a unique ID in a database table.

It's important to note that FcmConnection was designed as the common superclass of all actual implementations, thus it is an abstract class and it cannot be instantiated. JFCM core includes only one concrete implementation, ***WeightedConnection***, with all the features needed by popular cognitive maps models:

- *weight*: measures the influence of a concept over another;
- *delay*: propagation delay of a signal through the connection, measured in *epochs*, or *cycles*. [1]

Each Concept uses a ***ConceptActivator*** to calculate its next output. ConceptActivator is an interface, because there are several ways to calculate the next output of a Concept. JFCM core provides some implementations, using discrete and continuous functions often found in neural networks and artificial intelligence.

[1] Traditionally, this was implemented inserting additional intermediate concepts (and connections) between source and destination. In JFCM this has been optimized, it's just a matter of setting an integer parameter. We'll see how it works in a specific example.

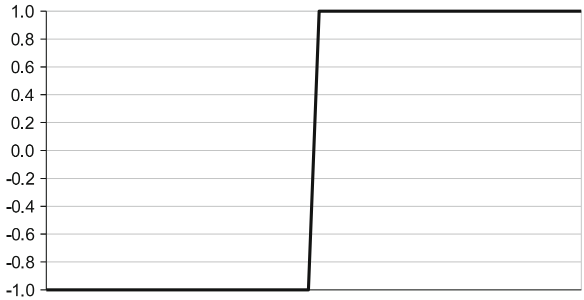

Fig. 1 SignumActivator (*mode = BIPOLAR, zeroValue = 0*)

2.2 Concept Activators (Transfer Functions)

SignumActivator

A configurable implementation of *Heaviside step function*:

- not differentiable;
- *zeroValue*: value of the function for $input = 0$. $zeroValue = 0$ is the default configuration, but many prefer to use $zeroValue = \frac{1}{2}$
- *threshold*: shifts function domain to the left (when negative) or right (when positive). Used to simulate *biased inputs*;
- *mode*: affects the output range:
  - (default) *BIPOLAR*: outputs one of the values in $\{-1, zeroValue, 1\}$
  - *BINARY*: outputs one of $\{zeroValue, 1\}$

LinearActivator

This activator linearly transfers its input to output, using this formula:

$$x_{t+1} = (x_t + input + th) \cdot factor$$

- *input* is the sum of all the inputs coming from inbound connections;
- *th* parameter corresponds to *threshold* (same as SignumActivator);
- *factor* is a scaling factor, controls function steepness;
- *min* and *max*, if set to finite values, limit the output of the function. By default are set to $\pm\infty$.

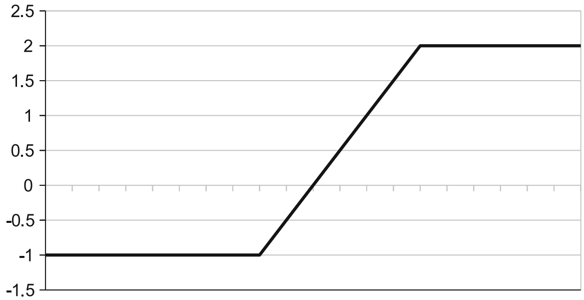

Fig. 2 Linear activator (*min* $= -1$, *max* $= 2$)

Things to remember about *min* and *max*:

- leaving default values ($\pm\infty$) makes the function differentiable (first derivate = constant) but usually makes concept output go outside of $[-1.0, 1.0]$. In some applications this is not acceptable;
- setting *min* or *max* to a finite value, instead, will make the function *not* differentiable in two points.
- In many applications the configuration is
  - $min = -1$ or $min = 0$
  - $max = 1$.

SigmoidActivator

Sigmoid transfer function, also called *logistic function*, with continuous values between 0 and 1:

$$x_{t+1} = \frac{1}{(1 + e^{(-k \cdot (x_t + input + th))})}$$

The k parameter directly affects curve steepness, by default it is set to $k = 1$ (no effect).

This function is differentiable on its entire domain and is often used in artificial intelligence (activation of neurons in neural networks), ecologic simulations, dynamic systems.

HyperbolicTangentActivator

Another popular transfer function which is differentiable and with sigmoid shape, but with continuous values between -1 and 1:

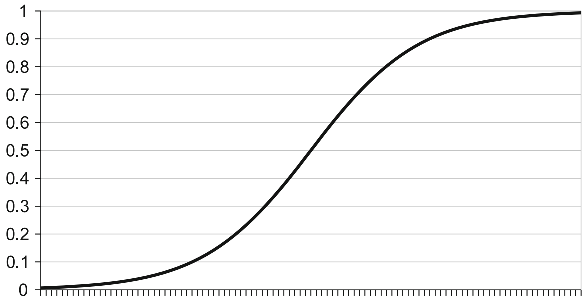

Fig. 3 Sigmoid activator

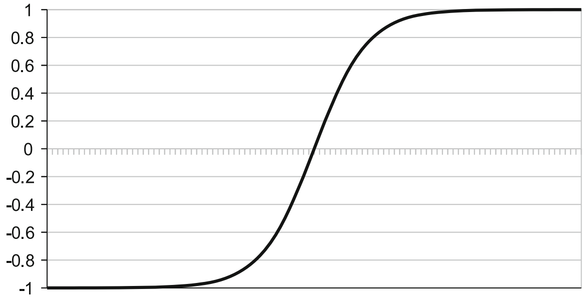

Fig. 4 Hyperbolic tangent activator

$$x_{t+1} = tanh(x_t + input + th)$$

2.2.1 GaussianActivator

Based on the *Gaussian function*, widely used in statistic as it describes the *Normal Distribution*:

$$x_{t+1} = e^{-\frac{(x_t - th)^2}{2 \cdot w^2}}$$

- differentiable;
- w: width of the bell-shaped curve (default = 1);
- th: threshold.

2.2.2 CauchyActivator

Another differentiable bell-shaped function, given by this formula:

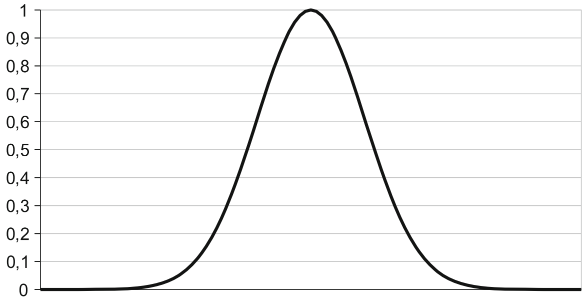

Fig. 5 Gaussian activator

Fig. 6 Cauchy activator

$$x_{t+1} = \frac{1}{\pi(1 + (x_t - th)^2)}$$

2.2.3 IntervalActivator

Activates only in a closed interval.

- not differentiable;
- *mode*: similar to SignumActivator, possible values are *BIPOLAR* (values in $\{-1, zeroValue, +1\}$) and *BINARY* (values in $\{zeroValue, +1\}$);
- *zeroValue*: the value assumed in the transition points;
- *amplitude*: semi-amplitude of the interval.

2.2.4 NaryActivator

This activator is very similar to LinearActivator but rounds output to n distinct values (default = 2), thus is not differentiable.

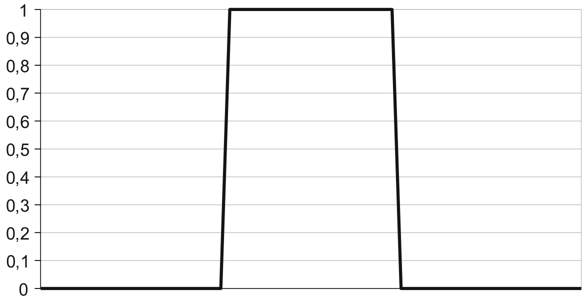

Fig. 7 Interval activator

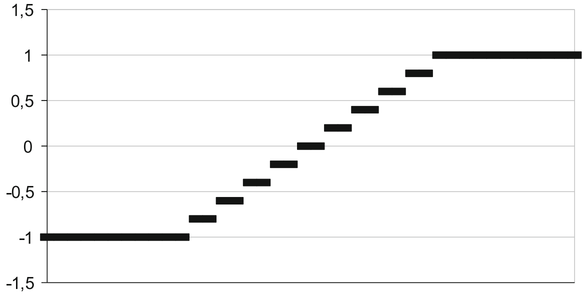

Fig. 8 Nary activator (n = *10*)

All these implementations extend a common abstract class, *BaseConceptActivator*, so they all inherit two parameters:

- *threshold*;
- *includePreviousOutput*: if *true* (default) it includes x_t in the calculations, otherwise considers $x_t = 0$ during evaluation phase.

Set *includePreviousOutput* parameter to *false* when the concept should have no memory of its previous state.

BaseConceptActivator is a handy superclass that makes very easy to implement a custom ConceptActivator, as we'll see in the *"Extend JFCM"* paragraph.

3 Code Examples

3.1 Project Setup

To keep things simple our examples will be shown using Eclipse Integrated Development Environment [9] (*IDE*), a popular development tool for Java. [2]

Project setup is very straightforward:

- download JFCM core library;
- from within Eclipse IDE: create a new Java project from *File / New / Java Project*;
- create a *lib* subfolder;
- copy *jfcm-core-1.x.x.jar* into *lib*. Here, *1.x.x* stands for version number, for example *jfcm-core-1.4.1.jar*;
- open project properties, and in *Java Build Path / Libraries* add the above jar file as library.

Remember also that **JFCM is compatible with Java 1.6** (sometimes labelled as *Java 6*) **and above**.

All code examples are packaged for your convenience as a single Eclipse project, and can be downloaded either from Springer or JFCM website.

3.2 First Example: Economic Simulation

This first example was inspired by [4] and models a very simple economic simulation. In this map there are four concepts:

- **c1**: Interest Rate;
- **c2**: Productive Investments;
- **c3**: Occupation;
- **c4**: Inflation.

All these concepts have a three-valued *signum* activation function with outputs -1, 0 and $+1$, and connected in a circular structure:

The number near each arrow is the *weight* of the connection (can also be negative). Here is the java code to build this map:

```
CognitiveMap map = new CognitiveMap(``Investments'');
SignumActivator af = new SignumActivator();
```

[2] Remember however that, since JFCM is simply a Java library, you can always use any other IDE (e.g. Netbeans, IntelliJ IDEA, vi, Emacs) and build tools (such as Ant or Maven). See JFCM website for more detailed examples on how to configure and use such tools.

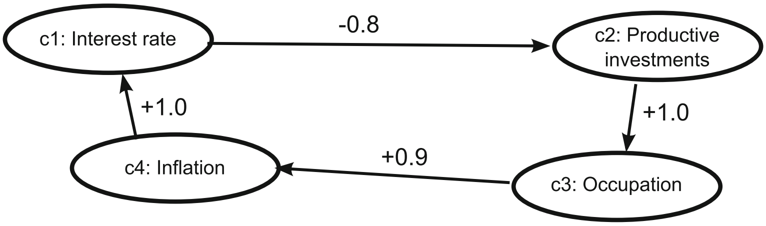

Fig. 9 Investments Example.java

```
af.setIncludePreviousOutput(false);

Concept c1 = new Concept(``c1'', ``Interest rate'',
                         af, 0.0, 0.0, false);
map.addConcept(c1);

Concept c2 = new Concept(``c2'', ``Productive
                                        investments'',
                         af, 0.0, 0.0, false);
map.addConcept(c2);

Concept c3 = new Concept(``c3'', ``Occupation'',
                         af, 0.0, 0.0, false);
map.addConcept(c3);

Concept c4 = new Concept(``c4'', ``Inflation'',
                         af, 0.0, 0.0, false);
map.addConcept(c4);

FcmConnection conn_1 = new WeightedConnection(
    ``c1 -> c2'',
    ``Interest rate -> Productive investments'',
    -0.8);
map.addConnection(conn_1);

FcmConnection conn_2 = new WeightedConnection(
    ``c2 -> c3'',
    ``Productive investments -> Occupation'',
    1.0);
map.addConnection(conn_2);

FcmConnection conn_3 = new WeightedConnection(
    ``c3 -> c4'',
    ``Occupation -> Inflation'',
```

```
    0.9);
map.addConnection(conn_3);

FcmConnection conn_4 = new WeightedConnection(
    ``c4 -> c1'',
    ``Inflation -> Interest rate'',
    1.0);
map.addConnection(conn_4);

map.connect(``c1'', ``c1 -> c2'', ``c2'');
map.connect(``c2'', ``c2 -> c3'', ``c3'');
map.connect(``c3'', ``c3 -> c4'', ``c4'');
map.connect(``c4'', ``c4 -> c1'', ``c1'');
```

Source code for this example:
InvestmentsExample.java

Things to note

- we are reusing a single SignumActivator instance for all concepts. This is a bit uncommon, because individual concepts usually have distinct activators, configured differently;
- *setIncludePreviousOutput(false)* is called on activator, meaning that the concept will not have memory of its past state;
- all concepts have unique names (among concepts), and so do connections (among connections);
- connections and concepts are first created, then connected using *CognitiveMap.connect()* method.

We will do now some experiments using this map, trying different initial states or modifying concepts configuration.

3.2.1 Experiment 1: Cyclic Behaviour

The initial map state for this experiment will be $S = (c1, c2, c3, c4) = (1, 0, 0, 0)$, obtainable with this code:

```
map.reset();
map.setOutput(``c1'', 1.0);
map.setOutput(``c2'', 0.0);
map.setOutput(``c3'', 0.0);
map.setOutput(``c4'', 0.0);
```

Table 1 Investments Example - Experiment 1: periodic behaviour

Iteration	Interest rate	Investments	Occupation	Inflation
-	1	0	0	0
1	0	-1	0	0
2	0	0	-1	0
3	0	0	0	-1
4	-1	0	0	0
5	0	1	0	0
6	0	0	1	0
7	0	0	0	1
8	1	0	0	0
9	0	-1	0	0
10	0	0	-1	0

The call to *map.reset()* puts the map back to a "neutral" state, with all outputs set to *null*. To execute the simulation we have to repeatedly call:

```
map.execute();
```

In Table 1, looking at the evolution of map state, we're observing an interesting periodic behaviour of length $l = 8$, i.e. after eight epochs we go back to initial state $S = (1, 0, 0, 0)$.

It seems that any initial state will fall into a cycle of length $l = 8$; this makes sense from simulation point of view, because economy itself exhibits cyclic behaviour.

3.2.2 Experiment 2: Fixed Values

In this experiment we will "clamp" the value of concept *c1*, which represents the *Interest rate* of our simulation:

```
map.setFixedOutput(``c1'', 1.0);
```

Setting a concept to "fixed" means that it will always have that output, regardless of its incoming connections and activation functions. As you can see from Table 2, the map no longer falls into a cycle but reaches a fixed attractor instead: $(1, -1, -1, -1)$.

3.3 Advanced Configurations

More realistic simulations can be built using different features of JFCM:

- continuous transfer functions like SigmoidActivator or HyperbolicTangentActivator:

Table 2 Investments Example - Experiment 2: fixed values

Iteration	Interest rate	Investments	Occupation	Inflation
-	1	1	1	1
1	1	−1	1	1
2	1	−1	−1	1
3	1	−1	−1	−1
4	1	−1	−1	−1
5	1	−1	−1	−1

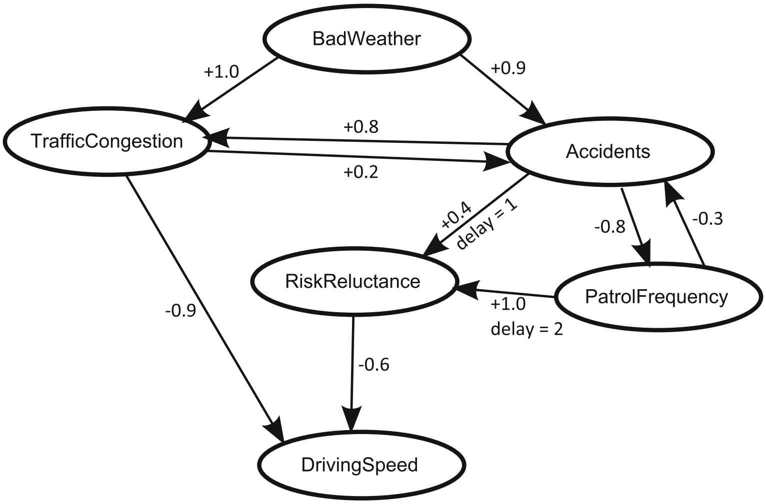

Fig. 10 RoadTrafficSimulatorWithDelay.java

  – cyclic behaviour becomes an exception, as it is very difficult to obtain;
  – many configurations converge into a stable attractor;
  – some configuration may even exhibit chaotic or fractal behaviour.

- change *k* parameter to vary slope of SigmoidActivator transfer function;
- use *delay* parameter.

As an example, in Fig. 10 we took the road traffic FCM taken from [3], then added delay to connections *Accidents-RiskReluctance* (delay = 1) and *PatrolFrequency-RiskReluctance* (delay = 2). Also, we applied SigmoidActivator on all connections and set *BadWeather* and *PatrolFrequency* as fixed, to test different security policies applicable by government to prevent road accidents. In Figs. 11 and 12 we can see how map outputs evolve and eventually converge to a stable configuration.

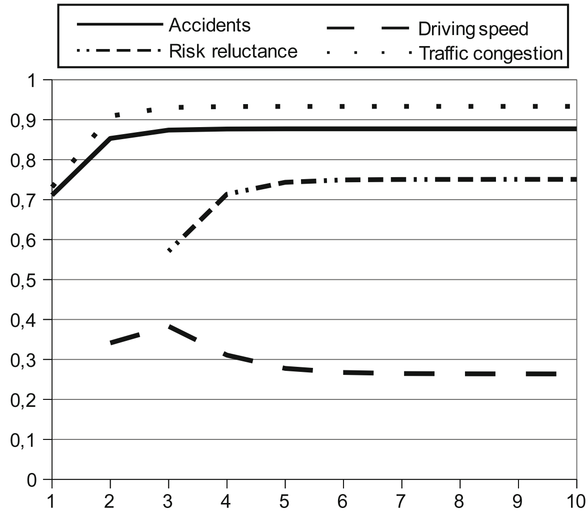

Fig. 11 Bad weather, few patrols

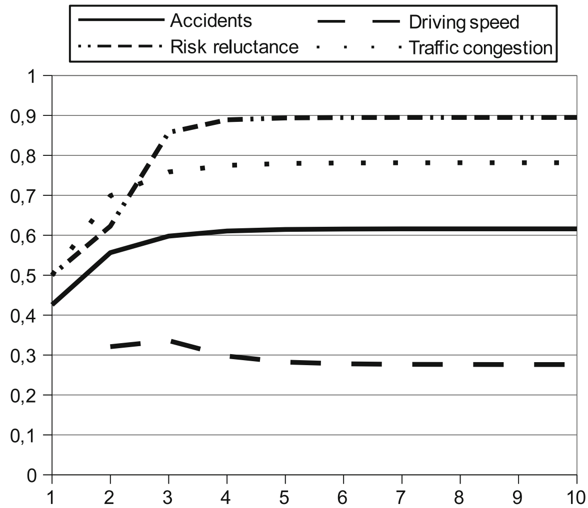

Fig. 12 Nice weather, lots of patrols

Source code for this example:

- RoadTrafficSimulatorWithDelay.java
- RoadTrafficSimulatorWithDelay.xml

3.4 XML Format

JFCM comes with a simple utility class with methods to load maps from XML files: ***org.megadix.jfcm.utils.FcmIO***. There are basically two kind of methods:

- saveAsXml(): saves a cognitive map;
- loadXml(): loads a cognitive map.

The format of XML file is strictly tied to *JFCM core* implementation, and it is specified by a XML Schema file with this URI:
http://www.megadix.org/standards/JFCM-map-v-1.2.xsd

Although the XML format is simple enough to be edited by hand, especially with the help of an XSD-compliant editor with auto-completion (such as jEdit or Eclipse), the real goal is to have an **open file format for cognitive maps**, without explicit dependency on JFCM. An open format will ease data exchange between systems, and foster the creation of advanced tools such as graphical editors or learning environments.

To get a taste of the XML format, here's an excerpt from *InvestmentsExample.xml* (some code omitted and replaced with *[...]*):

```
<?xml version="1.0" encoding="UTF-8"?>
<jfcm:maps
  xmlns:jfcm=''http://www.megadix.org/standards/
                      JFCM-map-v-1.2.xsd''>
  <map name=''Investments''>
    <concepts>
      <concept act=''SIGNUM'' input=''0.0'' name=''c1''
                         output=''0.0''>
        <description>Interest rate</description>
        <params>
          <param name=''includePreviousOutput''
                            value=''false'' />
        </params>
      </concept>

      [...]

    <connections>
      <connection from=''c1'' name=''c1 -&gt; c2''
                                    to=''c2''
        type=''WEIGHTED''>
        <description>Interest rate -&gt;
```

Table 3 Various implementation classes for each "act" attribute value

Code	Implementation class
CAUCHY	CauchyActivator
GAUSS	GaussianActivator
INTERVAL	IntervalActivator
LINEAR	LinearActivator
NARY	NaryActivator
SIGMOID	SigmoidActivator
SIGNUM	SignumActivator
TANH	HyperbolicTangentActivator

```
          Productive investments</description>
        <params>
          <param name=''weight'' value=''-0.8'' />
        </params>
      </connection>

      [...]

    </connections>
  </map>
</jfcm:maps>
```

Some highlights:

- <jfcm:maps> is the root element, that can store one or more <map> sub-elements;
- xmlns:jfcm="..." is an XML namespace declaration that tells to the editor which format our file will follow;
- <concept> element has an act="SIGNUM" attribute. This attribute specifies what ConceptActivator implementation to use, possible values are listed in Table 3;
- parameter values for concept activator go in the <params> section inside <concept>;
- <connection> elements have a from and to attributes, that reference concepts by their name (remember that names must be unique);
- in the <params> section we can set the value for weight parameter.

4 Extend JFCM

4.1 Custom Transfer Functions

Creating your own ConceptActivator is very simple, in most cases it is simply a matter of subclassing *BaseConceptActivator* and implementing *calculateNextOutputImpl(Concept c)* method. BaseConceptActivator in fact will do most of the job:

- discard *null* and indefinite values;
- accumulate input values into *Concept.input*, so you can retrieve it calling *Concept.getInput()*.

You can retrieve previous output of concept calling *Concept.getOutput()*, but your are not limited to this; in fact, you have access to the whole data model, so your implementation can use anything it needs for its calculations. Also, when creating custom implementations, is very important to know how calculations work in JFCM. Here is what happens when *CognitiveMap.execute()* method is fired:

- *Concept.startUpdate()* method is called on each concept of the map (order is not important);
- *ConceptActivator.calculateNextOutput(this)* is called on each concept activator;
- concepts activators calculate and set *Concept.nextOutput*;
- *Concept.commitUpdate()* is called on each concept. This method simply assigns Concept.output ← Concept.nextOutput.

Here is an example of a custom activator function that uses the sin function:

$$x_{t+1} = sin(x_t/2 + input)$$

and the corresponding Java code:

```
public class SinActivator extends BaseConcept
                                  Activator {
    protected double calculateNextOutputImpl
                                  (Concept c) {
        return Math.sin(c.getOutput() / 2.0 +
                                c.getInput());
    };
}
```

Source code for this example:
InvestmentsExampleCustomActivator.java

To use it, just instantiate your class instead of one of the standard ones:

```
SinActivator af = new SinActivator();
```

The output will be radically different now, as shown in Fig. 13.

If your activator is radically different you may consider to implement directly *ConceptActivator* interface. This way you will have complete freedom: you can do any calculation, use other libraries, inspect concepts and connections, and so on. Remember however that you will not have the help of BaseConceptActivator workflow, so you must manually validate input values.

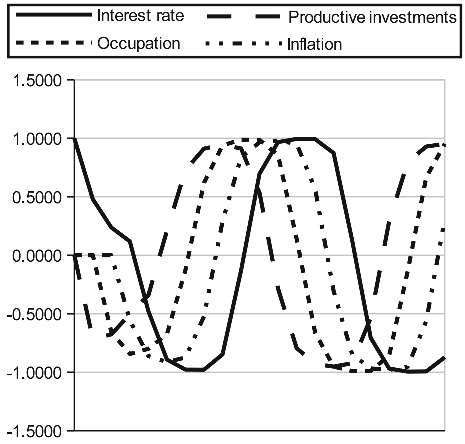

Fig. 13 Investments Example Custom Activator.java

Unfortunately custom activators cannot be directly stored in XML source format, but you can use a workaround:

- create your map using XML format;
- load map with FcmIO.loadXml();
- instantiate your specific activators classes then assign them to individual concepts by calling *Concept.setConceptActivator()*.

Remember that JFCM does not force you to use the same ConceptActivator through the whole map, you can choose any combination of them and create powerful "mixed-style" maps.

4.2 An Example of Custom Activators: jfcm-jfuzzylogic

jfcm-jfuzzylogic is an interesting example of custom concept activators. It's an experimental library, also freely available from the same author of JFCM [1], that uses fuzzy logic for concept activation. This package, based on the *jFuzzylogic* [10] library, implements its own concept activator, *FuzzyConceptActivator*, that execute rules written in *Fuzzy Control Language* (*FCL*), adding incredible expressive power to cognitive maps.

This is how it works:

- the sum of all signals from incoming connections are injected into evaluator as the special *input_total* fuzzy variable;
- variable are fuzzified, as configured by the user in the FCL source;
- inference rules are evaluated and a crisp (i.e. single) value is assigned as concept output.

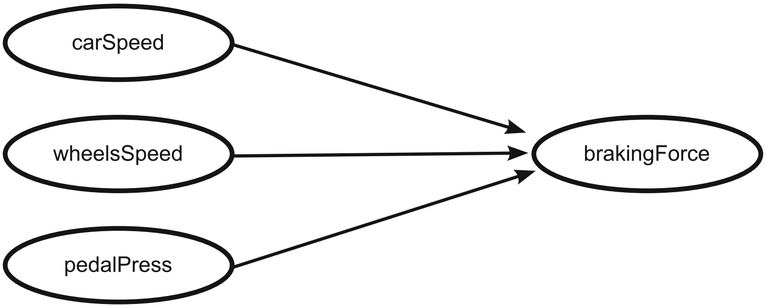

Fig. 14 Vehicle braking example

4.3 An Intelligent Braking System

As an example we will take a classic fuzzy logic problem: braking behaviour of a vehicle in difficult conditions, like rain or ice. Under these circumstances, a sudden obstacle makes the driver push hard on brake pedal, often blocking wheels and losing control of the vehicle. The job of the enhanced braking system is to mitigate this force, allowing for a more incremental deceleration. In modern vehicles this is usually implemented by *ABS* (*Antilock Braking System*) or some more recent development.

In Fig. 14 we can see the structure of a cognitive map that models a braking system. There are two logical types of concepts:

- input concepts: *carSpeed*, *wheelsSpeed*, *pedalPress*. The outputs of these concepts are fixed and are continuously updated by car sensors;
- output concepts: only *brakingForce* in this example. The outputs of these concepts are updated by fuzzy subsystem, then are sent to car actuators.

Behaviour of *brakingForce* concept is defined by an FCL-compliant source file, which has this structure:

- VAR_INPUT section defines variables available to rules;
- VAR_OUTPUT defines output variables;
- FUZZIFY sections define how to *fuzzify* input variables, i.e. which *membership functions* to apply;
- DEFUZZIFY section specify how to *defuzzify* output variables;
- RULEBLOCK section defines inference rules.

The complete example is available in book website, however the RULEBLOCK section of the FCL is much interesting:

```
RULE 1 : IF carSpeed IS high AND pedalPress IS high AND
            wheelsSpeed IS zero THEN output IS zero;
RULE 2 : IF carSpeed IS high AND pedalPress IS high AND
            wheelsSpeed IS low THEN output IS low;
```

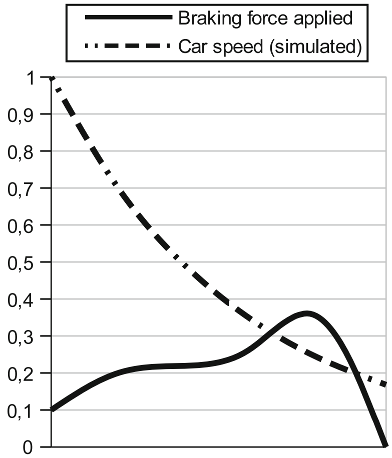

Fig. 15 Vehicle braking example - chart

```
RULE 3 : IF carSpeed IS high AND pedalPress IS high AND
            wheelsSpeed IS mid THEN output IS mid;
```

Source code for this example:

- FuzzyBrakesExample.java
- FuzzyBrakesExample.fcl

Here we have very few rules, but they are enough to make the system intelligent. In Fig. 15 we can see how the actuators progressively release brake force at high speed, but lower it when speed decreases.

4.4 Development of Learning Algorithms

Another interesting field of research where JFCM can help is the development of *learning algorithms*. As we saw in previous paragraphs, cognitive maps are very easy to manipulate and extend and the implementation should be straightforward. As an example we implemented *Nonlinear Hebbian Learning (NHL)*, an unsupervised learning technique described in [11–13].

Source code for this example:
NonLinearHebbianTrainingExample.java

In Nonlinear Hebbian Learning concepts are divided, as we already saw with jfcm-jfuzzylogic, into ***input*** and ***output***. Experts' adivce is very important and is used to determine the input/output subdivision and to provide parameters to the algorithm:

- map structure and initial weights of the connections;
- upper and lower bounds for each DOC node;
- maximum error (distance from average value) *maxDocDistance*;
- maximum change of weights between subsequent iterations *maxDelta*;
- weight decay learning coefficient γ;
- learning parameter η;
- maximum number of iterations *maxEpochs*.

Here is a summary of the algorithm:

- random values are assigned to concept outputs;
- calculated target value for each DOC (average between upper and lower bound);
- main loop:
  - map is evaluated, calling *CognitiveMap.execute()*;
  - weights are updated (see papers and example code for details);
  - termination functions are evalutated;
  - if any of the termination functions is satisfied, stop.

There are three termination functions:

- T_1: the average error is below *maxDocDistance*;
- T_2: the change of the weights, compared to previous iteration, is below *maxDelta*;
- T_3: the maximum number of iterations (*maxEpochs*) has been reached.

To assess the algorithm we reproduced the experiment described in [13], a simple process control problem often encountered in chemical industry. The goal of the simulation is to produce a liquid with specified characteristics, without execeeding the tank capacity.

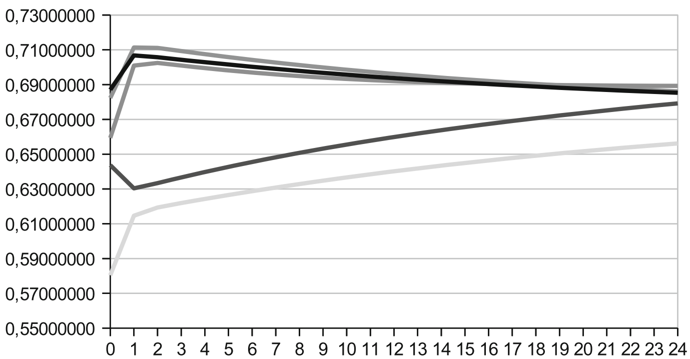

Fig. 16 Nonlinear hebbian learning: evolution of values

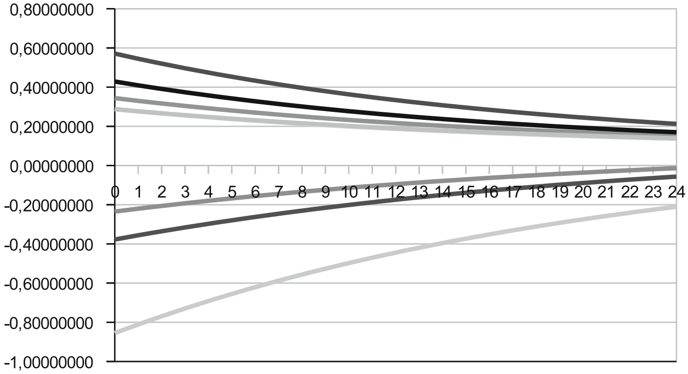

Fig. 17 Nonlinear hebbian learning: evolution of weights

In Fig. 16 and 17 we can see how weights and concept values evolve during the learning phase, reaching an equilibrium. It's interesting to note that, in our tests, the map always reached a stable configuration regardless of the initial input values.

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Chapter 13
Use and Evaluation of FCM as a Tool for Long Term Socio Ecological Research

Martin Wildenberg, Michael Bachhofer, KirstenG.Q. Isak and Flemming Skov

Abstract A halt in loss of biodiversity is an important issue in conservation management across Europe. As landscapes tend to be perceived as a combination of natural and social elements, and people's values and attitudes, research supporting conservation management is dealing with landscapes as socio-ecological systems. As part of ALTER-Net, we applied FCM to five cases and subsequently evaluated the approach by means of a SWOT framework. This examined the strengths and weaknesses of, and the opportunities and threats to FCM when applied as a tool in conservation management.

1 Introduction

This chapter focuses on the use of Fuzzy Cognitive Mapping (FCM) in the context of interdisciplinary environmental research and here especially in the emerging field of long term socio ecological research. Given the specific nature and challenges of this

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M. Wildenberg (✉)
Umweltforschungsinstitut, GLOBAL 2000, Neustiftgasse 36, 1070 Vienna, Austria
e-mail: martin.wildenberg@global2000.at

M. Bachhofer
FCMappers.net, Tokyo, Japan
e-mail: michaelbachhofer@gmx.net

K. G. Q. Isak
NIRAS, Aarhus, Denmark
e-mail: isa@niras.gl

F. Skov
Department of Wildlife Ecology and Biodiversity, National Environmental Research Institute, Aarhus University, Aarhus, Denmark
e-mail: fs@dmu.dk

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endeavor the center of attention is on the process of FCM and less on its technical implementation. See [14, 20, 22] for a detailed technical coverage of FCM applied in environmental research. See [23] for a recent review on FCM applications. In this chapter we will highlight the way the maps were obtained from stakeholders and experts, what kind of knowledge could be generated in different case-studies and on a SWOT-analysis of FCM in the context of conservation research.

1.1 Long Socio-Ecological Research

The objectives of Long Tern Socio-Ecological Research (LTSER) in Europe are to provide policy relevant and proactive research in the context of sustainability science and conservation. The historical development and the conceptual background of LTSER are elaborated in detail by [25] and in [18]. Chapter 2 will focus on FCM as a tool that allows addressing some of the challenges connected with LTSER type of research. The presented case studies and the following evaluation of the tool through a SWAT analysis were conducted in the frame of the Sixth Research Framework Program (FP6) of the European Commission promoted "Networks of Excellence" (NoE), ALTER-Net (A Long-term Biodiversity and Ecosystem Research and Awareness Network). ALTER-Net aimed to overcome fragmentation and foster disciplinary and interdisciplinary integration in the European research area along the topic of biodiversity in an ecosystem context. One of the goals of ALTER-Net was to provide a framework for identifying interdisciplinary research ideas, planning proposals and delivering syntheses on complex socio-ecological problems [5]. The use and evaluation of FCM was part of this framework (Wildenberg et al. submitted).

Loss of habitats, due to human induced land-use and land-cover change, is one of the main drivers of biodiversity loss across Europe and elsewhere [17]. The goal of conservation management is often to influence processes and drivers affecting changes in landscapes in ways that are beneficial for certain species or ecosystem configurations. It has increasingly been noticed that these attempts cannot be restricted to the conservation of biodiversity in reserves covering pristine or almost pristine areas alone. They must be extended to the cultural, semi natural and urban landscapes, which dominate most of Europe, and may contain the majority of biological diversity. By doing so, conservation management is confronted with a variety of stakeholders holding different interests and views, as well as with the multifunctional characteristic of the landscapes. Landscapes tend to be perceived as a combination of natural and social elements, and people's values and attitudes. In science ecosystems are increasingly conceptualized as complex adaptive systems. As such they are characterized by non-linear and path dependent behavior. They are, at various scales, inherently aligned with social systems. The term socio-ecological (or social-ecological) system was coined to emphasis the inseparable character of both systems. A landscape can be viewed as a typical example of a socio-ecological system—it is a hybrid between social and ecological systems [3, 29]. This view is also similar to the way how most people living and working in a landscape would describe it. They tend to include not only natural elements but also social and more personal elements in their landscape descriptions [11, 26]. For conservation science and management this implies that not only the physical and natural properties of a landscape or species are important variables to consider in planning. Also the values, conflicts and perceptions people have about a landscape or a species must be taken into account [9]. Therefore a growing need for concepts and tools that enable conservation management to deal with these new challenges has emerged [4, 28].

FCM can serve as a tool to involve stakeholders who are either the key actors of land-use and land-cover change or affected by conservation management in one way or the other—including scientists, conservation managers or lay people. It provides means of exploring, analyzing and communicating their perceptions of a landscape or socio-ecological systems in general (see also [14, 15]). Through its strong participative and interactive character, FCM is especially suitable to foster learning processes and to contribute to conflict management. Additionally it makes it possible to combine subjective and objective elements of science and other knowledge systems e.g. local or traditional knowledge and to display and analyze them in a consistent way.

As part of ALTER-Net we applied FCM to five cases and subsequently evaluated the approach by means of a SWOT framework. This examined the strengths and weaknesses of and the opportunities and threats to FCM when applied as a tool in conservation management. The strengths of FCM are its ability to combine diverse knowledge covering all aspects in a socio-ecological landscape, its potential for providing a basis for social learning among inter-disciplinary and trans-disciplinary teams and to direct thinking towards a problem solving approach. The weaknesses of FCM are its incomplete development due to the relative young age of this methodology, its risk of lack of use due to fear of over simplifications, and its risk of alienating participants from the project. The opportunities for FCM are its potential as a tool in conflict resolution and as a tool in policy making and management. The threats to FCM are that landscapes are not sufficiently described and that presented knowledge is perceived as genuine scientific knowledge. Use of FCM should pay attention to (1) the choice of participants, and whether to conduct the FCM in individual interviews or in groups sessions, (2) the depth of the discussions and the extent of the cognitive maps (3) which topic to cover in the discussions, (4) the possibilities for applying in conflict resolution, (5) the role of the interviewer/facilitator and (6) a future development of the methodology.

2 Fuzzy Cognitive Mapping in Alter-Net

In the scope of ALTER-Net FCM was applied to five case studies. Table 1 outlines the case studies by presenting the locations the way the FCM was conducted, the purpose of the studies and the question which was the basis for the fuzzy cognitive maps.

As the FCMs served distinct goals related to the specific sites and ongoing projects no common topic was chosen. To arrive at a common methodological approach two

Table 1 Overview over the different case studies

	Austria	Denmark	Finland	Poland	Spain
Location	The Long Term Socio-Ecological Research (LTSER) Platform Eisenwurzen (5784 km^2)	The core area of National Park Mols Bjerge(2915 hectares)	Lake Karvianjärvi in South-West Finland, part of the river Karvianjoki	West Polesie Biosphere Reserve	Doñana National Park is a UNESCO Biosphere Reserve, a Ramsar Site and a Natural World Heritage Site (537 km2)
Informants	6 stakeholder were interviewed individually	12 stakeholders each created maps for 6 locations in the area. The 6 maps from each stakeholder were subsequently aggregated into one map	One group session and three individual interview resulted in four maps	Three transdisciplinary groups created each their map	14 individual experts created each one map
Purpose	Information for agent-based model of the larger socio-ecological system	Contributing to discussions regarding the establishment of a National Park	Is part of a project which will produce scenarios for the river basin, and by that help the managers and other stakeholders to plan their activities	To identify knowledge gaps in conservation management	Collecting expert information on the drivers and pressures on biodiversity
Question	What are the important factors or agents determining the development in your region?	What is important for you at this place?	What issues comes to your mind when you think of the lake Karvianjärvi?	What influences the uniqueness and richness of the nature?	What are, from your point of view, the main drivers and pressures over Doñana biodiversity?

workshops were conducted where all facilitators[1] met and were introduced to the method and also could apply FCM in a test setting with stakeholders. Only the Spanish case study was conducted before the workshops—which is reflected in a very different structure of the resulting maps. The results of the FCM exercises have been utilized to collect information for agent based land-use change modeling, investigating what people see as important issues in a Danish national park [11], facilitate the design of an integrated conceptual DPSIR[2] model [8] and to inform scenario building and management decisions in a Finnish river basin management project.

2.1 How FCM was Applied

To cope with the large number of maps and to structure and streamline the workflow of analysis, the software FCMapper was developed by Bachhofer and Wildenberg (see www.fcmappers.net and [30]). This software is freely available, based on excel and allows to calculate the basic FCM indices, conduct dynamical analysis and visualize the fuzzy cognitive maps. The development of the software was already a response to an experience made early in the project: Although FCM was seen as a promising method there were no tools available that allowed an easy processing and analysis of the maps. For a short introduction to the software see the appendix.

When constructing fuzzy cognitive maps we largely followed the step wise approach as described by [12, 20]. The interview partners were chosen out of the specific project requirements. Some of the projects followed a more expert oriented approach some had the focus on stakeholder involvement. Our experience in the ALTER-Net case studies, as well as many discussions and questions asked by users of our software show that the use of FCM as a tool to interact with stakeholders has to be carefully designed with the goal of the study in mind. The interview phase is one of the most time- and resource consuming phases of the whole analysis. The insights and the data obtained in this phase can be very valuable. Often one will learn more about the system under question in this phase as compared to any other phase of analysis. Therefore it is a worthwhile exercise to carefully plan and prepare this part of the FCM analysis. Following was the basic approach used in all projects:

1. Setting the stage/explaining the basics
   The context of the interview is explained to the interviewee. A short introduction into FCM is given using example maps from very different cases to avoid influencing the outcome of the interviews. After the interviewee has understood the principal structure of fuzzy cognitive maps and how causality is represented within FCMs the central question is introduced. The central question should be

[1] Facilitators = interviewer that conducts a FCM session.

[2] DPSIR stands for **D**river **P**ressure **S**tate **I**mpact and is a conceptual framework to describe the human impact on biodiversity.

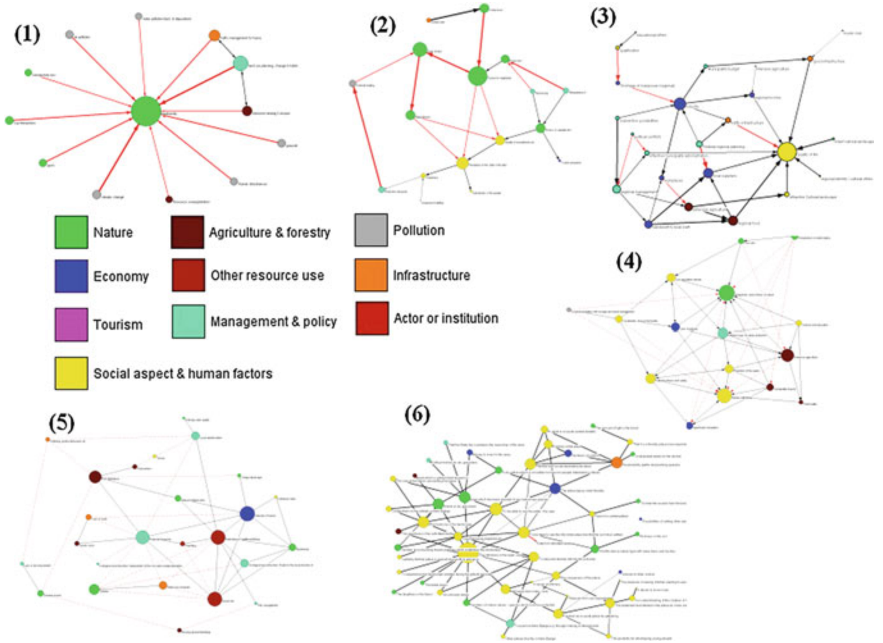

Fig. 1 Six FCMs with different structural patterns. FCM *1* is taken from the Spanish case study, FCM *2* from the Finnish, FCM *3* from the Austrian, FCM *4* from the Polish, FCM *5* from the Romanian and FCM *6* from the Danish case study

formulated in a rather open way allowing the interviewee to focus on the interrelation between factors. The way the interview question is formulated can have a considerable effect on the shape of the maps. The Spanish case used the most direct question. As can be seen in Fig. 1 the out-come are star-like maps with only few connections between the factors.

2. List of factors
   In the next step the interviewee is asked to write down a list of factors that he or she thinks is important in relation to the central question. The interviewee is asked to specify the meaning of each factor clearly and to state what an increase or decrease in this factor means. For example if the factor is "forest" it is important to understand if the area of forest or the quality of the forest e.g. regarding biodiversity, increases or decreases if the value of the factor changes. If Actors were present in the list of factors (e.g. companies or instructions) it has to be defined what an increase indicates for this actor e.g. economic growth, number of employees, number of branches. A clear definition of the factor is crucial if maps are to be compared, aggregated to social maps or condensed, even more if different facilitators are involved in the creation of the maps.
3. Drawing the maps
   After the factor list is finished the interviewee is asked to start with the drawing

of the map. The easiest way to start is by the factor the interviewee thinks is most important. He or she is then asked to think about the factors that influence the first factor and to add them to the map and connect them via arrows indicating their causal connection. While drawing the map the facilitator has to check if the interviewee is still using the factors in the way he or she defined them on the factor list. If this is not the case the factor either has to be renamed or the definition has to be adapted. New factors (that are not on the list established in the previous step) can be introduced. The role of the facilitator is crucial and critical in this step. The facilitator has to be supportive and ensure the quality of the map in terms of its conceptual correctness without influencing its content.

4. Weighing the connections
   After all the causal connections including their directions are stated, the strength of the connections is determined. In most cases the interviewees were asked to choose numerical values right away e.g. 0.1 for a very weak relation 1 for a very strong connection. In the case of an analysis of extreme weather events in [24] the interviewees had difficulties to distinguish between strength of causal relations and probabilities of events when using numbers. This might also be the case if experts are interviewed, which are familiar with Bayesian network approaches which also focus on probabilities of events and which are sometimes confused with FCM.
5. Closing the interview
   When the interview is finished the facilitator should inform the interviewee about the next steps in the process. The interviewee should be told if and when he or she can expect to see a visualization or analysis of the maps and what the nest steps in the project are.

After the interview sessions all maps were coded into adjacency-matrices and then analyzed and visualized with FCMapper.

3 Results of the Case Studies

3.1 Spain

The case study leaders found that there is a general agreement on drivers and pressures on Doñana’s biodiversity, although biodiversity is understood differently depending on the interviewee’s background. Even those experts aware of biodiversity being more than one single threatened species (flagship, umbrella species) had in their mind the most relevant drivers for a single species. The drivers are dominated by factors describing human actions, such as farming, urbanization, land management, pollution and policy (including conservation decisions). The relevance given to the social perception of biodiversity and associated threats, as well as the overall local biodiversity conservation, was surprising. Another unexpected result was the low importance given to the administrative policies effects on biodiversity. There is a common understanding amongst conservation managers to deal with biodiversity conservation by themselves, with no need for administrators to collaborate. This is also revealed by the missing links between socio-economic and natural drivers. No expert included concepts connected to conflicts in the Doñana National Park in the maps, although everyone was aware of them—but everyone argued that they are intrinsic, so they did not think much about solving them. Another interesting argument was the one in relation to corridors as a way of spreading alien species, diseases and pests, in addition to their main connectivity of populations and species migration roles.

3.2 Finland

In Finland much could be learned about changes in the agricultural economic structure. In this region the number of farmers has decreased but the farm size has increased. There are some old farmers on small farms left who are close to retiring. The younger farmers who have expanded their operations, however, are more environmentally aware when conducting their businesses, while the older generation is less so. During the mapping, the farmer emphasized that in the case of these small farmers who are close to retiring, it is understandable that they do not wish to make large technical investments to improve their farm's environmental performance.

The FCM produced by the expert group is clearly different from the three of the local stakeholders. The group FCM started with the "state of the lake", which is the central factor in this map. It also emphasizes socio-economic factors and the livability of the rural area. Thus it does not only reflect an environmentalist position. The group of experts also emphasized the internal loading process, which makes combating hypereutrophication harder and produces delays in reaching goals. In comparison to the other three stakeholders, this phenomenon is better known by the experts.

The other FCMs started from a users view on the lake. Recreational use, particularly fishing in the lake, is accentuated. These maps are more human centered in this sense. The internal loading process, namely the dead vegetation and the nutrients released from them as they compost at the bottom, was an issue only mentioned by the agriculturalist. External loading, on the other hand, was mentioned in all maps with a high centrality. The ongoing discussions and the experiences of the stakeholders regarding concrete water quality problems in the lake, as well as protection activities that have been conducted for some time are reflected in different degrees in all of the maps.

3.3 Romania

The experts group characterized the study area using a large spectrum of factors related to ongoing academic discussions. The most mentioned factors in this group referred to social aspects, human factors and management issues. The map shows a very high density reflection of the notion that "every thing is connected to every thing".

The group of local farmers and fishermen were more pragmatic. They had a more materialistic vision of their area. This was due to their livelihood dependence on the resources and services generated by the natural ecological systems. The farmers and fishermen discussed situations based on the extensive and severe structural changes in their area, which occurred during the 1960s up to the 1980s due to implementation of management plans. These plans substituted the natural and semi natural wetland ecosystems with intensive crop, livestock or fish farms and tree plantations.

The third group, consisting of managers and local administration staff, discussed the changes they have noticed in the last 50 years. The most central factors of this group are "Financial resources", "Agro-tourism" and "Biodiversity". They pointed out that everything has changed since rice plantations have been developed in the area. Topics discussed included the observed climate changes, which manifest themselves as droughts, higher temperature, less snow, the abandonment of agricultural land and the cutting of the forests. Other comments were made on the decreasing abundance of fish, increasing pollution and changes in the flood regimes. They also stressed the importance of ecological education in school and the need to increase local public awareness of the importance of using organic fertilizer. Research needs explicitly touched by this group were mainly about traditional values and the identification of the peasants' needs and problems.

3.4 Austria

All maps touched on a common set of problems and their influence on the quality of life in the region. They delineated the decline of active farmers and total population due to economic conditions and its connection to the ongoing forestation process in the central regions of the Eisenwurzen. Most interviewees focused on a regional scale, usually covering a small set of municipalities. Only the map made by the agricultural expert takes a smaller scale and concentrates on factors relating to conditions on single farms, like for example "Family situation on farm" or "Qualification of head of farm". The main issues discussed were connected to the availability of workplaces (which also shows the highest centrality in the social map) and a general need for economic development of the region to reduce outmigration. Through the mapping exercise, some possible adverse effects of economic development on 'quality of live' related factors become visible and were discussed, for example in regards to traffic infrastructure.

Agent Based Model versus FCM

To evaluate the results of the dynamic analysis of the Austrian FCM it was compared to the trends predicted by an agent based model of the same region [30]. The outcome of the FCM dynamical analysis show possible future trends in the factors. The results are influenced by the structure of the causal network. To evaluate the quality of these results we compared the outcomes of the dynamical analysis of the aggregated Austrian maps with the outcomes of an agent-based model of the same region. The outcome of three scenarios was calculated using FCMapper (see Appendix) with the aim to replicate the scenarios used in the Project SERD—(Simulation of Ecological Compatibility of Regional Development) [6]. The change of the values of ten variables under the different scenario assumptions was compared to their base run value to determine a positive (increase) or negative (decrease) trend. Both models showed a high overlap in the predicted trends. The divergences can be explained by the different scale covered by the two models. The FCMs focused on a larger region with a larger diversity of economic structures whereas the ABM modeled a single municipality in the same region [30].

4 Evaluation of FCM Though SWOT Analysis

The process of FCM in the five case studies was evaluated by the facilitators who conducted the interviews. They were asked to give their opinion on the strengths and weaknesses of FCM, and what they see as the threats and opportunities to FCM. The SWOT evaluation of FCM did not consider which strategies should be applied to improve FCM's contribution to the management of biodiversity but was used as described in Hossain et al. [10]. In the following chapter the experiences are organized into sections summarizing respectively the strength, weaknesses, opportunities and threats of FCM.

4.1 Results of the SWOT Analysis

The strength of FCM showed to be its potential to include all elements and their linkages in the landscape, independently of the details of knowledge about the elements and their exact interactions. FCM facilitated discussions of the specific landscape through outlining the important elements in the landscape and their interactions. Some were related directly to specific ecosystems such as water quality, number of alien species, area with forest, overgrazing and the area covered by agricultural land. Others were related to the socio-economic system such as urbanization, population size, quality of recreation, price of fertilizers and funding for management. Lastly, some elements related to more personal aspects such as the experience of peace, the personal feeling for the area, the awareness towards nature protection and perceptions of conflict in the area were included. In all case studies the process of depicting the landscape was experienced as positive and engaging, with a constructive atmosphere which provided interesting settings for social learning processes. Working with mixed stakeholder groups enhanced the appreciation between groups holding different views on the system. In the individual sessions, FCM was helpful in understanding common or diverging priorities and perceptions of different social groups and institutions. Working with FCM required thinking about how topics or elements influences each other and thus took the discussion about the landscape a step further than purely naming important elements found in the landscape. As FCM focuses on causality between the topics in the landscape, it naturally directed the thinking towards a problem solving approach.

The weaknesses of FCM showed to be that the methodology is not yet well described and developed especially concerning the analytical processing. This challenges the application of FCM beyond the use as a tool for engaging stakeholders or exploring their perceptions. A FCM requires a simplified representation of the elements in order to generate a model of the system under investigation. In some instances the simplification of the landscape showed to be too extensive. This resulted in elements being imprecise, unidentified and not reflecting the reality, which lead to cognitive maps, partly losing their meaning. Furthermore, as the maps described the perception of a current situation, it was difficult to work with future effects between the elements i.e. to include what people expected to happen in the future. Also mentioned as a weakness was that the cognitive maps, by adding more and more elements, became very complex. Through this some participants became partly alienated from the process as the descriptions became difficult to assess intuitively. It also affected the quality of the description itself, as the increase of factors resulted in more connections, which made it more difficult to assess if all the connections were present and given the perceived strength in the final map.

The opportunities in FCM are that a systemic understanding of the problem or landscape can be enhanced through showing the different ways a problem can be perceived and understood. When used as a participatory tool, learning about the landscape and the other participant's perception occurs, and a shared understanding of the problem dynamics emerges among the participants and the interviewer. The learning processes and the focus on problem dynamics can play an important role in conflict resolution. Through the FCM, different ways of understanding a system can be outlined in a consistent way and the different mind-models of the participants can be explicitly stated. This gives the opportunity to quickly exchange information on personal perception, key issues and hot topics that are usually not clearly visible. Through its close relation to conventional causal modeling approaches, and its ability to extract and represent the perceptions of different actors, FCM has a high potential to inform other land-use and land-cover change models especially agent based modeling approaches.

Additionally, FCM can present the complexity and dynamics of a system (e.g. a landscape) in an intuitive and graphic way which opens up new possibilities to communicate knowledge about those systems.

The threats to the methodology are similar to those of other modeling approaches. The major challenge is to reach a balance between simplicity and complexity (e.g.[2, 27] for a general discussion on this topic in modeling). Another threat is that very uncertain and/or preliminary thoughts can be presented in an apparently systematic and credible, scientific looking way, as the content of the maps may be taken as "the truth", and not as the participant's perception. Like in many other participative approaches, the role of the facilitator and the design of the process are critical [1]. The influence of the interviewer/facilitator on the process and possible lack of interview and facilitation skills may also heavily impact the quality of the results. Especially in group interviews, this may result in an incomplete representation of ideas and perceptions. Another problem can be that the facilitator does not find the right balance between supporting the interviewee in creating the map and at the same time not exerting influence on him/her/them.

If the size of the area depicted in the maps is large and diverse, FCM's ability to include a broad range of elements may be threatened. It can especially be difficult to include the personal values and perceptions into the maps. To include these types of element in the descriptions is important, as they can play a significant role in landscape planning and management [9]. The insufficiency to include the personal and emotional elements in the maps can be explained by the difficulties in including the sense of place, or *Genius Loci*. Nordberg-Schultz [19] defines the *genius loci* as a combination of five basic modes of mythical understanding.[3] As a case study area becomes larger it is more and more difficult to include the *genius loci in* the maps.

4.2 Important Issues in Application of Fuzzy Cognitive Mapping

The experience with the different case studies showed that a set of common issues must be considered when applying FCM. It is important to have the aim to which the FCM should contribute clear and to be aware of this during the process. The objective of the study will affect the choice of participants and determine if the FCM is conducted in groups or with individuals. During the process of FCM, it is important to use proper tools for interviewing and facilitating the process such as interview techniques [16] and group facilitation [13]. To become familiar with the method and to be aware of their own mind models, it is advisable for the facilitator to create a map showing his perception of the problem/system before starting with the interviews [21].

From the evaluation of the five case studies, we can conclude on six points that should be considered when applying FCM, in order to take advantage of the strengths and opportunities and take the weaknesses and threats into account:

(1) FCM can be applied in group sessions with mixed or homogenous stakeholder groups or in interviews with single persons, depending on the requirements of the

[3] These basic modes are: (1) *Things*, which are concrete natural elements, (2) *Cosmic order*, which is abstracting a systematic order from the flux of occurrences, (3) *Character*, which are the natural places related to human traits, (4) *Light*, which is the sun and its rays, and (5) *Temporal rhythms,* which are the seasons and time.

study. In sessions with mixed groups, the stakeholders can be challenged to produce a common model of the system. This will enhances social learning and may contribute to conflict resolution. In sessions with homogenous groups, the participants can discuss difficult issues and thus create a common map. Issues which are highly uncertain or to which conflicting views exist can be easily detected. When conducting group interviews, group dynamics, which can lead to the exclusion of certain elements, have to be considered. In sessions with individual participants, the focus is kept on individual perceptions and attitudes. The participant's opportunities for learning about other stakeholder's perceptions would require additional steps where the results of the individual mapping exercises are presented to and discussed with all participants.

(2) If single interviews are conducted to one topic, the interviewees may concentrate on different aspects or scales of the system. For instance, one interviewee might concentrate on the internal factors contributing to the survival of a farm while the other might draw a broader picture concentrating more on factors influencing regional development in general. The maps can also vary significantly in their complexity, according to the number of elements and connections mentioned. If the aim is an exploration of the system, the complexity of the maps should not be restricted. As mentioned above, maps covering different aspects of the systems can be aggregated to derive a more complete causal model. Aggregation and condensation can also be used to reduce the complexity of large maps (with many elements and connections) to arrive at a more comprehensible or focused map. The process of aggregation is not well documented or standardized by now and needs further development. The complexity and focus of the fuzzy cognitive maps can also be influenced by the facilitator during the interview. For example by restricting the number of elements which can be used to draw the map or by guiding the interviewee to concentrate on certain topics. This however, requires that the facilitator is familiar with the basic concepts of systems modeling and has knowledge about the topic himself.

(3) The elements included should focus on all types of topics in the landscape, in order to fully use FCM's ability for combining different types of knowledge and dealing with landscapes as socio-ecological systems. As mentioned above care has to be taken that the elements of the map meet the basic criteria and that all participants are clear what an increase or decrease of the element implies.

(4) If the focus of FCM is conflict resolution, FCM should be applied either in mixed stakeholder groups or followed by one or more joint groups sessions in order to confront the parties with the views of their opponents. Hereby a sharing of information, learning and understanding between the stakeholders can be facilitated.

(5) Similar to other qualitative interview techniques it may be difficult to compare maps produced by different facilitators. Preparing elaborate interview guidelines and compiling a list containing all mentioned elements and their meaning to which all facilitators can relate to can help in obtaining comparable maps.

(6) A mathematical analysis of FCM provides some useful indicators. The possibility to run simulations with the produced maps for scenario testing seems a promising application. However these applications are neither well developed nor documented, and should be further investigated before utilized. An alternative approach

is to use the information acquired by FCM as a basis for conventional modeling techniques. Especially agent-based modeling can benefit much from the information provided by FCM, as it relies on information about the perception and values of the modeled actors [7].

5 Conclusions

Our experience and the evaluation of the SWOT-analysis point out that FCM as a tool has the potential to fill a gap in the methods commonly utilized by conservation science and management. FCM showed to be able to combine different types of knowledge and to cover a broad and diverse set of issues. It thereby provides us with a comprehensive and more thoroughly understanding of a landscape or socio-ecological system. Not only of the elements and their cause-effect and feed back relations, but also how these are perceived and interpreted by human actors. In the same time it can be used to actively include stakeholders and their knowledge, values and perceptions by making them comprehensible to others. Its ability to lay open conflicting views by confronting the participants with the mind models of their opponents seems especially valuable for conservation management, where conflicts often determine the long term success or failure of the proposed actions. Lastly, we see a potential for further development of the methodology, which could focus on the perceptions of dynamics in the system and how this could play a role in planning and management of socio-ecological systems

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Chapter 14
Using Fuzzy Grey Cognitive Maps for Industrial Processes Control

Jose L. Salmeron and Elpiniki I. Papageorgiou

Abstract Recently, Fuzzy Grey Cognitive Maps (FGCM) has been proposed as a Grey System theory-based FCM extension. Grey systems have become a very effective theory for solving problems within environments with high uncertainty, under discrete small and incomplete data sets. The benefits of FGCMs over conventional FCMs make evident the significance of developing a greyness-based cognitive model such as FGCM. In this chapter, the FGCM model and the proposed NHL learning algorithm were applied within an industrial problem, concerning a chemical process control process with two tanks, three valves, one heating element and two thermometers for each tank. The proposed mathematical formulation of FGCMs and the implementation of the NHL algorithm have been successfully applied. This type of learning rule accompanied with the good knowledge of the given system, guarantee the successful implementation of the proposed technique in industrial process control problems.

1 Introduction

Fuzzy Cognitive Maps (FCMs) constitute neuro-fuzzy systems, which are able to model complex systems [5, 6]. Recently, Fuzzy Grey Cognitive Maps (FGCM) has been proposed as a FCM extension [15]. It is an innovative and flexible model based

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J. L. Salmeron (✉)
Computational Intelligence Lab, University Pablo de Olavide, 1st km. Utrera Road, Seville, Spain
e-mail: salmeron@acm.org

E. I. Papageorgiou
Department of Computer Engineering, Technological Educational Institute of Central Greece, 3rd Km Old National Road Lamia-Athens, 35100 Lamia, Greece
e-mail: epapageorgiou@teilam.gr

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on Grey Systems Theory and Fuzzy Cognitive Maps. FGCM is based on GST, that it has become a very worthy theory for solving problems within domains with high uncertainty, under discrete small and incomplete data sets [16, 18, 19].

FGCMs offer several advantages in comparison with others similar techniques. First, the FGCM model is designed specifically for multiple meanings (grey) environments. Second, FGCM allows the defining of relationships between concepts. Through this characteristic, more reliable decisional models for interrelated environments are defined. Third, the FGCM technique is able to quantify the grey influence of the relationships between concepts. Through this attribute, a better support in grey environments can be reached. Finally, with this FGCM model it is possible to develop a what-if analysis with the purpose of describing possible grey scenarios. IT projects risks are modelled to illustrate the proposed technique.

Furthermore, FGCMs provide an intuitive, yet precise way of expressing concepts and reasoning about them at their natural level of abstraction [18, 19]. By transforming decision modelling into causal graphs, decision makers with no technical background can understand all of the components in a given situation. In addition, with a FGCM, it is possible to identify and consider the most relevant factor that seems to affect the expected target variable.

In this work, it is investigated the application of the mathematical formulation of FGCMs and the efficient NHL algorithm for FGCMs in simulating process control problems in industry. More specifically, the FGCM modeling procedure and its new unsupervised learning algorithm of NHL are applied to model and analyze a benchmark two-tank process control problem in industry [20, 21].

The unsupervised Hebbian learning rule improves the FGCM structure, eliminates the deficiencies in the usage of FGCM and enhances the flexibility and dynamical behavior of the FGCM model. The FGCM model and its updated FGCM structure after learning, guarantee the successful implementation of the proposed modeling procedure for real case problems.

The outline of this chapter is as follows. Section 2 presents briefly the Grey System Theory. Section 3 describes the Fuzzy Grey Cognitive Maps technique. Section 4 introduces the experiments. In Sect. 5, the discussion of the results and Sect. 6 concludes the chapter.

2 Grey Systems Theory

Grey Systems Theory (GST) has become a worthy set of techniques within environments with high uncertainty, under discrete small and incomplete data sets [3]. GST is designed to study small data samples with poor information. It has been successfully applied in engineering, energy, agriculture, geology, meteorology, medicine, industry, military science, transportation, business, and so on.

According to the degree of known information, if the system information is fully known (whole understanding), the system is called a white system, while the system information is completely unknown is called a black system. A system with partial information known and partial information unknown is grey system.

GST considers the information fuzziness, because it can flexibly deal with it [7, 8, 23]. Moreover, fuzzy mathematics holds some previous information (usually based on experience); while grey systems deal with objective data, they do not require any more information other than the data sets that need to be disposed [22]. Moreover, GST fits better with multiple meanings environments than fuzzy logic.

Let U be the universal set. Then a grey set $\mathbf{G} \in U$ is defined by its both mappings. Note that

$$\mathbf{G} = \begin{cases} \overline{\mu}_G(g) : g \to [0, 1] \\ \underline{\mu}_G(g) : g \to [0, 1] \end{cases} \tag{1}$$

where $\underline{\mu}_G(x)$ is the lower membership function, $\overline{\mu}_G(x)$ is the upper one and $\underline{\mu}_G(x) \leq \overline{\mu}_G(x)$. Also, GST extends fuzzy logic, since the grey set $\mathbf{G}$ becomes a fuzzy set when $\underline{\mu}_G(x) = \overline{\mu}_G(x)$.

The crisp value of a grey number is unknown, but we know the range within the value is included.

A grey number with both a lower limit ($\underline{g}$) and an upper limit ($\overline{g}$) is called an interval grey number [8], and it is denoted as $\otimes g \in \left[\underline{g}, \overline{g}\right] | \underline{g} \leq \overline{g}$. If a grey number $\otimes g$ has just lower limit is denoted as $\otimes g \in \left[\underline{g}, +\infty\right)$, and if it has only upper limit is $\otimes g \in (-\infty, \overline{g}]$. A black number would be $\otimes g \in (-\infty, +\infty)$, and a white number is $\otimes g \in \left[\underline{g}, \overline{g}\right]$, $\underline{g} = \overline{g}$. There is not any information available about black numbers and the whole information is known about white numbers.

The conversion of grey numbers in white ones is called whitenization [8], and the whitenization value is computed as follows

$$\hat{g} = \alpha \cdot \underline{g} + (1 - \alpha) \cdot \overline{g} \mid \alpha \in [0, 1] \tag{2}$$

when $\alpha = 0.5$ is called equal mean whitenization.

The length of a grey number is computed as $\ell(\otimes g) = \mid \underline{g} - \overline{g} \mid$. In that sense, if the length of the grey number is zero ($\ell(\otimes g) = 0$), it is a white number. In other sense, if $\ell(\otimes g) = \infty$, the grey number is not necessarily a black number, because the length of a grey number with only one limit (lower or upper), $\otimes g \in \left[\underline{g}, +\infty\right)$ or $\otimes g \in (-\infty, \overline{g}]$, is infinite but it is not a black number.

A more detailed explanation of grey numbers operations and FGCMs can be found at [15].

3 Fuzzy Grey Cognitive Maps

3.1 Theoretical Background

Fuzzy Grey Cognitive Map is an innovative soft computing technique. FGCMs are dynamical systems involving feedback, where the effect of change in a node may affect other nodes, which in turn can affect the node initiating the change [15]. A FGCM models unstructured knowledge through causalities through imprecise concepts and grey relationships between them based on FCM [5, 6].

The FGCM nodes are variables, representing concepts. The relationships between nodes are represented by directed edges. An edge linking two nodes models the grey causal influence of the causal variable on the effect variable.

Since FGCMs are hybrid methods mixing grey systems and neural networks, each cause is measured by its grey intensity as

$$\otimes w_{ij} \in \left[\underline{w}_{ij}, \overline{w}_{ij}\right] \mid \underline{w}_{ij} \leq \overline{w}_{ij}, \{\underline{w}_{ij}, \overline{w}_{ij}\} \in [-1, +1] \tag{3}$$

where i is the pre-synaptic (cause) node and j the post-synaptic (effect) one.

FGCM dynamics begins with the design of the initial grey vector state $\otimes\mathbf{C}^0$, which represents a proposed initial grey stimuli. We denote the initial grey vector state with n nodes as

$$\begin{aligned} \otimes\mathbf{C}^{(0)} &= \left(\otimes c_1^{(0)} \quad \otimes c_2^{(0)} \quad \dots \quad \otimes c_n^{(0)}\right) \\ &= \left(\left[\underline{c}_1^{(0)}, \overline{c}_1^{(0)}\right] \quad \left[\underline{c}_2^{(0)}, \overline{c}_2^{(0)}\right] \quad \dots \quad \left[\underline{c}_n^{(0)}, \overline{c}_n^{(0)}\right]\right) \end{aligned} \tag{4}$$

The updated nodes' states [15] are computed in an iterative inference process with an activation function, which mapping monotonically the grey node value into its normalized range $[0, +1]$ or $[-1, +1]$. The unipolar sigmoid function is the most used one [2] in FCM and FGCM when the concept value maps in the range $[0, 1]$. If $f(\cdot)$ is a sigmoid, then the i component of the grey vector state $\otimes\mathbf{C}^{(t+1)}$ after the inference would be update with the Eq. 5.

$$
\begin{aligned}
\otimes c_j^{(t+1)} &= f\left(\otimes c_j^{(t)} + \sum_{i=1}^{n} \otimes w_{ij} \cdot \otimes c_i^{(t)}\right) \\
&= f\left(\otimes c_j^{(t+)}\right) \\
&= f\left(\left[\underline{c}_j^{(t+)}, \overline{c}_j^{(t+)}\right]\right) \\
&= \left[f\left(\underline{c}_j^{(t+)}\right), f\left(\overline{c}_j^{(t+)}\right)\right] \\
&= \left[\left(1 + e^{-\lambda\cdot\underline{c}_j^{(t+)}}\right)^{-1}, \left(1 + e^{-\lambda\cdot\overline{c}_j^{(t+)}}\right)^{-1}\right] \\
&= \left[\underline{c}_j^{(t+1)}, \overline{c}_j^{(t+1)}\right]
\end{aligned}
\tag{5}
$$

On the other hand, when the concepts' states map in the range $[-1, +1]$ the function used would be the hyperbolic tangent.

The nodes' states evolve along the FGCM dynamics. The FGCM inference process finish when the stability is reached. The steady grey vector state represents the effect of the initial grey vector state on the state of each FGCM node.

After its inference process, the FGCM reaches one stable state following a number of iterations. It settles down to a fixed pattern of node states, the so-called grey hidden pattern or grey fixed-point attractor. Furthermore, the state could to keep cycling between several fixed states, known as a limit grey cycle. Using a continuous activation function, a third state would be a grey chaotic attractor. It happens when, instead of stabilizing, the FGCM continues to produce different grey vector states for each iteration [1].

3.2 FGCM Construction

FGCMs, as FCMs [4, 9–11], can be built by experts or with raw data. We focus on a deductive approach based on experts' knowledge about the system's domain. The experts' team establish the number and categories of nodes (or concepts) relevant for the FGCM model. Furthermore, experts know which nodes influence others; for the corresponding nodes they determine the intensity of the influence and its sign (negative or positive). Each expert, indeed, determines the influence of one node on another as negative or positive and then evaluates the degree of influence using a linguistic variable, such as strong influence, medium influence, weak influence, etc. This is a procedure commonly used for FCM [13].

For FGCMs a grey causal weight should be determined. It is a little bit complex because it is not a fuzzy number, but a grey one. In this sense, we will use a class of grey numbers that vibrate around a base value, denoted as $\otimes w_{ij}^a \in \left[w_{ij}^a - \boldsymbol{\theta}, w_{ij}^a + \boldsymbol{\theta}\right]$.

Moreover, the vibration value $\boldsymbol{\theta}$ would be determined according with the uncertainty about the base value. If the base value has not uncertainty associated, then $\boldsymbol{\theta} = 0$. This is the case for a white number. If the base value is completely unknown, then $\boldsymbol{\theta} = \infty$ for the general case and $\boldsymbol{\theta} \leq \{1|2\}$ in FGCM models. The base value w_{ij}^{a} is calculated as weights in FCM [13].

The Eq. 6 shows the computation of the $\otimes w_{ij}^{a}$ upper and lower limits.

$$\otimes w_{ij}^{a} \in \begin{cases} [-1,+1] & if \quad (a+\boldsymbol{\theta} > +1) \wedge (a-\boldsymbol{\theta} < -1) \\ [a-\boldsymbol{\theta},+1] & if \ (-1 \leq a-\boldsymbol{\theta} \leq +1) \wedge (a+\boldsymbol{\theta} > +1) \\ [-1, a+\boldsymbol{\theta}] & if \ (-1 \leq a+\boldsymbol{\theta} \leq +1) \wedge (a-\boldsymbol{\theta} < -1) \\ [a-\boldsymbol{\theta}, a+\boldsymbol{\theta}] & if \ (-1 \leq a-\boldsymbol{\theta} \leq +1) \wedge (-1 \leq a+\boldsymbol{\theta} \leq +1) \end{cases} \tag{6}$$

3.3 FGCM's Benefits Over FCM

FGCMs have several benefits over conventional FCM [14]. A FGCM compute the desired steady states of the models by handling uncertainty and hesitancy present in the experts judgements for causal relations among concepts as well as within the initial concepts states.

FCM would need measures of the associated uncertainty in weights and concepts. The FGCM concepts have a greyness value to represent the degree of uncertainty associated to each node and each edge. Note that, even if the FCM dynamics would get the same steady state than FGCM after the whitenization process, the FGCM proposal handles the inner fuzziness and grey uncertainty.

Furthermore, it is possible to compute different whitenization state values. This paper uses the equal mean whitenization with $\alpha = 0.5$, but it is possible to calculate an optimistic or pessimistic whitenization. The whitenization value vibrates between the grey number limits. The final whitenization value depends of the parameter α. Lower α values generate higher whitenization values closer to the upper limit.

Furthermore, FGCM includes greyness as an uncertainty measurement. Higher values of greyness mean that the results have a higher uncertainty degree. It is computed as follows

$$\boldsymbol{\phi}(\otimes C_i) = \frac{|\ell(\otimes C_i)|}{\ell(\otimes \boldsymbol{\psi})} \tag{7}$$

where $|\ell(\otimes C_i)|$ is the absolute value of the length of grey node $\otimes C_i$ state value, and $\ell(\otimes \boldsymbol{\psi})$ is the absolute value of the range in the information space, denoted by $\otimes \boldsymbol{\psi}$. FGCM maps the nodes' states within an interval [0, 1] or $[-1, +1]$ if negative values are allowed. In this sense,

$$\ell(\otimes \boldsymbol{\psi}) = \begin{cases} 1 \ if \ \{\otimes C_i, \otimes w_i\} \subseteq [0, 1] \\ 2 \ if \ \{\otimes C_i, \otimes w_i\} \subseteq [-1, +1] \end{cases} \tag{8}$$

As an overview, FGCM model shows several advantages over the FCM one [17], as the following:

- The reasoning process' output would incorporate the greyness expressed in grey values.

- It is a generalization and can be applied to closer approximate decision making in humans.
- It enables modelling of the uncertainty and experts hesitancy associated to the description of the causal relations between the concepts and to the concept states.
- FGCMs are able to model more kinds of relationships than FCM do. For instance, it is possible to run models with relations where the intensity is not known at all ($\otimes w_i \in [-1, +1]$) or just partially known.

3.4 Learning FGCMs with Nonlinear Hebbian Rules

Recently, Nonlinear Hebbian (NHL) based algorithm has been applied to FGCM Learning [14]. The learning algorithm extracts hidden and worthy knowledge from experts. It can increase the FGCMs effectiveness and their implementation in real-world problems.

The NHL algorithm is based on that all FGCM nodes are triggering at each iteration and updating their states grey values. During the FGCM dynamics the edges' grey weights are updated and the new weight $\otimes w_{ji}^{(t)}$ is derived for iteration step t.

The NHL rule for updating FGCM grey weights is computed as follows

$$\varDelta \otimes w_{ji}^{(t)} = \boldsymbol{\eta}_k \cdot \otimes c_j^{(t-1)} \cdot (\otimes c_i^{(t-1)} - \otimes c_j^{(t-1)} \cdot \otimes w_{ji}^{(t-1)}) \tag{9}$$

Also, this proposal introduces three criteria for the NHL-FGCM algorithm. The first criterion is the maximization of the objective function J, which has been defined by Hebbs rule

$$\begin{array}{c} \text{maximize } J = E\{z^2\} \\ \text{subject to: } || \mathbf{w} || = 1 \end{array} \tag{10}$$

where $J = \sum_{k=1}^{m} (O_k)^2$, O are the output values, m the number of output nodes, $z = f(\cdot)$, and f is the activation function.

The second one is the minimization of the difference between two subsequent value of the outputs values.

$$| O_k^{(t+1)} - O_k^{(t)} | < \varepsilon \tag{11}$$

where ε is the tolerance value (usually 0.001). Finally, the third criterion is the stability of the grey vector state.

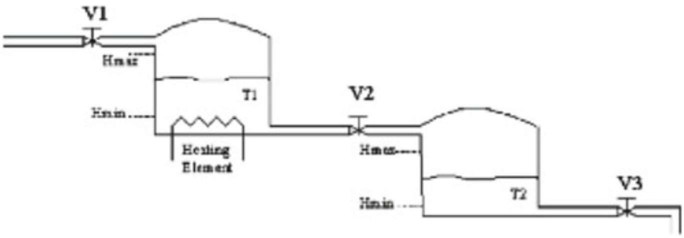

Fig. 1 An illustration of the chemical process example [12, 21]

4 Experiments

In order to investigate and demonstrate the performance of the proposed FGCM model, in comparison with conventional FCM, an industrial application, concerning a chemical process control problem, has been considered. FCMs were successfully applied to model control process [21] and in this study, our purpose is to show the functionality of FGCMs to effectively model and analyze known chemical process control problems in industry.

4.1 Process Control Problem Description

We consider the reference chemical process control system described in [20]. It consists of two tanks, three valves, one heating element and two thermometers for each tank, as depicted in Fig. 1.

Each tank has an inlet valve and an outlet valve. The outlet valve of the first tank is the inlet valve of the second tank. The objective of the control system is firstly to keep the height of liquid, in both tanks, between some limits, an upper limit H_{max} and a low limit H_{min}, and secondly the temperature of the liquid in both tanks must be kept between a maximum value T_{max} and a minimum value T_{min}.

The temperature of the liquid in tank 1 is regulated through a heating element. The temperature of the liquid in tank 2 is measured through a sensor thermometer; when the temperature of the liquid two decreases, valve 2 needs opening, so hot liquid comes into tank 2 from tank 1. The control objective is to keep values of these variables in the following range of values:

$$\begin{aligned} H1_{min} &\leq H1 \leq H1_{max} \\ H2_{min} &\leq H2 \leq H2_{max} \\ T1_{min} &\leq T1 \leq T1_{max} \\ T2_{min} &\leq T2 \leq T2_{max} \end{aligned} \tag{12}$$

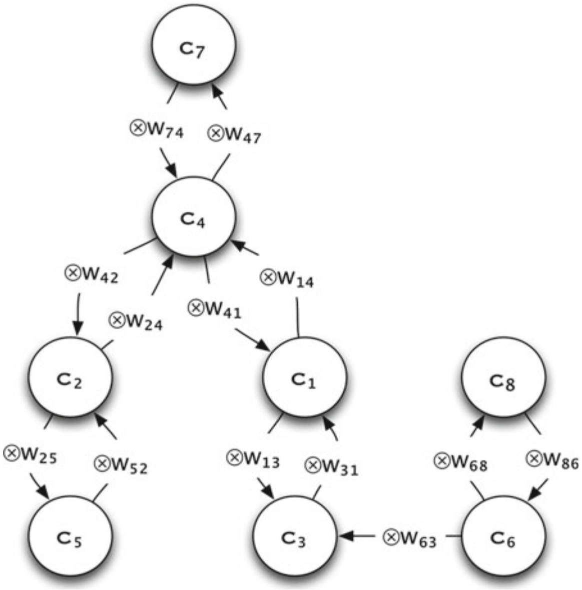

Fig. 2 FGCM control model

where, according to the experts, $H1_{min} = 0.55$, $H1_{max} = 0.75$, $H2_{min} = 0.75$, $H2_{max} = 0.80$, $T1_{min} = 0.75$, $T1_{max} = 0.82$, $T2_{min} = 0.65$, and $T2_{max} = 0.75$.

Three experts constructed the FCM and jointly determined the concepts of the FCM [13, 20]. Variables and states of the system, such as the height of the liquid in each tank or the temperature, are the concepts of the FCM model, which describes the system. The values of the concepts correspond to the real measurements of the physical magnitude. Each concept of the FCM takes a value, which ranges in the interval [0, 1] and it is obtained after threshold the real measurement of the variable or state, which each concept represent.

4.2 FGCM Model

Based on the conventional FCM proposed in [20] for the considered problem we constructed a FGCM model sharing a similar structure. It consists of eight concepts, as illustrated in Fig. 2.

For the purposes of our study, the three experts that participated in [20, 21] assigned new if-then rules that describe the influences from concepts c_i to concepts c_j, $i = 1 \ldots 5$, $j = 1 \ldots 5$. The inferences of the rules are linguistic weights described by grey weights as Eq. 3.

Table 1 FGCM nodes and their descriptions

Concept	Description
c_1	Represents the amount of liquid as measured by its height H within the tank 1; it depends on the operational state of valves 1 and 2
c_2	Represents the amount of liquid as measured by its height H within the tank 2; it depends on the operational state of valves 2 and 3
c_3	Represents the state of valve 1; it may be closed, open or partially open
c_4	Represents the state of valve 2; it may be closed, open or partially open
c_5	Represents the state of valve 3; it may be closed, open or partially open
c_6	Represents the temperature of the liquid in tank 1
c_7	Represents the temperature of the liquid in tank 2
c_8	Represents the operation of the heating element, which has different levels of operation and which increases the temperature of the liquid in tank 1

Table 2 FGCM edges and grey weights

Grey weight	Grey value	Greyness[a]	Grey weight	Grey value	Greyness[a]
w_{13}	$[0.13, 0.43]$	0.2	w_{42}	$[0.7, 0.9]$	0.1
w_{14}	$[0.28, 0.48]$	0.1	w_{47}	$[-0.16, 0.34]$	0.25
w_{24}	$[0.6, 0.8]$	0.1	w_{52}	$[-0.52, -0.32]$	0.1
w_{25}	$[0.5, 0.7]$	0.1	w_{63}	$[0.3, 0.5]$	0.1
w_{31}	$[0.51, 1.0]$	0.245	w_{68}	$[0.43, 0.63]$	0.1
w_{41}	$[-0.9, -0.7]$	0.1	w_{74}	$[0.2, 0.4]$	0.1
w_{86}	$[0.35, 0.85]$	0.25			

[a] Note that greyness is not the same value of vibration

For the construction process of FGCMs, the three experts were also assigned the vibration values of each one fuzzy relationship. Thus, grey weights with their vibration values as obtained from the experts for the construction of the FGCM model are apposed in Table 1. The greyness of each one weight is calculated following the mathematical formulation suggested by Salmeron [15] and described in Sect. 2.

The final grey weights with their greyness, apposed in Table 2, are used for the simulation analysis of FGCM dynamics.

4.3 FGCM Dynamics

We have performed two experiments. The first one aims to demonstrate the performance of FGCM instead of the conventional FCM, on a real case scenario, whereas the second one is more general and aims to demonstrate its performance on initial grey values of concepts.

- **First case study of FGCM control problem**. A set of real measurements were provided as input to FGCM as in the case of conventional FCM model in [21]. For

Table 3 First case study-results without learning

Node	Grey steady state	Greyness	Whitenization
c_1	[0.7295, 0.7500]	0.0205	0.7398
c_2	[0.8000, 0.8000]	0.0000	0.8000
c_3	[0.7553, 0.8291]	0.0738	0.7922
c_4	[0.5877, 0.7749]	0.1872	0.6813
c_5	[0.5280, 0.5804]	0.0534	0.5542
c_6	[0.7913, 0.8200]	0.0287	0.8056
c_7	[0.6920, 0.7409]	0.0489	0.7165
c_8	[0.7330, 0.8201]	0.0872	0.7765

the first case study, the initial grey vector is formed as follows

$$\otimes c_1 = \Big([0.48, 0.48], [0.57, 0.57], [0.58, 0.58], [0.68, 0.68], [0.58, 0.58], [0.59, 0.59], [0.52, 0.52], [0.58, 0.58]\Big) \tag{13}$$

The results of the reasoning process obtained with FGCM without learning (Eq. 5) and FGCM with NHL learning (Eq. 9), at each iteration t, till convergence at a steady state are apposed in Tables 3 and 5.

The results in both cases show that the four decision output nodes take values within the decision ranges. Especially in the case of FGCMs with NHL learning the values of concepts converge at a steady state which is the upper limit of the decision range with zero greyness. The zero greyness in decision concepts show that the system performs with an efficient way to the acceptable steady state. The updated adjacency matrix for case study 1 is shown at Eq. 16.

- **Second case study of FGCM control problem**. In this case, a more general scenario considering grey values (not white ones as the previous case study) of concepts as initial ones, in a measurement range was considered. For the second case study, the initial grey vector is formed as follows

$$\otimes c_2 = \Big([0.55, 0.75], [0.7, 0.8], [0.4, 0.7], [0.5, 0.8], [0.4, 0.7], [0.7, 0.85], [0.65, 0.8], [0.3, 0.7]\Big) \tag{14}$$

The results of the reasoning process obtained with FGCM without learning (Eq. 5) and FGCM with NHL learning (Eq. 9), at each iteration t, till convergence at a steady state are apposed in Tables 4 and 6.

The results in both cases also show that the four decision output nodes take values within the decision ranges. Especially in the case of NHL algorithm, the results show that the output values of four decision concepts reach the upper limit of the Eq. 12 with a zero greyness value. The zero greyness means that there is no uncertainty in the decision concepts at the steady state. This is a meaningful result

Table 4 Second case study-results without learning

Node	Grey steady state	Greyness	Whitenization
c_1	[0.7294, 0.7500]	0.0206	0.7397
c_2	[0.8000, 0.8000]	0.0000	0.8000
c_3	[0.7553, 0.8291]	0.0738	0.7922
c_4	[0.5875, 0.7750]	0.1875	0.6813
c_5	[0.5279, 0.5804]	0.0525	0.5542
c_6	[0.7912, 0.8200]	0.0288	0.8056
c_7	[0.6920, 0.7410]	0.0491	0.7165
c_8	[0.7329, 0.8201]	0.0872	0.7765

Table 5 First case study-results with NHL learning

Node	Grey steady state	Greyness	Whitenization
c_1	[0.7500, 0.7500]	0.0000	0.7500
c_2	[0.8000, 0.8000]	0.0000	0.8000
c_3	[0.9933, 0.9980]	0.0047	0.9956
c_4	[0.9917, 0.9986]	0.0068	0.9952
c_5	[0.9952, 0.9965]	0.0013	0.9959
c_6	[0.8200, 0.8200]	0.0000	0.8200
c_7	[0.7500, 0.7500]	0.0000	0.7500
c_8	[0.9922, 0.9981]	0.0059	0.9951

Table 6 Second case study-results with NHL learning

Node	Grey steady state	Greyness	Whitenization
c_1	[0.7500, 0.7500]	0.0000	0.7500
c_2	[0.8000, 0.8000]	0.0000	0.8000
c_3	[0.9939, 0.9986]	0.0046	0.9963
c_4	[0.9922, 0.9989]	0.0067	0.9956
c_5	[0.9960, 0.9975]	0.0015	0.9968
c_6	[0.8200, 0.8200]	0.0000	0.8200
c_7	[0.7500, 0.7500]	0.0000	0.7500
c_8	[0.9929, 0.9986]	0.0057	0.9958

which shows that the decision concepts can be calculated with a zero uncertainty degree. The updated adjacency matrix for case study 2 is shown at Eq. 17.

- **Third case study of FGCM control problem**. In this scenario, random grey values of concepts were used as initial ones. Following the reasoning process of FGCM without learning (Eq. 5) and FGCM with NHL learning (Eq. 9), the results apposed in Table 5 were produced. For the third case study, the initial grey vector is formed as follows

$$\otimes c_3^{rand} = \Big([0.34, 0.54], [0.25, 0.46], [0.19, 0.53], [0.37, 0.82], \\ [0.93, 0.94], [0.29, 0.83], [0.42, 0.84], [0.88, 0.98]\Big) \tag{15}$$

The results in both cases also show that the four decision output nodes take values within the decision ranges. The updated adjacency matrix for case study 2 is shown at Eq. 18.

It is obvious, that in all the examined cases, the output concepts take values with the accepted limits and with very small or zero greyness.

5 Discussion of Results

The most significant weaknesses of the FCMs, namely their dependence on the experts beliefs, and the potential convergence to undesired steady states, can be overcome by learning procedures. However, in this work, we succeeded to produce desired equilibrium regions for the four decision-outputs of the process control problem without using learning algorithms in FGCMs.

The results produced by the FGCM model without learning are acceptable and control the system without any learning process. Furthermore, if the NHL learning process is used in the case of FGCMs, the outputs continue to be within the desired limits having the advantage of zero greyness. The whitenization values reach the upper limit of the desired ranges (Eqs. 3, 4, 5 above).

Also, it is proved that using the NHL algorithm in FGCMs we improve the conventional FCM model trained with NHL algorithm [12], which exhibit equilibrium behavior within the desired regions. With the proposed procedure the experts suggest the initial grey weights of the FGCM, and then using the NHL algorithm a new weight matrix is derived that can be used for any set of initial values of concepts.

It is concluded that, the FGCM and the FGCM with NHL learning affect the dynamical behavior of the system and the equilibrium values for decision concepts are within desired regions defined at Eq. 12.

The NHL algorithm is problem-dependent, starts using the initial weight matrix but all the process is independent from the initial values for grey concepts and the system succeed to converge in desired equilibrium regions for appropriate learning parameters.

The results of the FGCM dynamics show that the capability of FGCM to produce a length and greyness estimation at the outputs offers an advantage over FCM; the output greyness can be considered as an additional indicator of the quality of a decision, with respect to the information incompleteness at the input of the cognitive map. This is an important cue regarding the quality of the decisions obtained from FGCM in the presence of uncertainty.

The new FGCM model that copes with the inability of the current models to co-evaluate the greyness introduced into a complex system due to uncertainty and imperfect facts is explored in this work. The mathematical formalization of the grey systems theory has been considered instead of the conventional fuzzy sets theory, which is the basis of the current FCM models. The applicability of the proposed FGCM model extends to a variety of domains. In this paper, we demonstrated its effectiveness with numeric, reproducible examples, on chemical process control for decision making.

6 Conclusions

In this work, the FGCM model and the proposed NHL learning algorithm were applied for processing an industrial process control problem. The proposed mathematical formulation of FGCMs and the implementation of the NHL algorithm have been effectively applied. Experimental results based on simulations of a process control system, verify the effectiveness, validity and especially the advantageous behavior of the proposed grey-based methodology of constructing and learning FCMs.

The benefits of FGCMs over conventional FCMs make evident the significance of developing a greyness-based cognitive model such as FGCM. The case studies presented in this paper are representative and facilitate both demonstration and benchmarking purposes. The development of more complex models are enabled by the proposed mathematical framework, involving more interacting factors, by following the same methodological approach.

The proposed NHL algorithm sustains a formal methodology for FGCMs training, improving the functional FCM reliability and providing the FCM developers with learning parameters to adjust the influence of concepts. This type of learning rule accompanied with the good knowledge of the given system, guarantee the successful implementation of the proposed process in industrial process control problems.

Future research objectives include the exploration of even more challenging applications and improvements of the presented model towards further approximation of human cognition and intuition.

Appendix

$$A_1 = \begin{bmatrix} [0.52,0.53][0.56,0.56][0.48,1.00][0.63,1.00][0.65,0.66][0.57,0.58][0.52,0.53][0.64,0.70] \\ [0.53,0.54][0.57,0.57][0.67,0.71][0.79,1.00][0.72,1.00][0.58,0.59][0.53,0.54][0.66,0.71] \\ [0.24,1.00][0.55,0.61][0.64,0.77][0.64,0.77][0.65,0.73][0.56,0.63][0.51,0.57][0.63,0.77] \\ [0.51,0.57][0.50,1.00][0.64,0.77][0.64,0.78][0.66,0.73][0.56,0.63][0.01,1.00][0.63,0.78] \\ [0.53,0.54][0.56,0.57][0.66,0.73][0.66,0.73][0.67,0.69][0.58,0.59][0.53,0.54][0.65,0.74] \\ [0.54,0.54][0.57,0.58][0.60,1.00][0.67,0.72][0.67,0.68][0.59,0.59][0.54,0.54][0.66,1.00] \\ [0.52,0.53][0.56,0.56][0.65,0.69][0.59,1.00][0.65,0.66][0.57,0.58][0.52,0.53][0.64,0.70] \\ [0.51,0.58][0.54,0.62][0.63,0.77][0.63,0.78][0.65,0.73][0.18,1.00][0.51,0.58][0.62,0.78] \end{bmatrix} \tag{16}$$

$$A_2 = \begin{bmatrix} [0.55,0.57][0.60,0.61][0.49,1.00][0.65,1.00][0.70,0.72][0.61,0.63][0.56,0.57][0.68,0.75] \\ [0.56,0.58][0.61,0.62][0.70,0.76][0.80,1.00][0.72,1.00][0.62,0.63][0.57,0.58][0.69,0.77] \\ [0.20,1.00][0.57,0.65][0.65,0.82][0.66,0.83][0.68,0.78][0.58,0.67][0.53,0.62][0.64,0.83] \\ [0.53,0.62][0.48,1.00][0.65,0.83][0.65,0.84][0.68,0.78][0.58,0.68][0.00,1.00][0.64,0.84] \\ [0.55,0.58][0.59,0.62][0.68,0.78][0.68,0.79][0.70,0.75][0.61,0.64][0.55,0.58][0.67,0.79] \\ [0.57,0.58][0.61,0.62][0.60,1.00][0.70,0.78][0.71,0.73][0.62,0.64][0.57,0.58][0.66,1.00] \\ [0.55,0.57][0.60,0.61][0.69,0.74][0.60,1.00][0.69,0.71][0.61,0.62][0.56,0.57][0.67,0.75] \\ [0.52,0.62][0.56,0.67][0.64,0.83][0.65,0.84][0.67,0.79][0.16,1.00][0.52,0.63][0.63,0.84] \end{bmatrix} \tag{17}$$

$$A_3 = \begin{bmatrix} [0.58,0.61][0.62,0.65][0.50,1.00][0.66,1.00][0.74,0.77][0.64,0.67][0.58,0.61][0.72,0.81] \\ [0.59,0.61][0.64,0.65][0.73,0.81][0.82,1.00][0.75,1.00][0.65,0.68][0.60,0.62][0.72,0.82] \\ [0.17,1.00][0.59,0.69][0.66,0.87][0.67,0.89][0.70,0.84][0.60,0.72][0.55,0.66][0.66,0.89] \\ [0.54,0.66][0.44,1.00][0.65,0.88][0.65,0.90][0.70,0.85][0.59,0.73][0.00,1.00][0.65,0.91] \\ [0.56,0.61][0.60,0.64][0.68,0.82][0.69,0.83][0.73,0.79][0.61,0.67][0.57,0.62][0.69,0.84] \\ [0.58,0.62][0.63,0.66][0.60,1.00][0.72,0.84][0.74,0.80][0.64,0.69][0.59,0.63][0.68,1.00] \\ [0.58,0.61][0.62,0.65][0.71,0.80][0.61,1.00][0.73,0.78][0.63,0.67][0.58,0.62][0.71,0.81] \\ [0.53,0.66][0.56,0.69][0.63,0.88][0.64,0.90][0.69,0.84][0.12,1.00][0.53,0.67][0.64,0.90] \end{bmatrix} \tag{18}$$

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Chapter 15
Use and Perspectives of Fuzzy Cognitive Maps in Robotics

Ján Vaščák and Napoleon H. Reyes

Abstract Fuzzy Cognitive Maps (FCM) started in the last decade to penetrate to areas as decision-making and control systems including robotics, which is characterized by its distributiveness, need for parallelism and heterogeneity of used means. This chapter deals with specification of needs for a robot control system and divides defined tasks into three basic decision levels dependent on their specification of use as well as applied means. Concretely, examples of several FCMs applications from the low and middle decision levels are described, mainly in the area of navigation, movement stabilization, action selection and path cost evaluation. Finally, some outlooks for future development of FCMs are outlined.

1 Introduction

Although FCMs were originally designed for modelling purposes in nontechnical areas only [5, 13] but their flexibility and ability to represent mainly causal relations between objects and notions enabled them to penetrate also to technical areas [20], first of all to the field of decision-making and its support. There are several reasons and motivations for use of FCMs in these systems. Firstly, technical systems have to process various kinds of imprecision and uncertainty. Secondly, many solved tasks require finding not only a solution but also regarding various constraints and

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J. Vaščák (✉)
Center for Intelligent Technologies, Technical University of Košice, Košice, Slovakia
e-mail: jan.vascak@tuke.sk

N. H. Reyes
Institute of Natural and Mathematical Sciences, Massey University,
Auckland, New Zealand
e-mail: N.H.Reyes@massey.ac.nz

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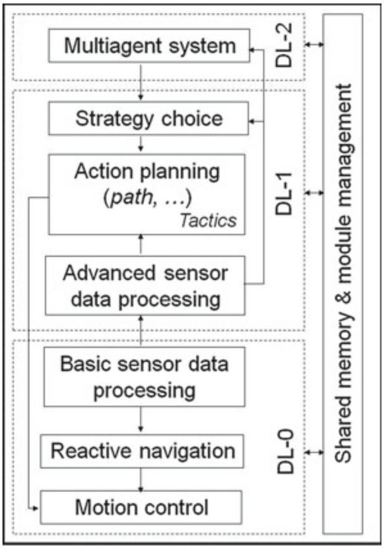

Fig. 1 Basic information structure of a mobile robot configured by decision levels DL-0–DL-2

limitations. Finally, knowledge representation and its human-friendliness play a very important role in selection of computational means from many practical reasons like safety and maintenance or compatibility with the reasoning of human operators. A broad description about the research in the area of FCMs can be found in [17].

Although robots are devices of diverse constructions but they all should be able to more or less reproduce human-like approaches in task solving, not only movements but also the way of thinking how to perform a kinematic task. From the informatics viewpoint they are characterized as multi-level hierarchical systems, as depicted in Fig. 1 [23], where basic information modules and their relations are divided into several *decision levels* (DL), which are mutually subordinated from DL-0 as the low, DL-1 as the middle and DL-2 as the high one, too. Usually, tasks of these DLs are solved by various and often very heterogeneous approaches in practice. Hence, the first motivation could be the effort at least to partially unify computational means in a robot. In the next sections we will show some examples how FCMs are or could be utilized for individual DLs.

In robotics, we can meet beside the notion *decision* also with expressions like *control, behaviour* or *strategy choice*, which express special parts or views of this very general notion. The first representative from this set of expressions is the control, a special kind of decision, which is placed on the lowest level, i.e. in DL-0 characterized by processing raw data from sensors and firmly connected to physical relations of mechanics. Tasks at this level require stable and robust solutions during very short time responses. Therefore, we can meet mainly with means of the conventional control theory and the role of DL-0 is concentrated on reactive acting by controlling basic movement primitives like stepping, turning, body stabilization, obstacle avoidance, etc. Although the nature of tasks encompassed in DL-0 is far away from 'intelligence' we can find some efforts using FCMs for mostly reactive navigation (e.g. [11, 26]) but also e.g. for movement stabilization [2, 10].

DL-1 is an overbuilt on DL-0, which enables to a robot to act fully independently. The approaches used reflect much more human manners than in the case of DL-0. Many of them belong to the area of artificial intelligence like decision trees, rule-based systems, fuzzy logic, neural networks and hereby FCMs, too. The advanced sensor data processing is practically the second stage after the basic one is done. Its objective is to extract such objects as obstacles, target, paths, etc. In other words it means firstly to recognize, secondly to localize them and eventually to describe them in a more detail, which would enable us to construct a scene with relevant objects and mutual relations, i.e. to transform numeric information in the form of e.g. an image pixel matrix to information of symbols. This is the first research challenge for FCMs in robotics as they interconnect numeric information form with its symbolic counterpart, i.e. to model scenes and to describe the surrounding environment [1]. Based on this information we can make decisions in a human-like manner.

Basically, we can divide decision-making into two stages a *strategic* and a *tactical* one, which is close to original intentions concerning the FCM use and we can find many analogues from various areas, e.g. a well known example of a sheepdog [18]. The strategic stage is responsible for selection of goals and subsequently, the tactic stage searches ways how to fulfil a given goal(s) and from this point of view it is subordinated to the strategy. Therefore, for successful performance of the strategy choice module the situation evaluation is the most important. Resulting activities from this module like selection and planning activities, the choice of a convenient path, etc. belong to the subordinated tactic stage. In this area a number of papers have been already published, e.g. [3, 9, 22, 24].

If we consider only one robot in a given environment without any others then DL-1 will be the top level without any additional modules. However, if there is a group of robots having the same goal they need to mutually communicate and cooperate. In such a case we get a *Multi-Agent System* (MAS), which represents the highest level DL-2 and considerably supersedes the strategic stage in DL-1. For solving complex robotic tasks MAS becomes an intrinsic part of any decision-making design. It is apparent FCMs could play, thanks to their structure as an oriented graph, an important role in constructing MAS not only in the robotics area. However, this research direction is still at its beginning and it is the second great challenge of FCM research.

However, technical systems require several modifications and extensions of FCMs to facilitate their effective use in general. Firstly, original design of processing FCM is isolated from its environment, which is represented by sensory data. However, instead of their steady reading they are allowed to influence the calculation only at the start in the form of initializing values of nodes. Secondly, concerning to the complexity of problems to be solved the adaptation (learning) of FCMs is their inseparable part. There have been developed various learning approaches, which can be divided into two basic groups—the *unsupervised* and *supervised* one, e.g. [4]. In this area the approaches of supervised learning are especially important. They are mostly based on evolutionary algorithms [21] but also further methods are possible [15], too. From capacity reasons, the reader is recommended a detailed overview about learning approaches in [12]. The following sections will deal with some applications of FCMs used in robotics to offer an overview of potential possibilities for this perspective means of artificial intelligence.

2 Modifications of FCM Inference and Structure

In the previous section the need of some modifications for FCM inference mechanism as well as the structure was mentioned. First of all, the original design of FCM inference is based on defining initial states of n nodes C_i (for the sake of simplicity we will not distinguish between the symbolic value C_i of a node and its numerical activation value A_i) and then their consecutive recalculations for individual time steps k using the so-called *connection matrix* E:

$$C_i(k+1) = L\left(C_i(k) + \sum_{j=1}^{n} e_{ij}.C_j(k)\right), \tag{1}$$

where e_{ij} is an element of the matrix E, which expresses the strength of a connection from the node j to the node i and L is the limiting function to keep the values of nodes in an interval [0, 1].

Such an approach is convenient for modelling a closed process, which is isolated from measured data of the sensors. However, sensors play a key role in technical systems and hence a modification of the inference mechanism is inevitable for receiving measured data. For this reason it is necessary to divide the nodes at least into two groups — *input* nodes and *output* (*decision*) nodes (eventually *intermediate* ones separated from the latter group if their values are no outputs from FCM). The modification is quite simple. After applying (1) the values of input nodes will be substituted by new sensory data, which are preprocessed by membership functions defining these nodes.

3 Low Level Applications of FCMs

The FCM structure is a distributed network of objects that operate in parallel. This property enables to include all activities performed at once because each node of FCM can be considered as an independent CPU and connections as information streams. Then we will get an overall parallel control structure involving all types of computations. Moreover, each node can represent further FCM as subroutine with its special subtask and hereby we get a property of hierarchism, too. Just a robot requires massive parallel processing like data processing from sensors, controlling actuators, many other calculations and decision operations (e.g. navigation), where each sensor needs an extra processing and each actuator (wheels and joints) needs an extra controller. Accordingly, FCMs seem to be a very convenient means for needs of robotics.

From the viewpoint of MAS there is another division possible, which is based on agents and their approaches in control: *reactive, deliberative, hybrid* and *behaviour-based* [7].

Reactive control represents the simplest type. Its approach can be expressed like: "*Do not think, act*." Such an agent only reacts immediately to an external stimulus. It uses a finite set of actions being known in advance and so it does not need any inner model of the surrounding world or communication with other agents. For this reason such agents are known as 'memoryless'. Their main advantage is computational simplicity and speed. Their use is on the lowest decision (control) level DL-0 based on direct inputs from sensors. Although, these agents seem to be very primitive but convenient growth of their complexity can lead to apparently intelligent behaviour with the help of the so-called *subsumption architecture*, which belongs to this category, too.

Deliberative control is based on: "*Think hard, then act*." It is characterized by proactive and intentional approach. Its main feature is communication with its surroundings and creating own inner world model with the aim to reach determined goals. The world model is strictly centralized and based on sequences *state — action*. Its purpose is to design plans of actions. Beside apparent advantages there are also drawbacks like their high information dependency and computational complexity. Such an approach strikes on needs as prediction, processing inaccurate information, change of model in a dynamic environment, etc. Therefore, the use of deliberative control is reasonable on higher decision levels as DL-1 or even DL-2.

Hybrid control is characterized by: "*Think and act independently, in parallel*." It tries to eliminate the disadvantages of the two mentioned types of control. Comparing real needs of robotic teams we can see the necessity of both approaches. Therefore, the reactive as well as the deliberative architecture are merged into one unit but they work independently each other. The reactive part ensures real-time responses at the level of sensory data, e.g. to avoid collisions with obstacles. The deliberative part works on high decision-making levels using an abstract world representation to make strategic decisions and plans.

Behaviour-based approach is a little of different nature. Its basic idea is: "*Think the way, you act*." This approach found its inspiration in biology. It is based on observed patterns of various kinds of behaviour. These behaviours are derived from interactions between a given agent and its environment. So incremental adaptation is supposed, where first basic (survival) actions are created and continuously more advanced patterns are added, e.g. starting with simple obstacle avoidance up to e.g. passing a ball in robotic soccer. Individual patterns are stored in the system in the form of distributed layers, which are mutually competitive. This is the main difference to the hybrid type, which also determines the use of these two control types.

Hybrid agents are used mostly in single robot control whereas the behaviour-based control is used in multi-robot applications, which comprises all three DLs and could be denoted as a *high level* application. However, this topic exceeds with its complexity the range of this chapter. In this section we will show some applications using FCMs in reactive navigation as well as balancing gait of a legged robot, which

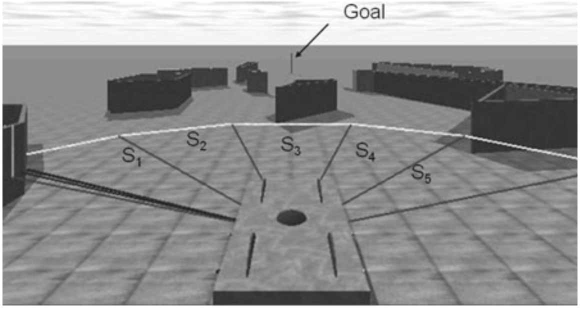

Fig. 2 A simulation scene for navigation of a wheeled robot through obstacles with ultrasonic sensors S_1–S_5

belong to the level DL-0 as indicated in Fig. 1 and further we will designate them as the so-called *low level* applications.

3.1 Reactive Navigation

The area of the navigation is represented by very manifold approaches (an exhaustive overview is e.g. in [6]), where *potential fields* [19] and the so-called *nearness diagrams* play an important role. As the navigation task can be described as a scene of objects with some mutual relations and rules of behaviour we can transform this task into an oriented graph, too. In such a manner we can construct FCM, whose nodes represent positions of obstacles, goal (target) and actions (types of movements).

In [25] there is a manual design of such a reactive navigation controlled by the positions of obstacles and a goal using FCM, see Fig. 2. There are in total 16 nodes, where 4 of them are output nodes C_0–C_3 with actions as *turn to left* (L), *go forward* (F), *turn to right* (R) and *stop* (S), Fig. 3. Other nodes represent calculated positions of the goal in relation to the vehicle C_4–C_7, with symbols G_L—*goal left*, G_S—*goal straight*, G_R—*goal right*, G_C—*goal close*, and signals from sensors C_8—C_{15}, where S_i denotes the i-th sensor (Fig. 2), c—*close* and cc—*critically close*. As defined in the previous section the nodes C_0–C_3 are decision nodes and others the input ones. Positive connections are depicted as solid lines and negative connections as dashed ones.

Concerning the functions, which were implemented in the input nodes, they are membership functions for evaluating signals from the sensors as obstacle closeness C_8–C_{15}, calculated position of the goal like *goal position* C_4–C_6 and *goal closeness* C_7. When the activation value in the node C_3 (stopping) achieves the value 0.95 then the vehicle will stop.

FCM in the previous case is built on a set of rules used by a human operator (the number of rules is given by the number of nonzero elements in E) and the quality of navigation depends on his/her experience. If a skilled operator is missing

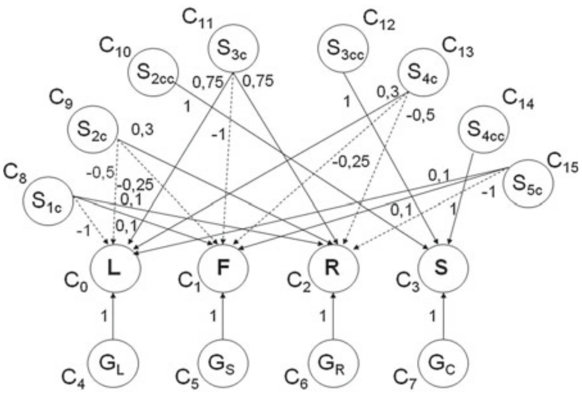

Fig. 3 Manually designed FCM for the navigation of a simulated vehicle

we can rely on adaptation methods. We prescribe optimal trajectories for a set of reference situations and in such a manner we get a training set. The fitness will depend on the difference between the prescribed and real (obtained if controlled by FCM) position of the robot. In [26] a design of automatically adapted FCM using migration algorithms (for more detail see [27]) is presented. In that case the proposed FCM is for direct control of the left and right wheel and sensory information is taken from a camera. The task can be further complicated. For instance we can take into consideration some undesired effects like slippage of the wheels, which is included in the FCM construction presented in [11], where a modification of (1) based on a sigmoid function is proposed, too.

3.2 Balancing Movements

Here we sketch an application for balancing (stabilization) movement of a legged robot. This robotic group is exclusively controlled by rotational joints, whose properly coordinated actions generate compound movements like stepping or turning. Each joint has its own controller and because of the cooperation necessity individual joints are strongly interconnected.

In [10] gait stabilization of a quadruped (four-legged) robot is proposed. The design supposes 12 *Degrees of Freedom* (DoF), i.e. each leg having three rotational joints. As the control of joints is fully angular there are three basic variables of *pitch* (P), *yaw* (Y) and *roll* (R) angles, which are sensed and controlled. In the body of a robot there are three sensors for these angles and a joint is used for controlling just one component of them, i.e. each leg is fully controlled for all three angles. The aim of stabilization is to achieve zero deviations of a robot for P, Y and R. We can do it if we define relations between sensors and individual joints as it is depicted in Fig. 4.

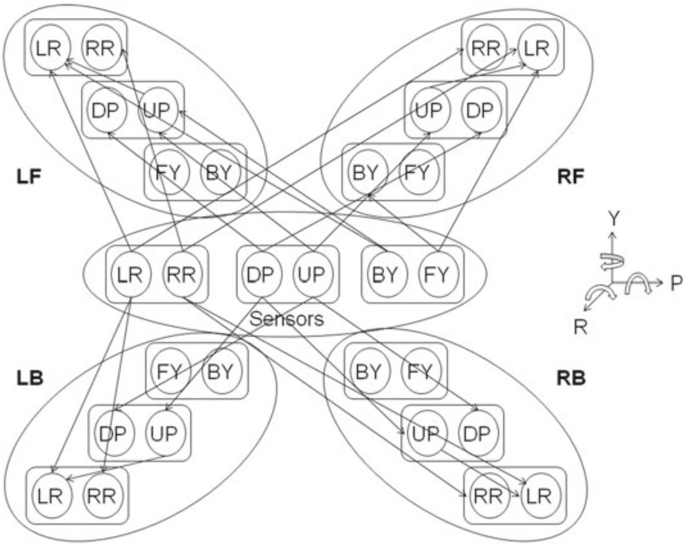

Fig. 4 FCM for gait balancing of a quadruped robot [10]

The basic idea of such a proposed FCM is based on neutralizing contradictory forces, i.e. rotating an R joint to left (LR) versus to right (RR), similarly for a P joint downward (DP) versus upward (UP) and for a Y joint to backward (BY) versus to forward (FY). In such a manner all joints as well as sensors are represented by a couple of contradictory nodes mutually interconnected by negative connections (for simplicity depicted only at one couple). Thanks mutual connections an effect of coordination is achieved between the joints as well as legs (in Fig. 4 bold letter L stands for *left*, R—*right*, F—*front* and B—*back* as positional combinations of legs) aiming to eliminate all kinematic forces and herby to attain equilibrium.

4 Middle Level Applications of FCMs

The main task of DL-1 is strategy and tactics choice, i.e. determination of objective(s) and action sequence for its (their) achieving. As the advanced sensor data processing requires intelligent methods for already preprocessed data it is also encompassed into DL-1 but it plays only an auxiliary role for strategy and tactics. In this section we show the use of FCMs in action selections and hybrid approaches including FCMs together with other mechanisms for navigation and path planning.

4.1 FCM for Discrete Action Selection

In many cases there is a set of possible actions (solutions) for a given object or actuator but only one of them can be selected because of their exclusiveness

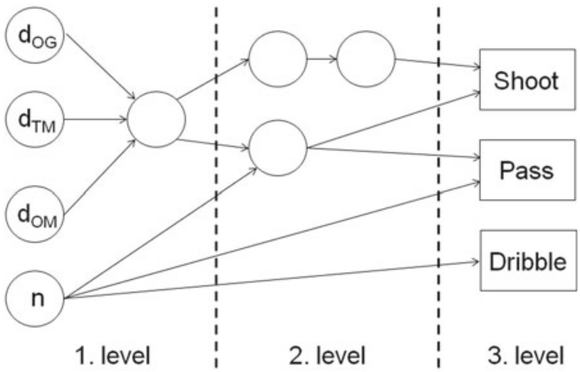

Fig. 5 Simplified FCM scheme of a striker for action selection

(e.g. go either to the right or to the left, both actions are mutually exclusive). Therefore, such actions are denoted as *discrete*. Being inspired by the well known approach *winner-takes-all* in neural networks also FCM was modified for such an operation mode in [3] and therefore it resembles more to a feed forward network than to a conventional, i.e. recursive, FCM.

The modified FCM utilizes three levels of nodes as it is shown in Fig. 5 of a simplified soccer player. The first level consists of inputs from sensors as well as other nodes for preprocessing inputs. For instance, a soccer player owning the ball needs to know distances to the opponent's goal d_{OG}, its closest teammate d_{TM} and opponent's mate d_{OM}, number of opponent's players n being close to the shooting line to their goal, etc. These data are merged to a smaller set of parameters, which define primary states. The task of the second level is to determine *suitability measure* of individual actions. Just on this level rules for calculating suitability are placed. Finally, the third level is created by the set of possible actions, e.g. shooting, passing or dribbling the ball. The action, whose node achieves the highest activation value, will be chosen.

Another design for an action selection FCM is described in [24], which is also constructed for purposes of robotic soccer. In this case it serves for choosing the object of shooting the ball. Either it is a direct shot to the opponent's goal (G) or passing to a teammate (TM), see Fig. 6.

The aim of the object selection is minimization of the risk that the ball will be caught by the opponent. The structure of such an FCM is in Fig. 6a. Each teammate has its operational range, i.e. area, which can be reached during a time step and is described by membership functions in Fig. 6b. Also the goal G (although static) can be described in such a manner because it occupies a certain area. The only difference is that because of the dynamic nature of teammates (they move during the play) their membership functions must be newly generated each time step (the same for the closest opponent O). Also the weights of connections w_{si} (Fig. 6a) change over time because they are indirectly proportional to the distances between the shooter

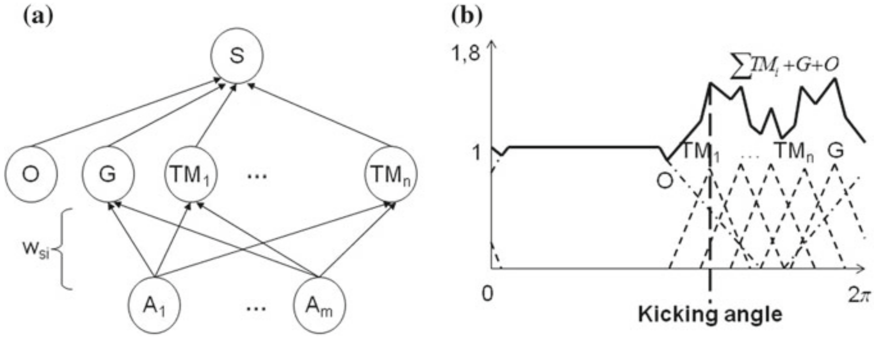

Fig. 6 FCM for selecting an object of shooting the ball: **a** structure and **b** inference scheme

and objects (the closer the smaller risk to be caught by the opponent). Peaks in the membership functions of the nodes TM_i represent angles of view for objects seen from the shooter's perspective. Values of nodes A_j are also indirectly proportional to the size of the turn angle needed for the shooter. These nodes represent possible angular ranges (intervals) of shooting to individual objects for a given shooter dividing the total range of $360°$ and calculating the cost of turning for the shooter to a given range. The calculation of resultant kicking angle is calculated in the node S.

As membership functions in nodes TM_i and G should help attract the ball and the function in node O should repel the ball, this function will be constructed in a manner reverse that of other functions, i.e. it will be minimized at the measured angle of the opponent, see Fig. 6b. The values of nodes A_j will then be multiplied together with weights w_{si}, yielding total costs of shooting that include turning and distance. These costs will be used to scale functions TM_i and finally all membership functions will be united in the node S using a sum or more correctly a t-conorm. The first maximum of such a final membership function determines the kick angle and its closest object will be selected (in Fig. 6b it is the teammate TM_1).

4.2 Hybrid Approaches Using FCM

Although FCMs show many excellent properties but they are of course no nostrum. Beside further high quality approaches also lots of highly specialized methods have been developed and against them means for general purposes cannot compete in their area of use. Therefore, the idea of hybridization plays in some applications an important role. Principally, we can distinguish two ways of hybridization, either FCM separately from other means cooperates with them as an element of a compound system or the structure of FCM absorbs further means. For instance, in [22] an application of FCM in path planning is described, which belongs to the first group. FCM is only one element of larger path planning systems usable, e.g. in automatized production lines or in navigating drivers on large parking places (just shown on such an example), etc. The planning system generates using a graph search algorithm A* several alternative paths, which will be then mutually compared by several criteria like path length, number of crossings, eventual waiting time in jams, etc. FCM is used just for calculation of total path costs being able to consider various significances of these criteria and their relations. Finally, the alternative with the lowest path costs is chosen. Further, we will show an example from the latter group of hybridization.

In Sect. 3.1 several approaches of reactive navigation were mentioned. In [9] a more advanced application for navigation purposes is described because *reactive control* reacts only ad-hoc on changed situations (e.g. moving obstacles) without any strategy of behaviour. It can easily lead to a chaotic-like movement with the risk to be trapped in an area with a complex structure of obstacles. For instance, if a robot starts to turn to the right due to an obstacle on the left hand side and in next step the sensor detects another obstacle on the right hand then the robots will intensively change turning to the opposite (left) side. To avoid such a behaviour the route planning is necessary [8], which is typical for the middle level, i.e. DL-1, where the low level reactive control (navigation) should be used only in collision situations (the own navigation is subordinated to the path planning goals). Such a route planning belongs to *deliberative control*, which is characterized with strategic planning that considers global aspects and is done over longer periods.

However, 'pure' FCMs are convenient only for reactive control because they are based on cause—effect relationships. They do not describe the dynamics of connections and are not able to distinguish between long-term and short-term events. For this reason a mechanism for dynamic changes of concepts and connections using an additional rule-based system was proposed and temporal information was incorporated, too. The proposed structure (see Fig. 7) consists of two layers—the reactive layer and the deliberative one. The first layer is addressed to direct actions on the lowest level (DL-0), e.g. turn to left, right, go straight, etc. and is realized by a conventional FCM. The deliberative layer fits characteristics of DL-1 and processes are modelled by a set of rules in the form of conditional declarations.

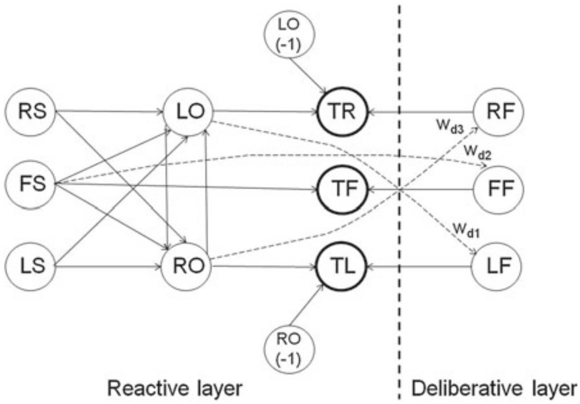

Fig. 7 An example of a two-layered hybrid FCM for path planning and navigation [9]

FCM depicted in Fig. 7 represents a single navigation task for a wheeled robot having three sensors for sensing obstacles on the *right* (RS), *frontal* (FS) and *left* (LS) hand side. The nodes RO and LO are output nodes for turning to the right and left, respectively, in the reactive layer. However, to soften potentially too extreme actions of these two nodes a deliberative layer is added, which considers the needs of the proposed route and together with output nodes from the previous step, i.e. RO(-1) and LO(-1) it gives a certain inertia aspect to the decision-making process. For this purpose a rule-based system using human heuristics is designed, which expresses decisions being made in the presence of conflicting situations together under considering planned objectives. In other words, it reflects relationship of a planned behaviour to the reactive one. The deliberative rules modify weights w_{d1}, w_{d2} and w_{d3} (dashed connections) in each time step and hereby using (1) the factoring nodes RF, FF and LF (*right, frontal, left*, respectively), too. Finally, the total outputs of both layers in nodes TR, TF and TL are products of activation values in factoring and total output nodes.

5 Conclusions

In this chapter a rough survey about the use of FCMs in robotics was given. Their main power is in decision-making and all related applications, e.g. navigation, modelling, scene construction and multi-criteria decision. FCMs can find use not only on higher decision levels, which require a certain measure of intelligence, but also on lower levels of control, where conventional PID controllers are used very often. Their intrinsic ability of parallelism is further significant property. FCMs can be used for giving a united form of all control and decision processes and in principle a global FCM joining all these processes can be built.

Moreover, after some necessary modifications various computational means and methods can be incorporated into individual nodes. This need of constructing various modifications of FCMs and their inference methods, not only like (1), is evident from the mentioned applications. In other words, hybridization becomes a new challenge to the theory of FCMs [14, 16] to spread them in decision-making and control applications in distributed systems in general and especially in robotics as it was sketched in [24], too.

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Chapter 16
Fuzzy Cognitive Maps for Structural Damage Detection

Ranjan Ganguli

Abstract Fuzzy cognitive map (FCM) is applied to the problem of structural damage detection. Structures are important parts of infrastructure and engineering systems and include buildings, bridges, aircraft, rockets, helicopters, wind turbines, gas turbines and nuclear power plants, for example. Structural health monitoring (SHM) is the field which evaluates the condition of structures and locates, quantifies and suggests remedial action in case of damage. Damage is caused in structures due to loading, fatigue, fracture, environmental degradation, impact etc. In this chapter, the damage is modeled in a cantilever beam using the continuum damage and natural frequencies are used as damage indicators. Finite element analysis, which is a procedure for numerically solving partial differential equations, is used to solve the mathematical physics problem of finding the natural frequencies. The measurement deviations due to damage are fuzzified. Then they are mapped to a set of damage locations using FCM. An improvement in performance of the FCM is obtained using an unsupervised neural network approach based on Hebbian learning.

1 Introduction

Structures such as bridges, buildings, nuclear power plants, aircraft, helicopters, turbines, vehicles etc. constitute a key component of modern engineering and economic infrastructure [6, 48]. However, such structures are susceptible to damage due to the environment and harsh operating conditions. Damage in structures can lead to degradation in performance and potential catastrophic failure. Therefore, a large amount of research has been expended on algorithms for accurate structural damage detection. These algorithms constitute the "brain" behind the so called structural health monitoring (SHM) systems which use measured sensor data to identify the presence,

R. Ganguli(✉)
Department of Aerospace Engineering, Indian Institute of Science, Bangalore 560012, India
e-mail: ganguli@aero.iisc.ernet.in

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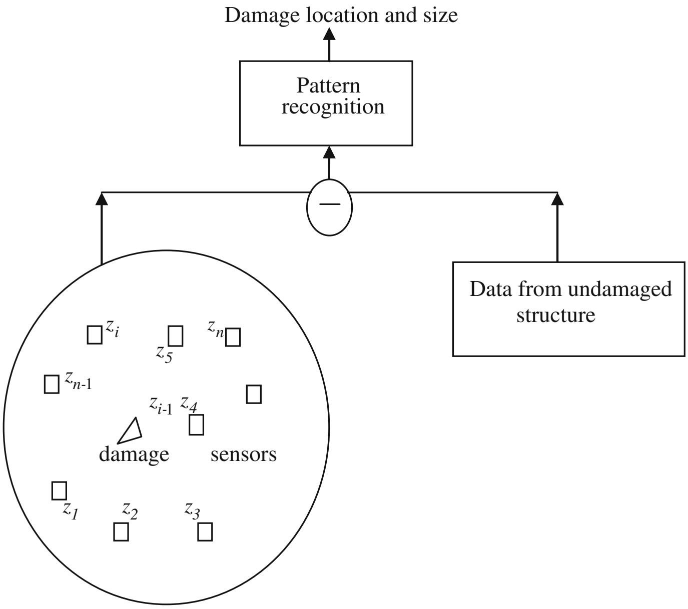


Fig. 1 Schematic of a structural health monitoring system

location and size of the damage in the structure. A schematic of a SHM system is shown in Fig. 1. A number of sensors are placed on the structure. The measurements obtained (z) are compared with the measurements of the undamaged structure (z_0) and the measurement deviations $\Delta z = z - z_0$ are calculated. These deviations are then given as inputs to a pattern recognition algorithm which calculates the damage location and size.

Structural health monitoring involves the solution of pattern recognition problems involving noisy measured data and its relation to damage [46]. The presence of noise in the measurements can make this pattern recognition problem quite intractable. Researchers have used several methods to address the pattern recognition problem. System identification [8, 41], neural networks [2, 22, 37, 38], genetic algorithm [12, 23, 33] and fuzzy logic [5, 9, 40] are some of the methods which have been used for structural damage detection. System identification methods are sometimes based on the weighted least square approach or the Kalman filter. These methods work well when the underlying numerics about the process and measurements are available and a good initial estimate of the state is known. Neural networks applied for damage detection are a nonlinear functional mapping between the change in measurements and the damage. Neural networks have good generalization capability and can detect damage from noise contaminated data. However, the appropriate selection of the neural network architecture is needed for the network to perform well. In addition, the training of the neural network must reflect a balance between using very few input-output pairs which leads to under-learning and using too much data which can lead to over-learning. It should be kept in mind that neural networks are multi-dimensional curve fits and therefore all the caveats known for curve fitting methods apply to neural networks. The genetic algorithm approach tries to identify the change in system properties which causes the change in measurements. A fitness function is created to minimize the difference between the actual and predicted measurements and design variables such as the structural elastic and mass properties are used. Genetic algorithm based damage detection systems are difficult to use in an online setting because they are computationally expensive and cannot work in real time. Recently, fuzzy logic systems have also been proposed for damage system. They link the measurement changes with the damage location and size through a set of fuzzy rules. Fuzzy systems are also robust to noise in the data but it is sometimes difficult to create a rule base and select the fuzzy sets for the different measurements in an optimal manner.

All the above mentioned approaches have their advantages and disadvantages. However, soft computing approaches based on neural networks and fuzzy logic are attractive due to their robustness to noisy data. It has been shown that hybridizing two or more soft computing methods can improve the performance of pattern recognition systems [15, 18, 26, 42, 47]. Also, unsupervised neural networks for learning permit the algorithm to adapt to the changing quality of incoming data [29, 35]. In this chapter, we illustrate the use of the Fuzzy Cognitive Map (FCM) with unsupervised Hebbian learning as a new approach for structural health monitoring. This chapter introduces the FCM with Hebbian learning for a simple damage detection problem involving a cantilever beam with frequencies serving as the damage indicators. The cantilever beam is a representative mathematical model of structures such as aircraft wings, turbine blades etc. Some of the ideas and the results discussed in this chapter are based on an earlier paper by the author [3].

A Fuzzy Cognitive Map (FCM) provides a graphical representation of a complex system. The state variables in the system are connected by links that symbolize cause and effect relations [24]. FCM technique was first created by fusing concepts from the fields of fuzzy logic and cognitive mapping. FCM is a soft computing technique which seeks to mimic human reasoning and human decision making process. FCM expresses the knowledge of human experts who operate or know the system and its behavior under different circumstances in a causal relationship between components of the system. Human knowledge and experience are reflected in the selection of concepts and weights for the interconnection between concepts of the FCM.

FCM's can also be developed from numerical data. They can also combine the effects of data with expert knowledge. The FCM has also been called as a "man-trained" or "object-oriented" neural network since it is a network whose weights are assigned by experts. Its advantage lies in ease of development and integration with learning methods such as unsupervised neural networks [17]. FCM has been used for representing knowledge [45], failure analysis [25], process control [13], data mining in internet [21], medical decision system [27], and tumor detection and tumor grading [27](a), [30]. Its use in medical diagnostics is becoming pervasive as the FCM can be developed by fusing expert knowledge and data [28](b).

Stylios et al developed a fuzzy cognitive map to develop medical decision support systems which can assist inexperienced medical professionals in reaching crucial clinical judgments. Papegeorgiou et al used FCM's for characterizing brain tumors. They showed the power of FCM to capture the expertise and experience of expert knowledge. They used an activation Hebbian learning algorithm to improve the classification performance of the FCM. When applied to clinical material for 100 test cases, the FCM approach gave accuracies over 90 percent. The main advantage of FCM over other algorithms was found to be easier interpretability and transparency. FCM does not share the black-box nature of algorithms such as the neural networks.

Some researchers have looked at constructing FCM's from historical data [10]. Ghazanfari et al. [43] used genetic algorithm (GA) and simulated annealing (SA) to construct the FCM graph topology. Both GA and SA are stochastic optimization algorithms. [10, 43] combined FCM's with fuzzy based inputs to carry out modeling and prediction for both numerical and linguistic situations. The use of fuzzy inputs typically improves the performance of FCM's probably because fuzziness leads to more realistic model of many systems [4]. The range of applications of FCM is vast. For example, FCM's have also been used for predicting the yield of cotton crops [34]. We see that the applications of FCM have increased steadily in recent years.

1.1 Fuzzy Cognitive Maps

A brief introduction to FCM's is provided in this section. A Fuzzy Cognitive Map is a graph which is constructed using nodes and edges. Nodes represent concepts in the problem domain and edges represent the causal relationships between the concepts. The causal relationship can be positive or negative. In a positive relationship, an increase or decrease in the cause variable causes the effect variable to move in the same direction. In a negative relationship, a change in the cause concept causes the effect concept to move in the opposite direction. All the values in the graph are fuzzy. So concepts take values in the range [0, 1], and weights of the edges take values in the range $[-1, 1]$. In the classical FCM proposed by Kosko (Kosko, 1996; [20]), the values are selected as 0 and 1 for concepts and -1, 0, 1 for weights. However, recent works have generalized this approach and weights and concepts can now often be selected between the prescribed bounds. In fact, this flexibility in selecting weights and concept values increases the capability of the FCM but also makes the process of developing them more complex. Therefore, learning approaches can be used for obtaining the weights and concept values.

An example of an FCM with five concepts is shown in Fig. 2. The FCM graph clearly shows the interconnections between concepts. The FCM also allows changes in the construction of the graph such as adding or deleting of a concept.

In Fig. 2, we have five concepts given by $C1$, $C2$, $C3$, $C4$, and $C5$. These are connected by weights. However, there may not be a connection between some concepts in a different manner. The first step in creating an FCM is to draw it as in Fig. 2. After drawing the FCM, the map needs to go through a diagram to matrix transformation.

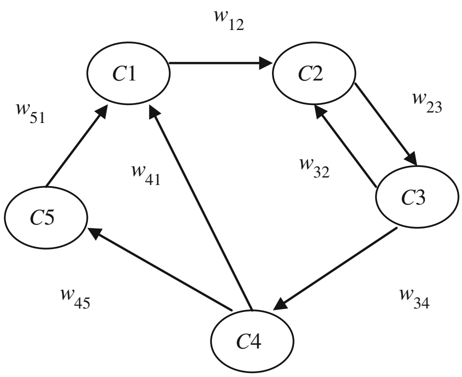


Fig. 2 A simple fuzzy cognitive map

The process begins with the creation of an N x N matrix where N is the number of concepts used in the map. The rows and columns in the matrix are labeled with domain concepts. The entry at row i, column j is the signed degree to which the ith concept (source concept) influences the j th concept (destination concept) in the absence of other influences. If there is no causal relationship between the ith and jth concept, zero is inserted as the entry at the element corresponding to (i, j) in the matrix. The fully populated weight matrix for the FCM in Fig. 2 can be written as,

$$w = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} & w_{15} \\ w_{21} & w_{22} & w_{23} & w_{24} & w_{25} \\ w_{31} & w_{32} & w_{33} & w_{34} & w_{35} \\ w_{41} & w_{42} & w_{43} & w_{44} & w_{45} \\ w_{51} & w_{52} & w_{53} & w_{54} & w_{55} \end{bmatrix}$$

Note that a general weight matrix can be fully populated as a connection can theoretically exist between all the given concepts. However, in reality, there may be no or negligible interaction between some concepts. For example, the FCM in Fig. 2 has several concepts with no interactions; the actual weight matrix is given by

$$w = \begin{bmatrix} 0 & w_{12} & 0 & 0 & 0 \\ 0 & 0 & w_{23} & 0 & 0 \\ 0 & w_{32} & 0 & \mathrm{w}_{34} & 0 \\ w_{41} & 0 & 0 & 0 & w_{45} \\ w_{51} & 0 & 0 & 0 & 0 \end{bmatrix}$$

The numerical value of each concept is influenced by the numerical values of the connected concepts with the appropriate weights. So the activation level A_i for each concept C_i is calculated using the relation

$$A_i = f\left(\sum_{j=1, j\neq i}^{n} A_j w_{ji}\right) \tag{1}$$

where A_i is the activation level of concept C_i at time t+1, A_j is the activation level of concept C_j at time t, w_{ji} is the weight of the interconnection between C_j and C_i, and f is a threshold function. The new state vector A_{new} is calculated using,

$$A_{new} = f\left(A_{old} * W\right) \tag{2}$$

So A_{new}, is calculated by multiplying the previous state vector A_{old} by the weight matrix W and thresholding the elements. The new state vector shows the effect of change in the value of one concept in the whole fuzzy cognitive map. Different threshold functions have been used by researchers. For example, we can use the sigmoid function

$$f(x) = \frac{1}{1 + e^{-cx}} \tag{3}$$

where $c > 0$ determines the steepness of the continuous function f. The sigmoid function is typically used when the concept interval is [0, 1]. Another function which can be used is

$$f(x) = \max(lb,\ \min(l, x)) \tag{4}$$

where lb is the value of the lower boundary values of the nodes (either 0 or -1). Another function

$$f(x) = \tanh(x) \tag{5}$$

is used when the concept interval is [-1, 1]. Thus the selection of threshold function depends on the description of concepts. The reader will note the similarity between the thresholds functions used for FCM with the activation functions used in neural networks. We can see that these functions can capture complex nonlinear relationships.

Once a FCM has been created, it can be used to model and simulate the behavior of the system. Firstly, the FCM should be initialized. For example, the activation level of each of the nodes of the map can take a value between -1 and +1 based on expert opinion of the current state. After initialization, the concepts are free to interact. The FCM goes through many cycles. In each step of cycling, the values of the concepts change according to Eq. (1). This interaction between concepts continues until one of the following three situations occur:

1. A fixed equilibrium is reached
2. A limit cycle is reached
3. Chaotic behavior is exhibited

The output of the FCM opens a window to the behavior of the complex system being analyzed. Among the three situations mentioned above, the fixed equilibrium state is most useful though the other states are also possible. The FCM converges to any of these states after several cycles in an iterative manner. A tutorial introduction to FCM can be found in [19]. More details are also available from the papers mentioned in the introduction of this chapter and the other chapters of this book.

1.2 Hebbian Learning

The most significant weaknesses of FCMs are the possibility of convergence to undesired regions and the need to recalculate the weights when new strategies are adopted. Learning algorithms can help to alleviate this weakness. The learning procedure is a technique which increases the efficiency and robustness of FCMs, by modifying the FCM weight matrix. Specifically, neural learning techniques are often used to train the FCMs and determine appropriate weights of interconnections among the concepts. The result is a hybrid neuro fuzzy system.

Learning rules can train FCMs by adjusting the interconnections between the concepts, as in the cases of synapses of neural networks. Adaptation and learning methodologies based on unsupervised Hebbian rules to adapt the FCM model and adjust its weights were proposed by Lee et al. [21]. The initial idea and description of using the nonlinear Hebbian rule in FCMs was proposed by Groumpos. In this chapter, we will adopt these ideas for application to the structural damage detection problem.

The Hebbian learning rule requires that the weights be initialized prior to learning. The Hebbian rule represents a purely feed forward, unsupervised learning approach.

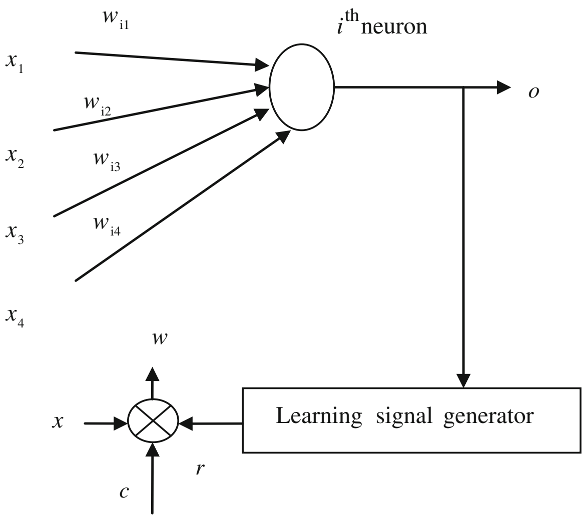


Fig. 3 Illustration for weight learning rules

In unsupervised learning, the desired response is not known. Thus, explicit error information cannot be used to influence and guide the network behavior. A neuron is considered to be an adaptive element. Its weights are modifiable depending on the input signal it receives and/or its output value.

Consider the learning problem of the weight vector w_i or its w_{ij}components connecting the j^{th} input with the i^{th} neuron. The learning procedure is shown in Fig. 3. Here $w_{i1}, w_{i2}, w_{i3}, w_{i4}$ are the components of the weight vector undergoing training. The weight vector increases in proportion to the product of input x and learning signal r. The learning signal r is a general function of w_i and x.

For the Hebbian learning rule, the learning signal is equal to the neuron's output [14]. Thus, we have

$$\begin{aligned} r &= f\left(w^t x\right) \\ f(x) &= \frac{2}{1+e^{-\lambda x}} - 1 \end{aligned} \tag{6}$$

where $c > 0$ determines the steepness of the function f. The increment Δw_i of the weigh vector becomes

$$\Delta w_i = cf\left(w^t x\right) x$$

where c is an arbitrary learning constant and is selected to be 1. A single weight w_{ij} is adapted using the following increment

$$\Delta w_{ij} = cf\left(w^t x\right) x_j \tag{7}$$

Eq. (7) can be written briefly as $w_{ij} = co_i x_j$ for (j =1, 2,…,n). The rule states that if the cross product of output and input, or correlation term $co_i x_j$ is positive, the weight w_{ij}increases, otherwise, the weight decreases. We can thus write the following six step Hebbian learning algorithm for FCM's used for structural damage detection:

1. Read input concept state A_0 and initial weight matrix w_0
2. Update the weights using Hebbian learning
3. Update the concepts using the new value of w using equation 2
4. Check for the damage and display the damage
5. Until all the input concept states (A_0 to A_n) are read, go to 1
6. Stop

2 Structural Model

Structures such as aircraft wings, helicopter rotor blades, tall buildings, wind turbine blades and towers etc. can be mathematically modeled as beams. An intrinsic property of these structures is the natural frequency which can be obtained for the beam by solving the Euler-Bernoulli partial differential equation,

$$\frac{\partial^2}{\partial x^2}\left(EI\frac{\partial^2 w}{\partial x^2}\right)+m\frac{\partial^2 w}{\partial t^2}=0 \tag{8}$$

Here $EI(x)$ is the flexural stiffness of the beam and $m(x)$ is the mass per unit length. The coordinate x represents any point along the beam and varies from 0 at the root to L at the tip of the beam. Also, E is a material property called Young's modulus and I is the moment of inertia of the cross section. A general solution to the beam vibration problem can be solved using the finite element method. The beam is divided into a number of finite elements. We assume that the displacement within an element can be written as

$$w(x,t)=N_1(x)w_1\,(t)+N_2(x)\theta_1\,(t)+N_3(x)w_2\,(t)+N_4(x)\theta_2\,(t) \tag{9}$$

Here $N_i\,(x)$ represents the shape functions and w_1,θ_1,w_2 and θ_2 are the nodal degrees of freedom. The finite element is shown in Fig. 4 where the nodes are located at the two ends.

We now apply the Galerkin method to the governing differential equation. In this approach, we multiply the governing equation by the shape function $N_i(x)$ and integrate over the finite element of length L.

$$\int_0^L N_i\,(x)\left(\rho A\frac{\partial^2 w}{\partial t^2}+EI\frac{\partial^4 w}{\partial x^4}\right)dx=0\ i=1,4 \tag{10}$$

The terms involving derivatives with respect to time in Eq. (10) can be expressed in a form which leads to the mass matrix of the system,

$$\begin{aligned}&\rho A\textstyle\int_0^L N_i\left(N_1\ddot{w}_1+N_2\ddot{\theta}_1+N_3\ddot{w}_2+N_4\ddot{\theta}_2\right)dx\\&=\rho A\textstyle\int_0^L N_i\,[N]\begin{Bmatrix}\ddot{w}_1\\\ddot{\theta}_1\\\ddot{w}_2\\\ddot{\theta}_2\end{Bmatrix}dx=\rho A\textstyle\int_0^L [N]^T\,[N]dx\begin{Bmatrix}\ddot{w}_1\\\ddot{\theta}_1\\\ddot{w}_2\\\ddot{\theta}_2\end{Bmatrix}=\left[m^{(e)}\right]\begin{Bmatrix}\ddot{w}_1\\\ddot{\theta}_1\\\ddot{w}_2\\\ddot{\theta}_2\end{Bmatrix}\end{aligned} \tag{11}$$

Here $[m^{(e)}]$ is the element mass matrix and is given by

$$\left[m^{(e)}\right]=\rho A\int_0^L [N]^T[N]dx \tag{12}$$

We now turn our attention to the term involving the spatial derivatives in Eq. (10), which will lead to the stiffness matrix. Consider the expression,

$$\int_0^L EIN_i\,(x)\,\frac{\partial^4 w}{\partial x^4}dx \tag{13}$$

Integrate the expression by parts,

$$N_i\,(x)\,EIw'''\,\Big|_0^L - .\,EI\int_0^L N_i^{'}\,(u)\,w'''dx\; i = 1, 4 \tag{14}$$

Again integrating by parts,

$$EI\int_0^L N_i''w''dx + N_i EIw''' \,\Big|_0^L - N_i' EIw''' \,\Big|_0^L \; i = 1, 4 \tag{15}$$

The second and third terms in the above equation are related to an external force being applied at the element node. If no such force is applied, the shear and moment terms of adjacent elements cancel during the assembly process. Then we get the discretized form of the expression as,

$$EI\int_0^L N_i''w''dx = EI\int_0^L N_i''\left(N_1''w_1 + N_2''\theta_1 + N_3''w_2 + N_4''\theta_2\right)dx$$
$$= EI\int_0^L N_i''\left[N''\right]\begin{Bmatrix} w_1 \\ \theta_1 \\ w_2 \\ \theta_2 \end{Bmatrix} dx = \left[k^{(e)}\right]\begin{Bmatrix} w_1 \\ \theta_1 \\ w_2 \\ \theta_2 \end{Bmatrix} \tag{16}$$

Here $[k^{(e)}]$ is the element stiffness matrix given by

$$\left[k^{(e)}\right] = EI\int_0^L \left[N_i''\right]^T \left[N''\right]dx \tag{17}$$

The discretized PDE in Eq. (8) is thus written in discrete form as,

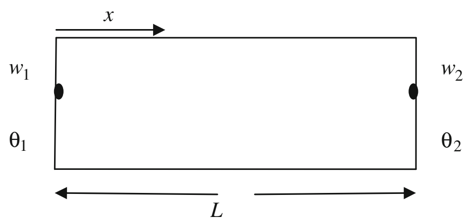
$$\left[m^{(e)}\right]\begin{Bmatrix} \ddot{w}_1 \\ \ddot{\theta}_1 \\ \ddot{w}_2 \\ \ddot{\theta}_2 \end{Bmatrix} + \left[k^{(e)}\right]\begin{Bmatrix} w_1 \\ \theta_1 \\ w_2 \\ \theta_2 \end{Bmatrix} = 0 \tag{18}$$

Here, we have assumed that *EI* and ρA are constant within the element and the nodal shear forces and bending moments are zero. The element matrices are then assembled and the boundary conditions are applied. The boundary conditions for a cantilever beam are that the displacement and slope at the fixed end should be zero. This leads to the set of ordinary differential equations,

$$M\ddot{q} + Kq = 0 \tag{19}$$

where M and K are the global mass and stiffness matrix and q is the displacement vector for the complete beam including all the elements.

Fig. 4 Beam finite element



In the above derivation, we did not discuss about the shape function $N_i(x)$, which occurs in the mass and stiffness matrix. These functions play a crucial role in the effective working of the finite element method. Since the beam element has 4 degrees of freedom given by w_1, θ_1, w_2 and θ_2, as shown in Fig. 4, we need a polynomial with four coefficients. So, we assume,

$$w(x) = a_0 = a_1 x + a_2 x^2 + a_3 x^3 \tag{20}$$

Now, we apply the conditions at the nodes to get,

$$\begin{aligned} w(0) &= w_1 = a_0 \\ w(L) &= w_2 = a_0 + a_1 L + a_2 L^2 + a_3 L^3 \\ w'(0) &= \theta_1 = a_1 \\ w'(L) &= \theta_2 = a_1 + 2a_2 L + a_2 L + 3a_3 L^2 \end{aligned} \tag{21}$$

Solving for the coefficients, we get

$$\begin{aligned} a_0 &= w_1 \\ a_1 &= \theta_1 \\ a_2 &= \tfrac{3}{L^2}(w_2 - w_1) - \tfrac{1}{L}(2\theta_1 + \theta_2) \\ a_3 &= \tfrac{2}{L^3}(w_1 - w_2) - \tfrac{1}{L^2}(\theta_1 + \theta_2) \end{aligned} \tag{22}$$

This finally leads to,

$$\begin{aligned} w(x) = {} & \left(1 - \frac{3x^2}{L^2} + \frac{2x^3}{L^3}\right) w_1 + \left(x - \frac{2x^2}{L} + \frac{x^3}{L^2}\right) \theta_1 + \left(\frac{3x^2}{L^2} - \frac{2x^3}{L^3}\right) w_2 \\ & + \left(\frac{x^3}{L^2} - \frac{x^2}{L}\right) \theta_2 \end{aligned} \tag{23}$$

or

$$w(x) = N_1(x) w_1 + N_2(x) \theta_1 + N_3(x) w_2 + N_4(x) \theta_2 \tag{24}$$

These shape functions N_i or interpolation functions are Hermite polynomials and can be used to calculate the element mass and stiffness matrices.

When there is damage in the structure, the value of E at the damage location decreases. We will often need to find the beam frequencies for all these cases to model the behavior of the damaged beam. Note that in structural systems, it is difficult and often impossible to make a large number of damaged structures to create a rule base linking the faults to the measurement changes. Therefore, modeling and simulation play a pivotal role in SHM.

To find the natural frequencies of the system, we put $q(t) = \phi e^{i\omega t}$ in Eq. (19) to yield the general eigenvalue problem

$$K\phi = \omega^2 M\phi \tag{25}$$

where K is the global stiffness matrix, M is the global mass matrix, ω are the natural frequencies and φ are the eigenvectors containing the mode shapes. In this chapter, we use the frequency ω as the indicator of damage, as has been done by many researchers [7, 16, 39]. For example, Salawu gives a review of research on structural damage detection through changes in frequency. Damage detection in a cantilever beam using change in natural frequencies is used to illustrate the FCM approach. A finite element approach is used to calculate the natural frequencies of the beam. Damage is modeled as a reduction in element stiffness and a percentage damage parameter D is defined such that

$$D = 100\left(\frac{E^{(u)} - E^{(d)}}{E^{(u)}}\right) \tag{26}$$

where E is the Young's modulus of the material and the superscripts u and d points to the undamaged and damaged state of the structure, respectively. The beam is divided into five uniform segments of equal lengths. These segments are labeled as "Root", "Inboard", "Center", "Outboard" and "Tip" as shown in Fig. 5.

The structural damage in each segment is modeled by a stiffness reduction (D) of 15 percent. The measurement suite consists of the first six natural frequencies of the cantilever beam. For numerical results, the undamaged beam is modeled as a uniform structure with flexural stiffness $EI = 1.0396 \times 10^5\ (Nm^2)$ mass per unit

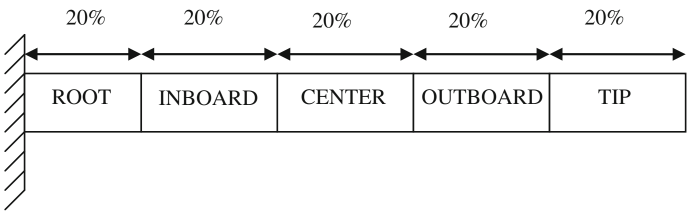


Fig. 5 Schematic representation of a cantilever beam

length $m = 6.46\,(kg/m)$ and length $L = 4.94$ (m). The first six non-dimensional frequencies of this structure are 3.5160, 22.0345, 61.6972, 120.9021, 199.8604 and 298.5585, respectively. These results match exactly with the closed form solution for the cantilever beam.

The difference between the frequency of the damaged and undamaged beam is referred to as the measurement delta and is used as the system indicator for damage. This measurement delta is positive for structural damage since the reduction in stiffness for a damaged beam decreases the frequency. The measurement delta is expressed as a percentage change

$$\Delta\omega = 100\left(\frac{\omega^{(u)} - \omega^{(d)}}{\omega^{(u)}}\right) \tag{27}$$

3 Structural Damage Detection Using FCM

The schematic diagram of the developed structural damage detection system using FCM is shown in Fig. 6. The frequencies of the damaged structure are measured and compared to the frequencies of the undamaged structure to obtain the measurement deltas $\Delta\omega$. Due to progress in sensor and actuator technologies, it is now possible to obtain online measurements of frequencies for structural health monitoring [1, 36]. The measurement deltas are then scaled between -1 and 1 and used with the initial FCM. Hebbian learning is then used to update the weights and the updated FCM is used to predict the damage location.

The FCM developed for structural damage detection is shown in Fig. 7. It consists of 11 concepts ($C1$ to $C11$). Concepts $C1$–$C6$ represent the six measurement deltas and concepts $C7$–$C11$ represent the five damage locations. Concepts are connected to one another by weights. The procedure for calculating the weights will be discussed later in the chapter. We use the finite element simulations to obtain the change in

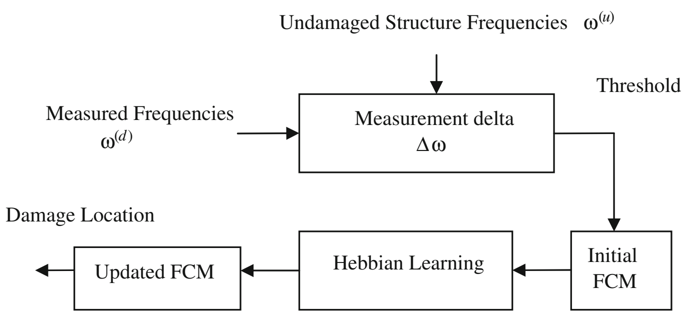


Fig. 6 Structural damage detection system

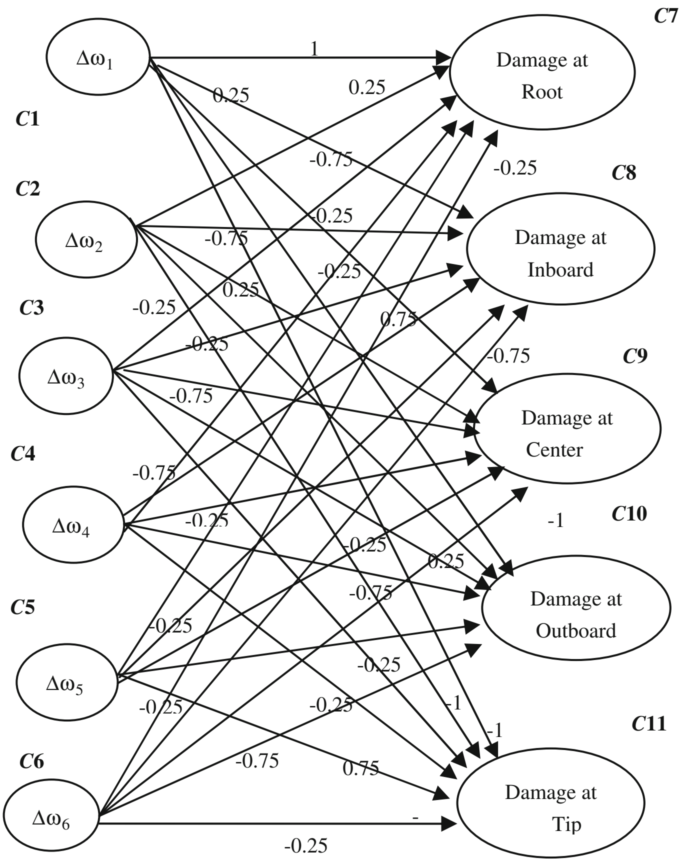


Fig. 7 FCM for structural damage detection

frequency for different damage locations. These numerical results are obtained using fifty finite elements and are shown in Table 1.

Some clear trends can be observed from Table 1. Damage at the root section causes a large change in the first frequency. As the damage moves towards the center of the beam, the second, third and the fourth modes show a larger effect. Also, damage at the tip region affects the fifth and sixth modes. Table 1 thus represents information which an expert may learn after observing the damage in many cantilever beam structures over a long period of time.

We convert the measurement deltas shown in Table 1 into fuzzy variables. Then each measurement delta is split into linguistic variables. For example $\Delta\omega_1$, can be decomposed into a set of terms:

$$T(\Delta\omega_1) = \{Negligible, VeryLow, Low, LowMedium, Medium, High\} \quad (28)$$

Table 1 Change in frequencies at different damage locations

	$\Delta\omega_1$	$\Delta\omega_2$	$\Delta\omega_3$	$\Delta\omega_4$	$\Delta\omega_5$	$\Delta\omega_6$
Damage at root	4.9132	2.2009	1.5154	1.7031	1.9111	1.7702
Damage at inboard	2.4221	0.8568	2.2165	1.3106	1.5339	1.4739
Damage at center	0.8451	3.1436	0.6402	2.1687	1.5370	1.4308
Damage at outboard	0.1540	1.9173	3.1229	1.6030	1.5851	1.4571
Damage at tip	0.0055	0.1491	0.7138	1.4704	1.8860	1.7921

Table 2 Gaussian fuzzy sets used to fuzzify numerical data

Linguistic measure	Symbol	Midpoints $\Delta\omega$
Negligible	N	0
Very low	VL	1
Low	L	2
Low-medium	LM	3
Medium	M	4
High	H	5

Here, each term in $T\ (\Delta\omega_1)$ is characterized by a fuzzy set in the universe of discourse $U\ (\Delta\omega_1) = \{0, 5\}$. The other five measurement deltas are also defined using the same set of terms as $\Delta\omega_1$.

We use fuzzy sets with Gaussian membership functions for the measurement deltas. These fuzzy sets are then defined using,

$$\mu\ (x) = e^{-0.5((x-m)/\sigma)^2} \tag{29}$$

where m is the midpoint of the fuzzy set and σ is the uncertainty (standard deviation) associated with the variable. Table 2 shows the linguistic measures associated with each fuzzy set and the midpoint of the set for each measurement delta. The standard deviation for $\Delta\omega$ is selected as 0.35 % to provide sufficient intersection between fuzzy sets. The fuzzy sets are shown in Fig. 8.

The data in Table 1 is converted to a fuzzy rule base as follows,

1. A set of six measurement deltas corresponding to a given damage location is input to Fuzzy Logic System (FLS) and the degree of membership of the elements of $\Delta\omega_1, \Delta\omega_2, \cdots, \Delta\omega_6$ are obtained.
2. Each measurement delta is then assigned to the fuzzy set with the maximum degree of membership.
3. One rule is obtained for each fault by relating the measurement deltas with the maximum degree of membership to a fault. The rules are tabulated in Table 3.

These fuzzy rules are then transformed to the $[-1, 1]$ space by using the transformation shown in Table 4.

After drawing the FCM, the map undergoes a diagram to matrix transformation and the matrix is known as the weight matrix or the edge matrix. The initial weight matrix considered is

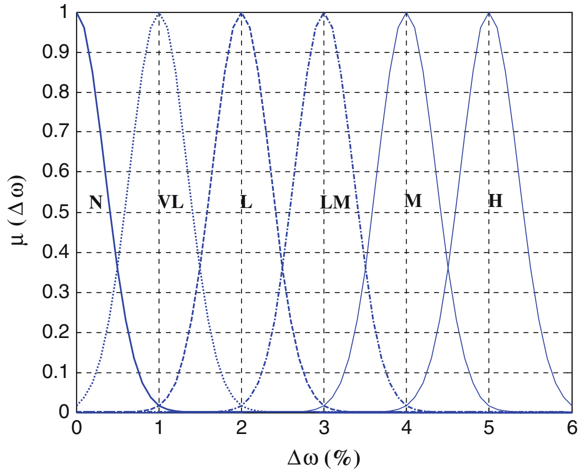


Fig. 8 Fuzzy sets representing measurement deltas over universe of discourse $(0 - 5\,\%)$

Table 3 Rules for fuzzy system

	$\Delta\omega_1$	$\Delta\omega_2$	$\Delta\omega_3$	$\Delta\omega_4$	$\Delta\omega_5$	$\Delta\omega_1$
Damage at root	H	L	VL	L	L	L
Damage at inboard	LM	VL	L	VL	L	VL
Damage at center	VL	LM	VL	L	L	VL
Damage at outboard	N	L	LM	L	L	VL
Damage at tip	N	N	VL	L	L	VL

$$w = \begin{bmatrix} 0\,0\,0\,0\,0\,0 & 1 & 0.25 & -0.75 & -1 & -1 \\ 0\,0\,0\,0\,0\,0 & -0.25 & -0.75 & 0.25 & -0.25 & -1 \\ 0\,0\,0\,0\,0\,0 & -0.75 & -0.25 & -0.75 & 0.25 & -0.75 \\ 0\,0\,0\,0\,0\,0 & -0.25 & -0.75 & -0.25 & -0.25 & -0.25 \\ 0\,0\,0\,0\,0\,0 & -0.25 & -0.25 & -0.25 & -0.25 & -0.25 \\ 0\,0\,0\,0\,0\,0 & -0.25 & -0.75 & -0.75 & -0.25 & -0.25 \\ 0\,0\,0\,0\,0\,0 & 0 & 0 & 0 & 0 & 0 \\ 0\,0\,0\,0\,0\,0 & 0 & 0 & 00 & 0 & \\ 0\,0\,0\,0\,0\,0 & 0 & 0 & 0 & 0 & 0 \\ 0\,0\,0\,0\,0\,0 & 0 & 0 & 0 & 0 & 0 \\ 0\,0\,0\,0\,0\,0 & 0 & 0. & 0. & 0 & 0 \end{bmatrix}$$

It can be seen that the weight matrix connects the first six concepts (measurement deltas) with the next five concepts (damage locations). The knowledge in Table 5 and in Fig. 5 is also contained in the weight matrix.

Table 4 Scaled inputs used to create initial FCM

Fuzzy set	Scaled inputs of FCM
N	−1
VL	−0.75
L	−0.25
LM	0.25
M	0.75
H	1

Preliminary tests on the FCM are performed using scaled measurements corresponding to known faults. The numerical results obtained are shown in Table 6. The fault with the highest concept value is selected as the most likely fault and is shown using bold font in Table 6. It can be seen that the FCM works very well for damage detection as the correct damage (concept) is found in each case.

learning is used to update the FCM. From Table 7, simulation No.1, if the initial state of the concepts are [1 −0.5 −0.5 −0.25 −0.5 −0.25] then the output of FCM is [0.94 0.87 −0.14 −0.60 0.14] the maximum being 0.94 represent concept $C7$ which indicates that there is a Damage at root. The updated weight matrix obtained using Hebbian learning is

$$w = \begin{bmatrix} 0\,0\,0\,0\,0\,0 & 1 & 0.28 & -0.69 & -0.94 & -0.91 \\ 0\,0\,0\,0\,0\,0 & -0.27 & -0.71 & 0.23 & -0.251 & -0.92 \\ 0\,0\,0\,0\,0\,0 & -0.72 & -0.25 & -0.68 & 0.24 & -0.69 \\ 0\,0\,0\,0\,0\,0 & -0.25 & -0.70 & -0.22 & -0.22 & -0.23 \\ 0\,0\,0\,0\,0\,0 & -0.27 & -0.25 & -0.22 & -0.21 & -0.23 \\ 0\,0\,0\,0\,0\,0 & -0.25 & -0.70 & -0.68 & -0.68 & -0.23 \\ 0\,0\,0\,0\,0\,0 & 0 & 0. & 0. & 0 & 0 \\ 0\,0\,0\,0\,0\,0 & 0 & 0 & 0 & 0 & 0 \\ 0\,0\,0\,0\,0\,0 & 0 & 0 & 0 & 0 & 0 \\ 0\,0\,0\,0\,0\,0 & 0 & 0 & 0 & 0 & 0 \\ 0\,0\,0\,0\,0\,0 & 0 & 0. & 0. & 0 & 0 \end{bmatrix}$$

We will see the change in the weight matrix caused by the Hebbian learning improves the damage detection capability of the FCM when used with noisy data.

Table 5 Scaled information matrix at different damage locations

	$\Delta\omega_1$	$\Delta\omega_2$	$\Delta\omega_3$	$\Delta\omega_4$	$\Delta\omega_5$	$\Delta\omega_1$
Damage at root	1	−0.25	−0.75	−0.25	−0.25	−0.25
Damage at inboard	0.25	−0.75	−0.25	−0.75	−0.25	−0.75
Damage at center	−0.75	0.25	−0.75	−0.25	−0.25	−0.75
Damage at outboard	−1	−0.25	0.25	−0.25	−0.25	−0.75
Damage at tip	−1	−1	−0.75	−0.25	−0.25	−0.25

Table 6 Damage detection using FCM

No.	$C1$ $\Delta\omega_1$	$C2$ $\Delta\omega_2$	$C3$ $\Delta\omega_3$	$C4$ $\Delta\omega_4$	$C5$ $\Delta\omega_5$	$C6$ $\Delta\omega_6$	$C7$ Damage at root	$C8$ Damage at inboard	$C9$ Damage at center	$C10$ Damage at outboard	$C11$ Damage at tip
1	1	−0.5	−0.5	−0.25	−0.5	−0.25	0.94	0.84	−0.12	−0.55	0.12
2	0.25	−0.5	−0.5	−0.25	−0.5	−0.75	0.80	0.89	0.67	0.46	0.76
3	0.2	−0.75	−0.25	−0.75	−0.25	−0.75	0.78	0.95	0.55	0.59	0.80
4	−0.75	0.25	−0.75	−0.25	−0.25	−0.75	0.06	0.55	0.95	0.82	0.87
5	−1	−0.25	0.25	−0.25	−0.25	−0.75	−0.67	0.59	0.82	0.94	0.87
6	−1	−1	−0.75	−0.25	−0.25	−0.25	0	0.80	0.87	0.87	0.99
7	−0.75	−0.5	−0.75	−0.25	−0.25	−0.25	0.12	0.67	0.86	0.76	0.96
8	−0.75	−0.5	0.5	−0.25	−0.5	−0.25	−0.59	0.63	0.55	0.91	0.82
9	−0.5	−0.5	−0.5	−0.5	−0.25	−0.5	0.12	0.55	0.92	0.76	0.63
10	0.5	0.5	−0.75	−0.5	−0.25	−0.75	0.89	0.86	0.59	−0.06	0.55
11	0.25	−0.25	−0.5	−0.25	−0.25	−0.5	0.73	0.76	0.55	0.18	0.55
12	0.5	0.5	−0.5	−0.25	−0.25	−0.5	−0.06	0.06	0.82	0.50	0.55
13	1	−0.25	−0.75	−0.25	−0.25	−0.25	0.94	0.78	0.06	−0.67	0

Table 7 Damage detection using FCM with hebbian learning

No.	*C*1 $\Delta\omega_1$	*C*2 $\Delta\omega_2$	*C*3 $\Delta\omega_3$	*C*4 $\Delta\omega_4$	*C*5 $\Delta\omega_5$	*C*6 $\Delta\omega_6$	*C*7 Damage at root	*C*8 Damage at inboard	*C*9 Damage at center	*C*10 Damage at outboard	*C*11 Damage at tip
1	1	−0.5	−0.5	−0.25	−0.5	−0.25	0.94	0.87	−0.14	−0.60	0.14
2	0.25	−0.5	−0.5	−0.25	−0.5	−0.75	0.90	0.95	0.80	0.59	0.87
3	0.2	−0.75	−0.25	−0.75	−0.25	−0.75	0.89	0.98	0.69	0.73	0.90
4	−0.75	0.25	−0.75	−0.25	−0.25	−0.75	0.08	0.67	0.97	0.90	0.93
5	−1	−0.25	0.25	−0.25	−0.25	−0.75	−0.70	0.63	0.84	0.94	0.81
6	−1	−1	−0.75	−0.25	−0.25	−0.25	0	0.87	0.92	0.92	0.99
7	−0.75	−0.5	−0.75	−0.25	−0.25	−0.25	0.14	0.71	0.88	0.79	0.96
8	−0.75	−0.5	0.5	−0.25	−0.5	−0.25	−0.67	0.71	0.63	0.94	0.88
9	−0.5	−0.5	−0.5	−0.5	−0.25	−0.5	0.17	0.71	0.97	0.88	0.78
10	0.5	0.5	−0.75	−0.5	−0.25	−0.75	0.94	0.92	0.71	−0.08	0.66
11	0.25	−0.25	−0.5	−0.25	−0.25	−0.5	0.81	0.83	0.64	0.22	0.64
12	−0.5	0.5	−0.5	−0.25	−0.25	−0.5	−0.08	0.08	0.90	0.61	0.61
13	1	−0.25	−0.75	−0.25	−0.25	0.25	0.94	0.81	0.06	−0.7	0

The other tests can be similarly interpreted and show the working of the FCM in a simple and transparent manner. For ideal or zero noise data, the initial FCM as well as the one developed after Hebbian learning gives 100 percent success rates.

There is always some difference between predictions by mathematical models and experimental or operational results. This difference is called modeling uncertainty. Modeling uncertainty can be reduced by developing and using more accurate mathematical models of the system. In addition to modeling uncertainty, noise may be present in the measured data. This measurement uncertainty can originate from sensor noise and measurement errors. Though the use of modern instruments has reduced measurement uncertainty considerably, it can never be eliminated, especially in an operational setting. When the diagnostic system is deployed on a real structure such as an airplane wing or a building, there are more sources of noise present due to environmental effects. Therefore in any real life application, it can be expected that uncertainty is present in the frequency measurement deltas ($\Delta\omega$). We shall assume noise of about $10 - 70\,\%$ is present in the measurement delta, originating from a combination of model and measurement uncertainty. A good damage detection system should not only show good performance with ideal data, as has already been shown, but also with noise contaminated data. FCM based decision systems provide an effective method for making damage detection from such uncertain data, as we shall show next.

The FCM is tested using noise contaminated data. The added noise in the data simulates the uncertainty present in experimental measurements and the modeling process. Given a computed frequency measurement delta $\Delta\omega$, a random number u in the interval $[-1, 1]$, and a noise level parameter α, the noisy simulated measurement delta is given as

$$\Delta\omega_{noisy} = \Delta\omega + \alpha u \tag{30}$$

The parameter α defines the maximum variance between the computed value $\Delta\omega$ and the simulated measured value $\Delta\omega_{noisy}$.For example, if $\alpha = 0.1$, then the simulated measurement delta can be different by as much as $10\,\%$ from the ideal value predicted by the simulations. Thus α can be used to control the noise levels in the simulated data used for testing the FCM system.

The simulated measurement deltas with added noise are used for testing the FCM. In each case, 100 noisy data points are generated for each damage location and the percentage success rate of the FCM in isolating damage is calculated. The percentage success rate is defined as follows:

$$S_R = \left(\frac{N_c}{N}\right) 100 \tag{31}$$

where N is the number of simulations (100 here) and N_c is the number of correct classifications.

Table 8 shows that $100\,\%$ success rate is obtained up to noise levels of $10\,\%$ with the FCM and the performance deteriorates at higher noise levels. However, the fall in performance is gradual and not abrupt which shows the advantage of using

Table 8 Success rate for amage detection using FCM with noisy data

Damage	$\alpha = 0.1$	$\alpha = 0.3$	$\alpha = 0.5$	$\alpha = 0.7$
At root	100	99	92	84
At inboard	100	96	90	80
At center	100	85	80	71
At outboard	100	86	82	70
At tip	100	100	99	98
Average success rate	100	93.2	88.6	80.6

Table 9 Damage detection using FCM with hebbian learning and noisy data

Damage	$\alpha = 0.1$	$\alpha = 0.3$	$\alpha = 0.5$	$\alpha = 0.7$
At root	100	100	100	99
At inboard	100	100	100	99
At center	100	100	100	98
At outboard	100	100	100	98
At tip	100	100	100	100
Average success rate	100	100	100	98.8

soft computing techniques [31][32](a). This problem of performance deterioration is alleviated by the use of Hebbian learning which is clear from the results in Table 9. The Hebbian learning approach improves the weights linking the concepts so that the success rate is improved. For example, at 30 % noise levels the success rate is now 100 % and remains the same at high noise levels of 50 % in the data. Note that this improvement does not involve any supervised learning to improve the success rate and therefore represents a novel approach to improve the FCM performance. Moreover, the good performance at fairly high levels of noise makes the FCM attraction for operational deployment on structures.

We should point out that the results in this chapter depend on the structure selected and the number of inputs and outputs considered. As the number of inputs and outputs increase the use of FCM becomes more complex due to the 'curse of dimensionality'. However, for the important practical beam structure, the use of FCM for structural damage detection has been demonstrated in this chapter. As FCM research evolves [11, 31] the methods can be adapted for SHM problems.

4 Summary

A fuzzy cognitive map based approach for detecting structural damage in a cantilever beam from measured natural frequencies is proposed. The first six modal frequencies of the structure are used. Fuzzy cognitive map is used to account for the uncertainty that is typically present in measurements and modeling processes. The beam is divided into five uniform segments. Numerical simulations from a finite element model are used to create a fuzzy rule base which is used to design the FCM.

Hebbian learning allows the FCM to improve itself and the numerical results show that the FCM with Hebbian learning is a robust tool for damage detection with noisy data. The final FCM obtained after Hebbian learning shows a success rate of damage detection of 100 % up to noise levels of 50 % in the measured data. Even at a noise level of 70 %, the proposed damage detection system works with an accuracy of 98.8 %. The FCM developed in this study can be used as a robust and powerful tool for structural damage detection. It is conceptually simple to understand and is transparent relative to neural network based approaches. FCM has a huge untapped potential for application in structural health monitoring.

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Chapter 17
Fuzzy Cognitive Strategic Maps

M. Glykas

Abstract This paper presents the application of a Fuzzy Cognitive Map (FCM) based theoretical framework and its associated modeling and simulation tool to Strategy Maps (SMs). Existing limitations of SMs are presented in a literature survey. The need for scenario based SMs with inherited ability to change scenarios dynamically as well as the missing element of time are highlighted and discussed upon. FCMs are presented as an alternative to overcome these shortfalls with the introduction of fuzziness in their weights and the robust calculation mechanism. An FCM tool is presented that allows simulation of SMs as well as interconnection of nodes (performance measures) in different SMs which enable the creation of SM hierarchies. An augmented FCM calculation mechanism that allows this type of interlinking is also presented. The resulting methodology and tool are applied to two Banks and the results of these case studies are presented.

1 Introduction to Strategy Maps and the Balanced Scorecard

Strategy maps (SMs) represent visually relationships among the key components of an organization's strategy [17]. We could argue that SMs describe strategy in a picture; they are powerful tools which show how value is created through cause and effect relationships. Kaplan and Norton argue that they create "the missing link between strategy formulation and strategy execution" [38].
Strategy maps are particularly helpful for:

- Promoting understanding and clarity of strategy

M. Glykas (✉)
Department of Financial and Management Engineering, University of the Aegean, Chios, Greece
e-mail: mglikas@aegean.gr

M. Glykas
Aegean Technopolis, The Technology Park of the Aegean Region, Chios, Greece

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- Encouraging greater engagement and commitment to strategy
- Ensuring alignment of resources
- Identifying gaps or blind spots
- Making more effective and efficient use of resources
- Aligning remuneration with strategy—particularly in the soft areas and where objectives have a duration > 12 months

A strategy map describes how an organization creates value by connecting strategic objectives in explicit cause and effect relationships. They provide an excellent snapshot of strategy and are supported by measurable objectives and initiatives.

Strategy maps enable organizations to [49]:

- Describe strategy in a single picture
- Clarify strategies and communicate them to employees
- Identify the key internal processes which drive success
- Align investments in people, technology and organizational capital for maximum impact
- Expose gaps in strategies so that early corrective action can be taken
- Identify explicit customer value propositions
- Map the critical internal processes for creating and delivering the value proposition
- Align human resources, information technology and organization culture to internal processes

Strategy maps can be used for developing and reviewing strategy at organizational, departmental and even project level.
The strategy map [34, 35, 38] evolved from the four-perspective model of the balanced scorecard, adding a visual dimension which improves clarity and focus.

There are five main principles behind strategy maps:

- Strategy balances contradictory forces
- Strategy is based on a differentiated customer value proposition
- Value is created through internal business processes
- Strategy consists of simultaneous complementary themes
- Strategic alignment determines the value of intangible assets

Strategy maps are used in many frameworks as part of their strategy and change management offerings. The balanced scorecard [34, 35, 38] is a performance management system that enables organizations to implement a business vision and strategy.

1.1 The Balanced Scorecard

The measurement focus of the scorecard forms the basis of a strategic management system enabling the organization to:

- Clarify and translate vision and strategy
- Communicate and link strategic objectives and measures
- Plan, set targets, and align strategic initiatives
- Enhance strategic feedback and learning

This is achieved by considering four perspectives:

- Financial
- Customer
- Internal process
- Learning and growth

These perspectives give an organisation balance between internal and external measures, and balance between outcomes—results from past efforts—and measures that drive future performance.

Financial Perspective

The financial perspective retains the need for traditional financial data. However it recognises that the programmes, initiatives and change management processes drive the need for measures that reflect the intangible assets of an organisation.

Customer Perspective

Recent management philosophy has acknowledged the importance of the customer perspective as an indicator of future performance. In developing metrics for customer satisfaction, customers should be benchmarked against value propositions which reflect product and service attributes, image or brand and relationships.

Internal Perspective

The internal business perspective focuses the organisation on the processes that are most critical for achieving customer and financial objectives. The focus is on mission-oriented processes as opposed to support processes, and targets and initiatives which use resources to best effect.

Learning and Growth

Learning and growth relates to individuals and information, but perhaps most importantly to the organisation as a whole. Culture, leadership and teamwork, and the alignment and readiness of an organisation to meet strategic objectives, leads to successful outcomes.

Strategy maps are used in conjunction with the balanced scorecard to help identify the key internal processes and communicate strategy.

2 Shortcomings of Strategy Maps

Although there may be benefits related to the design and use of strategy maps, a number of authors have highlighted possible shortcomings (e.g. [1, 10, 66]).

Feedback Loops

The development of strategy maps could be criticized as too much of an inward-looking exercise. Also, the cause-and-effect relationships depict a one-way, linear approach often starting with the 'learning and growth' perspective and culminating in financial results instead of depicting non-linear, two-way linkages. However since the Balanced Scorecard perspectives are not independent, feedback loops should be included in the maps [21].

Need for Fuzziness in Causal Relationships

Predictions about the future state of a market and values that business goals and objectives can reach always contai the issue of uncertainty. Also the influence values of cause and effect relationships in strategy maps contain by themselves the issue of vaguenes or fuzzines as more than one cause node can be linked to the same effect node with different levels of influence. There is a need therefore for a theory that will accommodate this fuzzines in causal relationships.

The Missing Element of time

Norreklit [65] argues that strategy maps do not discriminate amongst logical and causal links. Typically, in many organizations, there are inconsistencies in the frequency of gathered values and the range in which the values vary over a period of time.

Othman [67] argues that a very serious drawback of strategy maps is the lack of representing the time evolution element in strategic plans. This missing time element also influences the ability to model performance indicators in SMs.

Need for Dynamic-Flexible SMs

According to [10] relying on a static SM over the mid and long term, is equivalent to assuming not only that the organization and its strategy will stay the same, but also that competitors will continue to behave in the same way. Furthermore, if strategy maps are supposed to have predictive abilities, one could question the validity of analyzing past data to predict future states.

Need for Tools with Simulation Capabilities

Currently there are no tools in the literature that provide simulation capabilities of composed-decomposed and linked strategic maps. There are only tools that allow the composition of performance calculation of performance measures that are based on values of other performance measures the values of which need to be calculated beforehand.

3 Scenario-Based Strategic Maps

In order to resolve the aforementioned issues Buytendijk et al. [10] argue that scenario analysis [31, 60, 74, 75, 81] could play an important role in the design of strategy maps, as it is an effective method to look at the future.

They believe that strategy maps should not be closed, static representations of strategy. Organizations and the environment they operate change continuously based on 'PESTEL factors' (Political, Economical, Social, Technological, Environmental and Legal). In many situations past performance can not be a source of data analysts can rely on.

According to Wack Scenario planning, assists managers and strategists to explore different alternatives in present, intermediate and future desired states and even conclude in states that would seem unthinkable [81].

Strategy in fact is based on scenarios [19], which in contrast to forecasting techniques, which aim to provide answers about only the final future states, encourage people to pose questions about different pathways that can be followed [31].

Scenarios can be used for a number of purposes [74]:

1. Identify early warning signals
2. Assess the robustness of the organization's core competencies
3. Generate better strategic options
4. Evaluate the risk/return of each option in view of the uncertainties

The combination of strategy maps and scenario analysis has a number of advantages (building on [60], and [35]):

- Strategy maps and scenarios are effective means to communicate the present and future strategy of an organization.
- Both tools are built on a holistic view of the organization and its environment, and on how key activities and processes are interrelated.
- The internal focus of strategy maps is complemented by focus of scenario analysis on environmental factors.
- Through strategy maps and scenarios, both qualitative and quantitative aspects can be taken into account.
- Both tools require the participation of several stakeholder groups; this could increase the validity and robustness of the organization's strategy.
- The development of strategy maps and scenarios also imply the comparison of mental models [76] and the achievement of intersubjective agreement between participants.
- Finally, contingencies, uncertainties, trends, and opportunities, which are seldom anticipated, could be identified and evaluated through scenario analysis, incorporated in the strategy maps, and thus acted upon Miller and Waller [60].
- Although the joint development of scenarios and strategy maps could result in major benefits, we are not suggesting that the complete process of developing a strategy map should be driven solely by external influences as identified in various scenarios.

Even though the literature on strategy mapping is fairly vast, few authors have suggested the combination of strategy maps and scenario analysis [19, 67] and none of them has described the actual design process and nobody using any tools with simulation capabilities.

To address this issue, Buytendijk et al. [10] propose a series of steps to create a scenario-based strategy map:

1. Consider the strategy map and identify the strategic objectives that describe the assumptions for the business model. For instance, 'cost leadership' for a budget airline, or 'ultimate safety' for a car manufacturer, or 'superior service' in a hotel chain.

2. Create different scenarios, for example using PESTEL analysis. Identify the new (or unchanged) critical success factors in each of those scenarios.
3. Create a strategy map with objectives for each of those scenarios, based on the specifics of that scenario.
4. Establish the commonality of objectives across the various scenarios. The more an objective is present across scenarios, the more 'future-proof'2 such an objective will be, and the higher the probability that these goals could be reached in a changing environment. In order for this commonality analysis to work, objectives will have to be specific; this implies that predominantly high-level objectives such as "maintain profitability" and "seek growth" do not provide practical guidance and will most likely only change in the gravest of discontinuities.

In the next sections we will present a tool that assists in the creation, monitoring and simulation of Strategic Maps based on the theory of fuzzy cognitive maps. With the use of this tool strategists and managers can explore different strategic scenarios and see the impact of their thinking and the evolution of these scenarios over time in a step by step simulation.

4 Fuzzy Cognitive Maps

Fuzzy Cognitive Maps is a modeling methodology for complex decision systems, which originated from the combination of Fuzzy Logic [89] and Neural Networks. An FCM describes the behavior of a system in terms of concepts; each concept represents an entity, a state, a variable, or a characteristic of the system [15].

Kosko in [44] defined a concept $\mathbf{C_i}$ that constitutes causal relationships in FCM as

$$\mathbf{C_i} = (\mathbf{Q_i} \cup \sim \mathbf{Q_i}) \cap \mathbf{M_i}$$

where $\mathbf{Q_i}$ is a quantity fuzzy set and $\sim\mathbf{Q_i}$ is a dis-quantity fuzzy set. $\sim\mathbf{Q_i}$ is the negation of $\mathbf{Q_i}$. Each $\mathbf{Q_i}$ and $\sim\mathbf{Q_i}$ partitions the whole set $\mathbf{C_i}$. Double negation $\sim\mathbf{Q_i}$ equals to $\mathbf{Q_i}$, implying that $\sim\mathbf{Q_i}$ corresponds to $\mathbf{Q_i^c}$, the complement of $\mathbf{Q_i}$. However, negation does not mean antonym. Therefore, if a dis-quantity fuzzy set $\sim\mathbf{Q_i}$ does not correspond to the complement of $\mathbf{Q_i}$, we will call it as anti-quantity fuzzy set to clarify the subtle meaning in the dis-quantity fuzzy set, as proposed by [41]. $\mathbf{M_i}$ is a modifier fuzzy set that modifies $\mathbf{Q_i}$ or $\sim\mathbf{Q_i}$ concretely. The modifier fuzzy set fuzzily intersects the fuzzy union of a quantity fuzzy set and a dis-quantity fuzzy set.

Kosko in [44] also formally defined the positive and negative fuzzy causal relationships (or fuzzy causality) as follows.

Definition 1. $\mathbf{C_i}$ causes $\mathbf{C_j}$ iff $(\mathbf{Q_i} \cap \mathbf{M_i}) \subset (\mathbf{Q_j} \cap \mathbf{M_j})$ and $(\sim \mathbf{Q_i} \cap \mathbf{M_i}) \subset (\sim\mathbf{Q_j} \cap \mathbf{M_j})$

Definition 2. $\mathbf{C_i}$ causally decreases $\mathbf{C_j}$ iff $(\mathbf{Q_i} \cap \mathbf{M_i}) \subset (\sim \mathbf{Q_j} \cap \mathbf{M_j})$ and $(\sim\mathbf{Q_i} \cap \mathbf{M_i}) \subset (\mathbf{Q_j} \cap \mathbf{M_j})$

Here "$\subset$" stands for fuzzy set inclusion (logical implication).

A more insightful and practical definition of FCMs follows. FCM nodes are named by concepts forming the set of concepts $\boldsymbol{C}=\{\mathbf{C_1}, \mathbf{C_2}, \ldots, \mathbf{C_n}\}$. Arcs $(\mathbf{C_j}, \mathbf{C_i})$ are oriented and represent causal links between concepts; that is how concept $\mathbf{C_j}$ causes concept $\mathbf{C_i}$. Arcs are elements of the set $\boldsymbol{A} = \{(\mathbf{C_j}, \mathbf{C_i})_{\mathbf{ji}}\} \in \boldsymbol{C}\times\boldsymbol{C}$. Weights of arcs are associated with a weight value matrix $\mathbf{W_{n\times n}}$, where each element of the matrix $\mathbf{w_{ji}} \in [-\mathbf{1}, \ldots, \mathbf{1}] \in \boldsymbol{R}$ such that if $(\mathbf{C_j}, \mathbf{C_i}) \in \boldsymbol{A}$ then $\mathbf{w_{ji}} = \mathbf{0}$ else excitation (respectively inhibition) causal link from concept $\mathbf{C_j}$ to concept $\mathbf{C_i}$ gives $\mathbf{w_{ji}} > \mathbf{0}$ (respectively $\mathbf{w_{ji}} < \mathbf{0}$). The proposed methodology framework assumes that $[-\mathbf{1}, \ldots, \mathbf{1}]$ is a fuzzy bipolar interval, bipolarity being used as a means of representing a positive or negative relationship between two concepts.

In practice, the graphical illustration of an FCM is a signed graph with feedback, consisting of nodes and weighted interconnections (e.g. $\xrightarrow{\text{Weight}}$). Signed and weighted arcs (elements of the set $\boldsymbol{A}$) connect various nodes (elements of the set $\boldsymbol{C}$) representing the causal relationships that exist among concepts. This graphical representation illustrates different aspects in the behavior of the system, showing its dynamics [44] and allowing systematic causal propagation (e.g. forward and backward chaining). Positive or negative sign and fuzzy weights model the expert knowledge of the causal relationships [45]. Concept $\mathbf{C_j}$ causally increases $\mathbf{C_i}$ if the weight value $\mathbf{w_{ji}} > \mathbf{0}$ and causally decreases $\mathbf{C_i}$ if $\mathbf{w_{ji}} < \mathbf{0}$. When $\mathbf{w_{ji}} = \mathbf{0}$, concept $\mathbf{C_j}$ has no causal effect on $\mathbf{C_i}$. The sign of $\mathbf{w_{ji}}$ indicates whether the relationship between concepts is positive ($\mathbf{C_j} \xrightarrow{\mathbf{W_{j,i}}} \mathbf{C_i}$) or negative ($\mathbf{C_j} \xrightarrow{\mathbf{W_{j,i}}}\sim \mathbf{C_i}$), while the value of $\mathbf{w_{ji}}$ indicates how strongly concept $\mathbf{C_j}$ influences concept $\mathbf{C_i}$. The forward or backward direction of causality indicates whether concept $\mathbf{C_j}$ causes concept $\mathbf{C_i}$ or vice versa.

Simple variations of FCMs mostly used in business decision-making applications may take trivalent weight values **[–1, 0, 1]**. This paper allows FMCs to utilize fuzzy word weights like strong, medium, or weak, each of these words being a fuzzy set to provide complicated FCMs. In contrast, [47] adopted only a simple relative weight representation in the interval [**-1**, … ,**1**]. To this extend, research [47] offered reduced functionality since it did not allow fuzzy weight definitions.

Generally speaking FCM concept activations take their value in an activation value set $\boldsymbol{V} = \{\mathbf{0}, \mathbf{1}\}$ or $\{-\mathbf{1}, \mathbf{0}, \mathbf{1}\}$ if in crisp mode or $[-\boldsymbol{\delta}, \mathbf{1}]$ with $\boldsymbol{\delta} = \mathbf{0}$ or $\mathbf{1}$ if in fuzzy mode. The proposed methodology framework assumes fuzzy mode with $\boldsymbol{\delta} = \mathbf{1}$. At step $\mathbf{t} \in \boldsymbol{N}$, each concept $\mathbf{C_j}$ is associated with an inner activation value $\mathbf{a_j^t} \in \boldsymbol{V}$, and an external activation value $\mathbf{e_{a_j}^t} \in \boldsymbol{R}$. FCM is a dynamic system. Initialization is $\mathbf{a_j^0} = \mathbf{0}$. The dynamic obeys a general recurrent relation $\mathbf{a}^{t+1} = \mathbf{f}(\mathbf{g}(\mathbf{e_a^t}, \mathbf{W^T a^t})), \mathbf{t} \neq 0$, involving weight matrix product with inner activation, fuzzy logical operators (**g**) between this result and external forced activation and finally normalization (**f**). However, this paper assumes no external activation (hence no fuzzy logical operators), resulting to the following typical formula for calculating the values of concepts of FCM:

$$\mathbf{a_i^{t+1}} = \mathbf{f}\Big(\sum_{\mathbf{j}=1,\mathbf{j}\neq\mathbf{i}}^{\mathbf{n}} \mathbf{w_{ji}} \mathbf{a_j^t}\Big) \tag{1}$$

where $\mathbf{a_i^{t+1}}$ is the value of concept $\mathbf{C_i}$ at step $\mathbf{t+1}$, $\mathbf{a_j^t}$ the value of the interconnected concept $\mathbf{C_j}$ at step $\mathbf{t}$, $\mathbf{w_{ji}}$ is the weighted arc from $\mathbf{C_j}$ to $\mathbf{C_i}$ and $\mathbf{f}$:$\boldsymbol{R} \rightarrow \boldsymbol{V}$ is a threshold function, which normalizes activations. Two threshold functions are usually used. The unipolar sigmoid function where $\boldsymbol{\lambda} > \mathbf{0}$ determines the steepness of the continuous function $\mathbf{f(x)} = \frac{\mathbf{1}}{\mathbf{1+e^{-\lambda x}}}$. When concepts can be negative ($\boldsymbol{\delta} < \mathbf{0}$), function $\mathbf{f(x)} = \mathbf{tanh(x)}$ is used.

To understand better the analogy between the sign of the weight and the positive/negative relationship, it may be necessary to revisit the characteristics of fuzzy relation [40, 53]. A fuzzy relation from a set $\boldsymbol{A}$ to a set $\boldsymbol{B}$ or ***(A,B)*** represents its degree of membership in the unit interval **[0,1]**. Generally speaking, sets $\boldsymbol{A}$ and $\boldsymbol{B}$ can be fuzzy sets. The corresponding fuzzy membership function is $\boldsymbol{\mu f}$:$\boldsymbol{A} \times \boldsymbol{B} \in [\mathbf{0}, \mathbf{1}]$. Therefore, $\boldsymbol{\mu f}$ **(x,y)** is interpreted as the "strength" of the fuzzy membership of the fuzzy relation **(x,y)** where $\mathbf{x} \in \boldsymbol{A}$ and $\mathbf{y} \in \boldsymbol{B}$. Then this fuzzy relation concept can be denoted equivalently as $\mathbf{x} \xrightarrow{\mu \mathbf{f}} \mathbf{y}$ and applied to interpret the causality value of FCM, since $\mathbf{w_{ji}}$ (the causality value of the arc from nodes $\mathbf{C_j}$ to $\mathbf{C_i}$) is interpreted as the degree of fuzzy relationship between two nodes $\mathbf{C_j}$ and $\mathbf{C_i}$. Hence, $\mathbf{w_{ji}}$ in FCMs is the fuzzy membership value $\boldsymbol{\mu f}(\mathbf{C_j}, \mathbf{C_i})$ and can be denoted as $\mathbf{C_j} \xrightarrow{\mathbf{w_{j,i}}} \mathbf{C_i}$.

However, we understand that the fuzzy relation (weight) between concept nodes is more general than the original fuzzy relation concept. This is because it can include negative (-) fuzzy relations. Fuzzy relations mean fuzzy causality; causality can have a negative sign. In FCMs, the negative fuzzy relation (or causality) between two concept nodes is the degree of a relation with a "negation" of a concept node. For example, if the negation of a concept node $\mathbf{C_i}$ is noted as $\mathbf{\sim C_i}$, then $\boldsymbol{\mu f}(\mathbf{C_j}, \mathbf{C_i}) = \mathbf{-0.6}$ means that $\boldsymbol{\mu f}(\mathbf{C_j}, \mathbf{\sim C_i}) = \mathbf{0.6}$. Conversely, $\boldsymbol{\mu f}(\mathbf{C_j}, \mathbf{C_i}) = \mathbf{0.6}$ means that $\boldsymbol{\mu f}(\mathbf{C_j}, \mathbf{\sim C_i}) = \mathbf{-0.6}$.

FCMs help to predict the evolution of the system (simulation of behavior) and can be equipped with capacities of hebbian learning [43, 46]. FCMs are used to represent and to model the knowledge on the examining system. Existing knowledge of the behavior of the system is stored in the structure of nodes and interconnections of the map. The fundamental difference between FCMs and a Neural Networks is in the fact that all the nodes of the FCM graph have a strong semantic defined by the modeling of the concept whereas the nor input/nor output nodes of the neural network have a weak semantic, only defined by mathematical relations.

4.1 Applications of Fuzzy Cognitive Maps

Over the last years, a variety of FCMs have been used for capturing—representing knowledge and intelligent information in engineering applications, for instance, GIS [54] and fault detection (e.g. [62, 68]). FCMs have been used in modeling the supervision of distributed systems [79]. They have also been used in operations research [13], web data mining [32, 53], as a back end to computer-based models and medical diagnosis (e.g. [23]).

Several research reports applying basic concepts of FCMs have also been presented in the field of business [86] and other social sciences. Research in [3] and [69] have used FCM for representing tacit knowledge in political and social analysis. FCMs have been successfully applied to various fields such as decision making in complex war games [42], strategic planning [16, 70], information retrieval [33] and distributed decision process modeling [90]. Research like [50] has successfully applied FCMs to infer rich implications from stock market analysis results. Research like [51] also suggested a new concept of fuzzy causal relations found in FCMs and applied it to analyze and predict stock market trends. The inference power of FCMs has also been adopted to analyze the competition between two companies, which are assumed to use differential games mechanisms to set up their own strategic planning [52]. FCMs have been integrated with case-based reasoning technique to build organizational memory in the field of knowledge management [63]. Recent research adopted FCMs to support the core activities of highly technical functions like urban design [87]. Summarizing, FCMs can contribute to the construction of more intelligent systems, since the more intelligent a system becomes, the more symbolic and fuzzy representations it utilizes.

In addition, a few modifications have been proposed. For example, the research in [77] proposed new forms of combined matrices for FCMs, the research in [28] extended FCMs by permitting non-linear and time delay on the arcs, the research in [73] presented a method for automatically constructing FCMs. More recently, [54] has carried extensive research on FCMs investigating inference properties of FCMs, proposed contextual FCMs based on the object-oriented paradigm of decision support and applied contextual FCMs to geographical information systems [55].

4.2 Updated FCM algorithm

This paper extends the basic FCM algorithm [47] by proposing the following new FCM algorithm:

$$\mathbf{a_i^{t+1}} = \mathbf{f}(\mathbf{k_1 a_i^t} + \mathbf{k_2} * \sum_{\mathbf{j=1, j \neq i}}^{\mathbf{n}} \mathbf{w_{ji} a_j^t}) \tag{2}$$

This paper assumes that coefficients $\mathbf{k_1}$ and $\mathbf{k_2}$ can be fuzzy sets.

Coefficient $\mathbf{k_1}$ represents the proportion of the contribution of the value of the concept $\mathbf{a_i}$ at time $\mathbf{t}$ in the computation of the value of $\mathbf{a_i}$ at time $\mathbf{t+1.}$ In practice, this is equivalent to assume that $\mathbf{w_{ii}} = \mathbf{k_1}$. The incorporation of this coefficient results in smoother variation of concept values during the iterations of the FCM algorithm. Coefficient $\mathbf{k_2}$ expresses the "influence" of the interconnected concepts in the configuration of the value of the concept $\mathbf{a_i}$ at time $\mathbf{t+1.}$ It is the proposal of this paper that such a coefficient should be used to align indirectly causal relationships (essentially, the value of concept $\mathbf{C_i}$) with the influence of concept $\mathbf{C_j}$ as follows:

If the set of identified performance concepts $\mathbf{C_j}, \mathbf{j} \neq \mathbf{i}$, is incomplete (e.g. incomplete maps, missing concepts, etc), then the estimation of the value of concept $\mathbf{C_i}$ may prove imprecise. In this case coefficient $\mathbf{k_2}$ may indicate the sufficiency of the set of concepts $\mathbf{C_j j} \neq \mathbf{i}$, in the calculation of the value of the concept $\mathbf{C_i}$.

If the information necessary to approximate the input values of concepts $\mathbf{C_j}, \mathbf{j} \neq \mathbf{i}$, is incomplete (e.g. incomplete estimation of bad loans), then the estimation of the value of concept $\mathbf{C_i}$ may also prove imprecise. In this case coefficient $\mathbf{k_2}$ may indicate the completeness of information utilized in the approximation of the input values of concepts $\mathbf{C_j}$ during the calculation of the value of the concept $\mathbf{C_i}$.

Ideally, coefficient $\mathbf{k_2}$ could break down into two separate coefficients (say $\mathbf{k_2} = \mathbf{x{*}k_2^x} + \mathbf{y{*}k_2^y}$), where $\mathbf{k}_2^{\mathbf{x}}$ aligns indirectly the value of concept $\mathbf{C_i}$ with the completeness of the set of concepts $\mathbf{C_j}$ (e.g. completeness of P&L performance indicators), while $\mathbf{k}_2^{\mathbf{y}}$ aligns indirectly the value of concept $\mathbf{C_i}$ with the completeness of available information for concepts $\mathbf{C_j}$ within the enterprise (e.g lack of information for certain P&L indicators). Parameters $\mathbf{x}$, $\mathbf{y}$ could present the relative importance of $\mathbf{k}_2^{\mathbf{x}}$ and $\mathbf{k}_2^{\mathbf{y}}$ in mixed interconnection problems (e.g. incomplete set of P&L indicators with partial accounting results). However, preliminary experiments showed that this separation imposed unnecessary initialization overheads without increasing significantly the accuracy of the FCM algorithm.

In contrast to the basic FCM algorithm adopted by most relevant research practices the updated one may suit better the financial domain because:

- Coefficient $\mathbf{k_2}$ "normalizes" the FCM calculations based on incomplete information sets. The updated algorithm supports better the qualitative and trend-based financial planning, providing less conservative results. This normalization proves important at business domains mainly because:
- It relaxes the need for extra calculations of error margins as a result of incomplete background information,
- It provides reasonable decision modeling approximations without requiring extensive background financial analysis (e.g. complete estimation of bad loans, identification of all financial concept links, etc).
- Coefficient $\mathbf{k_1}$ results in smoother variation of concept values during the iterations of the algorithm.

5 FCM-based Strategy Map Scenarios in Financial Planning

In this section we present the use of the methodology and tool called FCM Modeler [11, 25–27, 83–88] in SMs in a real case studies in two banking institutions in which the proposed mechanism focuses on supplementing a typical financial strategy methodology by providing a holistic evaluation framework based on banking Profit & Loss (P&L) performance indicators augmented by external environment stimuli. In practice the mechanism supplements the recurring feedback loop between the current financial status, the future strategic objectives and the action plans for improving profitability (the action plan, in turn, affects the future financial status). This mechanism creates a strategy-level utilization of P&L model based on a qualitative and trend-based technique. The proposed mechanism actually generates two financial assessment flows:

- Flow A: "Current financial status analysis → Financial objectives" to estimate the gap between existing ("as-is") and future ("to-be") profitability and support the establishment of objectives which should bridge this gap.
- Flow B: "Action plans → Financial objectives" to estimate the impact of strategic change actions to the evolution of financial status, assess anticipated financial maturity and align financial objectives to meet any potential deviations.

During the third phase of this typical financial strategy formulation exercise, the top management of the bank sets the overall financial performance targets (measured by associated metrics). These targets are exemplified further to action plan performance targets (measured by tactical financial metrics) and then to operational financial performance targets (measured by operational financial metrics). All such targets and metrics present inherent relationships. In practice, overall financial strategy metrics must cascade to tactical financial metrics to allow the middle management to comprehend inherent relations among the different managerial levels of the bank. Similarly, tactical financial metrics must propagate up the overall financial metrics. While P&L inheritance is usually clear, external stimuli with no apparent relationships to financial indicators are not always well defined.

This paper proposes the utilization of such indicators (Fig. 1) to develop the FCMs and reason about the impact of strategic positioning changes to the desired ("to-be") financial models. The proposed mechanism utilizes FCMs to interpret:

- Financial metrics (P&L indicators, external stimuli, etc) as concepts (graphically represented as nodes),
- Decision weights as relationship weights (graphically represented as arrowhead lines),

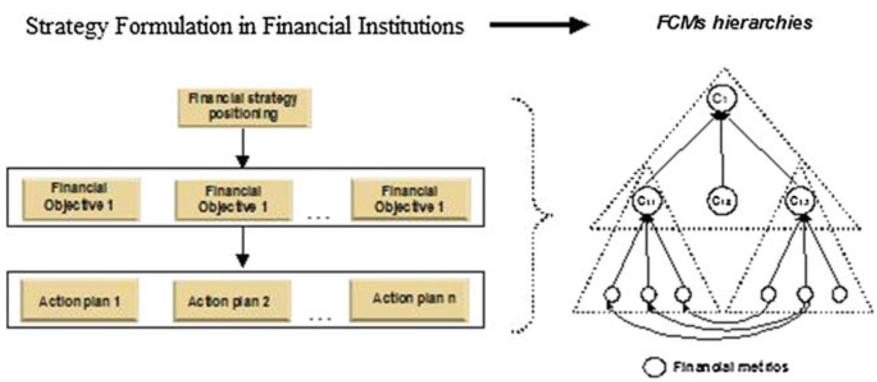


Fig. 1 Inherent relationships between financial strategy and FCM hierarchies

- Decision variables as financial concept values,
- Hierarchical decomposition (top-down decomposition) of financial metrics to constituent sub-metrics as a hierarchy of FCMs. This interpretation allows the stakeholders to reason about lower level FCMs first (constituent financial metrics indicators) before they reason about higher-level metrics (affected metrics).

The proposed mechanism supports reasoning about the overall or partial financial strategy implementation using indicators from the P&L philosophy. In contrast to [47], the proposed mechanism builds on hierarchical metrics interrelationships identified and utilized by the financial strategy formulation methodology. The proposed approach does not perform or guide the implementation of any stage of the strategy formulation methodology. Also, the approach does not perform or guide the estimation of the absolute value of any of the financial metrics and/or the overall P&L performance. It only allows the stakeholders to reason about the qualitative state of financial maturity metrics using fuzzy linguistic variables like high-neutral-margin, high-neutral-low impact of loans volume to income, etc.

5.1 FCM Map Modeling in Financial Scenarios

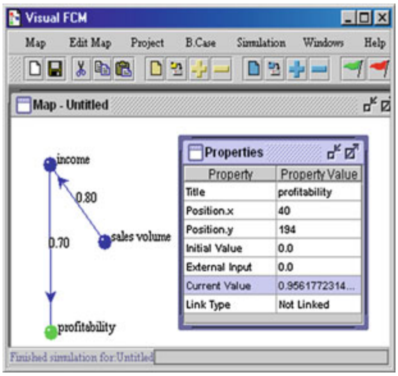
The following basic steps demonstrate the utilization of FCMs in ex-ante financial modelling and planning, that is modelling information flow "Action plans → Financial objectives".

- Step 1—Financial planning: Assume that a bank has already developed a strategic-level financial plan.
- Step 2—Skeleton FCMs: FCMs are constructed to interpret strategic objectives and actions to skeleton maps. Skeleton FCMs present concepts and links with no value assignments, in practice, generic P&L interconnections.
- Step 3—Weight value assignment: Bank experts are asked to provide linguistic weight variables for the map developed during the second step. Different weight value assignments generate different business cases for the same skeleton map.
- Step 4—Quantify potential changes: Stakeholders assign fuzzy linguistic input values to P&L concepts, to quantify potential actions.
- Step 5—Simulation: The FCM model simulates the impact of strategic changes (actions) to the financial objectives.

Similar steps demonstrate flow "Current financial status analysis → Financial objectives".

The following generic example demonstrates financial modelling using FCMs.

- Step 1—Financial planning: Assume that a bank has already developed a simple strategic-level financial plan. Assume that an objective asks for increased profitability. Also, assume that the financial plan proposes the increase of sales volume as the sole action to achieve this objective.



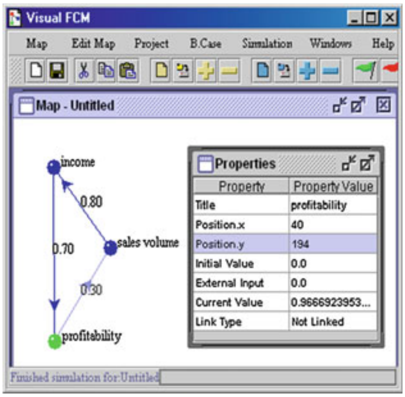
Concept	External input value (t=0)		Current Value	
	Change case A	Change case B	Change case A	Change case B
Sales volume	0.5	0.2	0.5	0.2
Income	0	0	0.8807	0.5986
Profitability	0	0	0.9561	0.8904

Fig. 2 Sample FCM calculations with no feedback loop

- Step 2—Skeleton FCMs: Utilization of the technique to interpret strategic objectives and actions to skeleton maps.
- Step 3—Weight value assignment: Experts provide linguistic weight variables which are interpreted to weight values (Figure , LHS)
- Step 4—Quantify strategic changes: Stakeholders assign input values to concept "sales volume" (Figure , RHS)
- Step 5—Simulation: The FCM model simulates the impact of sales volume changes to the financial objectives and outputs the estimated effect.

Figure depicts a graphical example with no feedback loops followed by sample numerical calculations using formula (2). This example assumes that $\mathbf{k_1} = \mathbf{k_2} = \mathbf{1}$ and $\boldsymbol{\lambda} = \mathbf{5}$ as the steepness of the normalization function. Setting the input variable of "sales volume" to "positively medium" (defuzzified to 0.5 or 50 %) triggers the FCM formula (1st case). A zero external concept value indicates that the concept remains neutral, waiting for causal relationships to modify its current value. A generic interpretation of the first case indicates that a "positively medium" increase in sales volume increases the income 88 % and the profitability by 95 %. In contrast, a "positively very low increase" in "sales volume" (defuzzified to 0.2 or 20 %) increases the income and the profitability by 59 % and 89 % respectively (2nd scenario).

Figure 3 presents a typical example of a feedback loop. Similarly to Fig. 2, changing the external input value of "sales volume" triggers the FCM formula. However, the feedback loop dictates that calculations stop only when an equilibrium state for all affected concepts has been reached, modifying all input values accordingly.



Concept	Initial input (t=0)		Current Value	
	Change case A	Change case B	Change case A	Change case B
Sales volume	0.5	0,2	0,81	0,5128
Income	0	0	0.9623	0,8860
Profitability	0	0	0,9666	0,9569

Fig. 3 Sample FCM calculations with feedback loop

6 Decomposition of Business Goals and Objectives at Different Organisational Levels

Every organisation has to set its strategy and objectives which in turn specify the goals to cascaded down the organisational hierarchy for each division, department, organisational unit up to the level of the individual manager. At this latter level Critical Success Factors for the achievement of corporate objectives and goals play a very important role. These factors are finally represented as measurable performance measures in job descriptions. In real life performance measurement and monitoring problems that affect organisational performance may arise. These problems are used as a feedback loop for readjusting goals and objectives in all organisational problems.

For issues of clarity we provide the following definitions on the concepts used in the strategic planning process (Fig. 4):

1. Critical Success Factors (CSFs): the limited numbers of areas in which satisfactory results will ensure successful competitive performance for the individual, department, or organization. CSFs are the few key areas where “things must go right” for the business to flourish and for the manager’s goals to be attained.
2. Strategy: the pattern of missions, objectives, policies, and significant resource utilization plans stated in such a way as to define what business the company is in (or is to be in) and the kind of company it is or is to be. A complete statement of strategy will define the product line, the markets and market segments for which products are to be designed, the channels through which these markets will be reached, the means by which the operation is to be financed, the profit objectives, the size of the organization, and the “image” which it will project to employees, suppliers, and customers.
3. Objectives: general statements about the directions in which a firm intends to go, without stating specific targets to be reached at particular points in time.

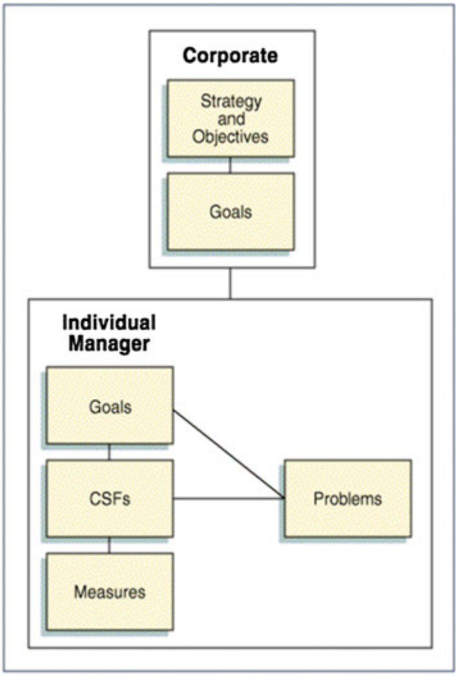


Fig. 4 Overview of the strategic planning process

4. Goals: specific targets which are intended to be reached at a given point in time. A goal is thus an operational transformation of one or more objectives.
5. Measures: specific standards which allow the calibration of performance for each critical success factor, goal, or objective. Measures can be either "soft"—i.e., subjective and qualitative—or "hard"—i.e., objective and quantitative.
6. Problems: specific tasks rising to importance as a result of unsatisfactory performance or environmental changes. Problems can affect the achievement of goals or performance in a CSF area.

6.1 Decomposition of Balanced Scorecards

Following the decomposition hierarchy presented in the previous section it is evident that if we use the balance scorecard technique in performance measurement then the same type of decomposition should be followed.

The picture bellow (Fig. 5) depicts the balanced scorecard decomposition in a real life case study of a retail banking division of a Bank. The division contains two departments. The Micro business and the Individuals. The high level balanced scorecard for the Retail banking division contains measures that are calculated fully or partially at lower level balanced scorecards in the other two divisions.

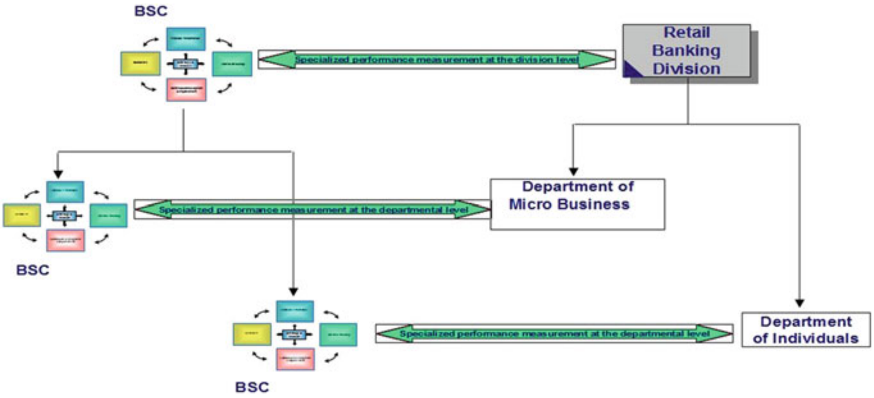


Fig. 5 Decomposed balanced scorecards

In the same way the measures and strategy maps for the retail banking division should be also decomposed in a similar way.

6.2 Decomposed FCMs-SMs

The current implementation of the proposed methodology tool encodes generic maps that can supplement the maturity modeling by storing concepts under different map categories, namely:

- Business category: all concepts relating to core financial activities.
- Social category: all personnel related financial concepts and external stimuli concepts.
- Technical category: all concepts relating to infrastructure and technology related expenses.
- Integrated category: all top-most concepts (e.g. a concept $\mathbf{C_i}$ with no backward causality such that $\forall \mathbf{j} : \mathbf{w_{ji}} = \mathbf{0}$), or concepts which may fall under more than one main categories.

The dynamic nature of the approach allows easy reconfiguration. Further P&L indicators may be added, while concepts may be decomposed further to comply with specialized analyses of the bank. This categorization is compatible with the P&L view of the bank to allow greater flexibility in modeling dispersed financial flows. The hierarchical decomposition of concepts generates a set of dynamically interconnected hierarchical maps (Fig. 6: Sample maps and map links).

Currently, the mechanism integrates more than 250 concepts, forming a hierarchy of more than 10 maps. The dynamic interface of the mechanism lets its user to utilize a sub-set of these concepts by setting the value of the redundant ones and/or the value of their weights to zero. Concepts and weight values have been obtained as follows:

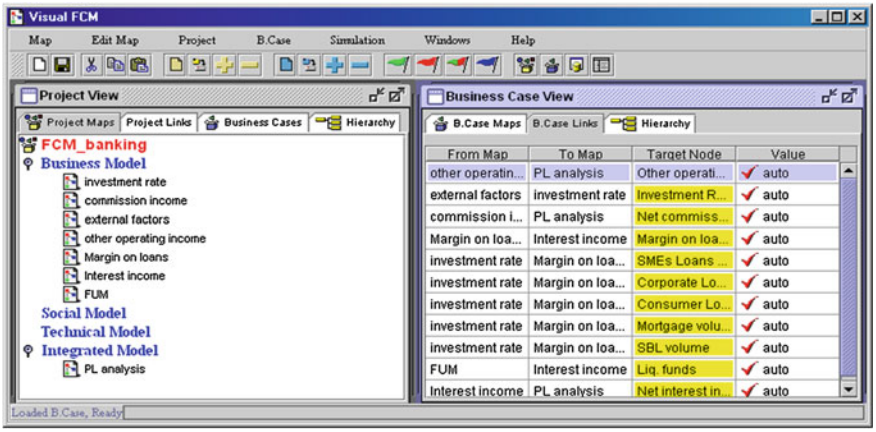


Fig. 6 Sample maps and map links

- Strategic-level financial plans of two typical (though major) E.U. commercial banks have been selected and analyzed.
- The interpretation of financial plans into FCM hierarchies using the technique presented has generated the skeleton maps.
- FCM hierarchies comply with the typical P&L reports of most financial sector enterprises.
- Financial sector and bank experts have provided weight values for skeleton FCMs.

It should be noted that as a working hypothesis for the FCM-based financial modelling, this paper adopted the operational and financial characteristics of typical/average European Union (EU) commercial banks, currently the majority of financial sector enterprises. Therefore, experts assigned values under the assumption that the market for intermediated finance was characterised by relationship rather than arm's length lending. Also, experts considered that fact that both banks operated in a bank-oriented (rather than a market-oriented) environment, in which banks predominated as financial intermediaries by collecting savings (through deposits) and providing the bulk of external funding to the non-financial sector.

6.3 Decomposed Scenarios with FCM Map Linking

A typical example of the interconnection mechanism in now commented briefly. Consider now maps "PL analysis" and "Interest income". Linking a concept, which is defined into two maps, generates a hierarchy. Figure presents the system interface for the generation of the hierarchical relationship between maps "PL analysis" and "Interest income". Map "PL analysis" decomposes further concept "net interest income" by using this concept as the link to map "Interest income".

$$a_i^{t+1} = f(k_1 a_i^t + k_2 * (w_{hi} a_h^t + \sum_{j=1, j \neq i, j \neq h}^{n} w_{ji} a_j^t))$$

$$a_h^t = f(k_1 a_h^{t-1} + k_2 * \sum_{j=1, j \neq h}^{n} w_{jh} a_j^{t-1})$$

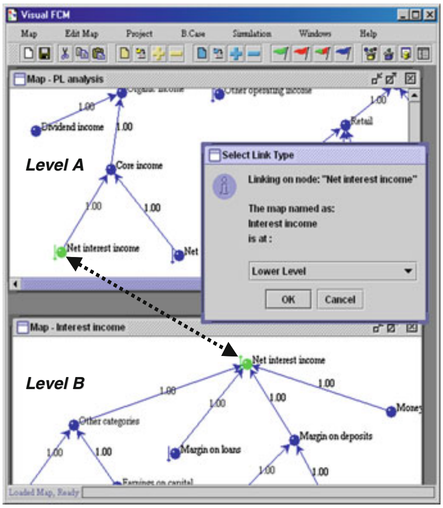


Fig. 7 Interconnection mechanism

Figure 7 also presents how algorithm (2) is decomposed to integrate hierarchical links. The proposed system can portray the financial model following either a holistic or a scalable approach. This is analogous to seeing the bank either as a single, "big bang" event or as an ongoing activity of setting successive financial targets to selected banking operations. The proposed mechanism can accommodate both approaches. Essentially, the implementation can decompose financial concepts to their constituent parts (sub concepts) on demand and let the user reason about lower level hierarchies of FCM before it passes values to the higher-level hierarchies. The proposed mechanism also allows the user to specify the degree of FCM decomposition during the map traversal (Fig. 8). Instead of waiting for a lower level FCM to traverse its nodes and pass its value to higher level map hierarchies, the user may assign directly an external value to nodes which link hierarchies. In practice, the simulation is carried out as if there are no links with other maps.

The following table summarizes the available variations of the proposed FCM algorithm, which encode dynamic map decomposition and user-defined decomposition bound.

Also the current implementation allows:

- Easy customization of the function **f** and easy re-configuration of the formula $\mathbf{A}_i^{t+1}$ to adapt to the specific characteristics of individual enterprises,
- Generation of scenarios for the same skeleton FCM,
- Automatic loop simulation until a user-defined equilibrium point has been reached. Alternatively, step-by-step simulation (with graphical output of partial results) is also available to provide a justification for the partial results.

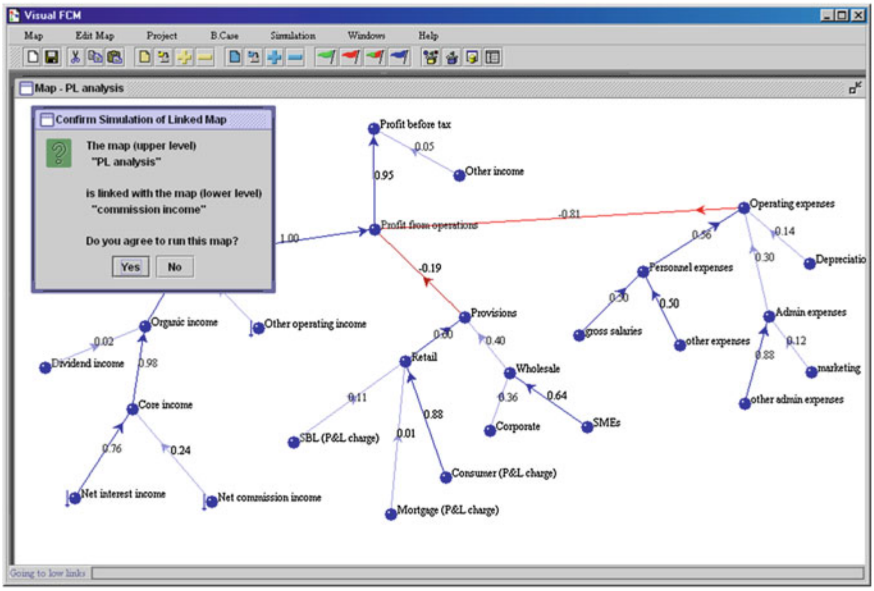


Fig. 8 User-defined map decomposition

Map decomposition	FCM algorithm hierarchical calculations	
	Higher level hierarchy	Lower level hierarchy
Unrestricted	$\mathbf{a_i^{t+1}} = \mathbf{f}(\mathbf{k}_1\mathbf{a_i^t} + \mathbf{k}_2*(\mathbf{w_{hi}a_h^t} + \sum_{j=1,j\neq i,j\neq h}^{n} \mathbf{w_{ji}a_j^t}))$	$\mathbf{a_h^t} = \mathbf{f}(\mathbf{k}_1\mathbf{a_h^{t-1}} + \mathbf{k}_2 * \sum_{j=1,j\neq h}^{n} \mathbf{w_{jh}a_j^{t-1}})$
User-defined, no external value assigned	$\mathbf{a_i^{t+1}} = \mathbf{f}(\mathbf{k}_1\mathbf{a_i^t} + \mathbf{k}_2*(\mathbf{w_{hi}a_h^t} + \sum_{j=1,j\neq i,j\neq h}^{n} \mathbf{w_{ji}a_j^t}))$	$\mathbf{a_h^t} = \mathbf{f}(\mathbf{k}_1\mathbf{a_h^{t-1}})$
User-defined, external value assigned	$\mathbf{a_i^{t+1}} = \mathbf{f}(\mathbf{k}_1\mathbf{a_i^t} + \mathbf{k}_2*(\mathbf{w_{hi}a_h^t} + \sum_{j=1,j\neq i,j\neq h}^{n} \mathbf{w_{ji}a_j^t}))$	$\mathbf{a_h^t} \in [-\mathbf{1}, \ldots, \mathbf{1}]$

The proposed framework exemplifies further financial performance by decomposing maps into their consistent concepts. The following sections exhibit sample (though typical) skeleton maps for all categories, which provide relevance and research interest to this paper.

7 Financial Planning Scenarios in Two Case Studies

The proposed tool was used extensively in two Retail Banks. Several planning scenarios were developed and simulated with the assistance and supervision of knowledge experts.

The majority of the financial concepts of these examples cascade to several constituent metrics. This allows the mechanism to express its reasoning capabilities by traversing complicated concept interrelations spreading over different maps and hierarchies. As an example, the FCM mechanism was asked to support the following decision problem: “is a certain change in interest rates and administration expenses and consumer charge, and FUM, etc, going to have a certain change in the operating income”. The first experiment involves a bank with limited retail market share seeking to penetrate the customer base of its competitors. The second experiment involves a bank with an established retail market presence seeking to enhance further its customer base. The following table presents sample actions/objectives, the associated nodes and their input/desired values.

Change action	Associated node	Input value—Bank A	Input value—Bank B
Increase FUM	FUM	0.65	0.9
Increase deposits	Deposits	0.8	0.65
Increase consumer P&L charge	Consumer P&L charge	0.1	0.35
Increase SBL margin	SBL margin	0.5	0.68
Increase other administration expenses	Other administration expenses	0.68	0.8
Increase interest rates	Interest rates	0.58	0.68
Etc	Etc	Etc	Etc
Objective	**Associated node**	**Desired value—Bank A**	**Desired value—Bank B**
Increase operating income	Operating income	$>$ positively high $\Rightarrow\ > 0.65$	$>$ positively high $\Rightarrow\ > 0.65$
Increase profit from operations	Profit from operations	$>$ positively very low $\Rightarrow\ > 0.21$	$>$ positively very low $\Rightarrow\ > 0.21$

For both cases, the Quanta tool iterated a subset of approximately 120 concepts spread over 10 sample hierarchical maps in order to calculate their equilibrium values.

Figure 9 compares two decision values for a set of nodes as estimated by the FCM mechanism and the team of experts respectively for the first bank.

Given the input values and Fig. 9, the following table presents the estimated impact of the change actions. These sample calculations indicate that if the actions are implemented as planned then the impact to the first objective will exceed the expectations. On the other hand, the impact to the second objective will not meet the expectations. Figure 9 also presents the values of other affected nodes for comparison purposes.

Similarly, Fig. 10 compares decision values as estimated by the FCM mechanism and the team of experts respectively for the second bank.

Given the input values and Fig. 10, the following table presents the estimated impact of the change actions. These sample calculations indicate that if the actions are implemented as planned then the impact to the first objective will marginally fail the expectations. The impact to the second objective will meet the expectations. Figure 10 also presents the values of other affected nodes for comparison purposes.

Fig. 9 Financial performance—Bank A

Objective	Associated node	Desired value	FCM estimation	Expert estimation
Increase operating income	Operating income	> positively high ⇒ > 0.65	0.698	0.780
Increase profit from operations	Profit from operations	> positively very low ⇒ > 0.21	0.120	0.100

Objective	Associated node	Desired value	FCM estimation	Expert estimation
Increase operating income	Operating income	> positively high ⇒ > 0.65	0.644	0.730
Increase profit from operations	Profit from operations	> positively very low ⇒ > 0.21	0.246	0.216

8 Discussion

8.1 *Theoretical and Practical Value*

The proposed modeling mechanism and the developed tool has contributed on managing performance in the the two case studies in real life. From a theoretical foundation point of view the theory developed enhances previous attempts as it:

- Allows the introduction of fuzziness in SMs with the use of fuzzy cognitive maps,
- Enhances the theory of fuzzy cognitive maps through the proposition of a new FCM algorithm,

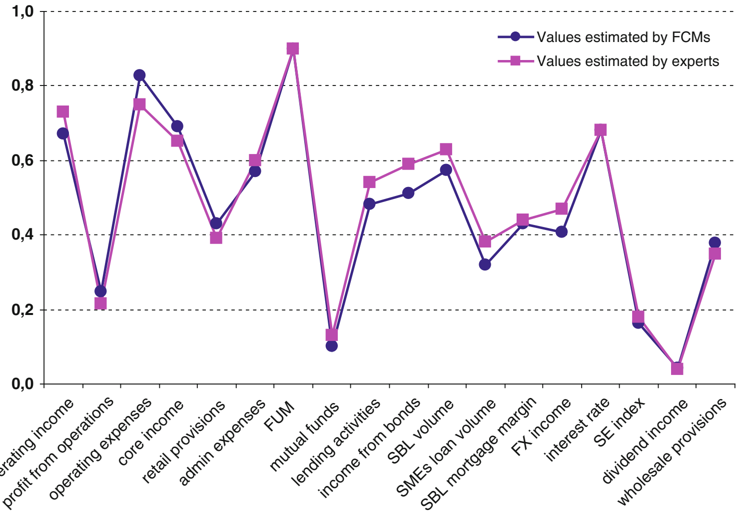


Fig. 10 Financial performance—Bank B

- Introduces the notion of linked nodes in different SMs which creates SM hierachies,
- Allows the introduction of simulation capabilities in FCM calculations and thus resulting in simulated scenarios in SMs with the time variant inherited in it,
- Allows dynamic scenario decomposition and reconfiguration, and thus dynamic SMs

Overall the proposed theoretical framework has provided solutions to most of the SM problems stated in the literature by researchers and proves that FCMs are one of the most suitable theories for Sms.

8.2 Added Value

Having established the theoretical and practical value of the proposed mechanism, it is useful to discuss also the added value of incorporating such a mechanism into SMs. It is the belief of this paper that the resulting tool provides real value to SM projects. For example:

- This decision aid mechanism proposes a new approach to supplementing SMs. It provides a qualitative though "intelligent" support during the business analysis and objectives composition phases of typical strategy formulation projects. It utilizes cognitive modeling and offers a strategy-level utilization of SMs in order to shift focus from quantitative analysis to strategy-level impact assessment.
- The main purpose of this approach is to drive strategic change activities for continuous improvement rather than limit itself to qualitative simulations.

- The mechanism eases significantly the complexity of deriving expert decisions concerning strategic planning. Informal experiments indicated that the time required by experts to estimate manually the extensive impact of major strategic changes to realistic SMs could impose considerable overheads. On the other hand the elapsed time for automated estimations using FCM decision support can be insignificant, onc strategy formulation projects should involve continuous argument of strategic change options (e.g. application of best practices, alternative scenarios, alternative customer focus, etc) until an equilibrium solution has been agreed by all stakeholders. Informal discussions with the principle beneficiaries and stakeholders of the two financial planning projects revealed that the proposed FCM decision support can reduce significantly the estimation overheads of financial maturity, letting the stakeholders focus on the actual planning exercise while exploring in depth all alternatives and controlling effectively major strategic change initiatives.
- The proposed mechanism can also assist the post strategic and operational planning evaluation of the enterprise on a regular basis. FCMs may serve as a back end to performance scorecards (e.g. [6, 36, 37]) to provide holistic strategic performance evaluation and management. However a detailed analysis of this extension falls out of the scope of this paper.

8.3 Preliminary Usability Evaluation

Senior managers of the two major financial sector enterprises have evaluated the usability of the proposed tool and have identified a number of benefits that can be achieved by the utilization of the proposed FCM tool as a methodology framework for financial planning. Detailed presentation of the usability evaluation results falls out of the scope of the paper. However, a summary of major business benefits (as identified by senior managers) is provided to improve the autonomy of this paper:

- Shared Goals
  - Concept-driven simulated SMs pull individuals together by providing a shared direction and determination of strategic change.
  - Shared SMs and performance measurement enables business units to realize how they fit into the overall business model of the bank and what their actual contribution is.
  - Senior management receives valuable inputs from the business units (or the individual employees) who really comprehend the weaknesses of the current strategic model as well as the opportunities for performance change.
- Shared Culture
  - Managers at all business units feel that their individual contribution is taken under consideration and provide valuable input to the whole change process.
  - All business units and individuals feel confident and optimistic; they realize that they will be the ultimate beneficiaries of the planning exercise.

  - The information sharing culture supports competitive strategy and provides the energy to sustain this by exploiting fully the group and the individual potential.

- Shared Learning
  - Top management realizes a high return from its commitment to its human resources.
  - There is a constant stream of improvement within the company.
  - The company becomes increasingly receptive to strategic changes, since the benefit can be easily demonstrated to individual business units.

- Shared Information
  - All business units and individuals have the necessary information needed to set clearly their objectives and priorities.
  - Senior management can control effectively all aspects of the strategic re-design process
  - The bank reacts rapidly to threats and opportunities.
  - It reinforces trust and respect throughout the bank.

Summarizing, experimental results showed that FCM-based *ex ante* reasoning of the impact of strategic changes (actual or hypothetical) to the status of business performance can be effective and realistic. This is considered to be a major contribution of the proposed methodology tool to actual strategic change exercises.

9 Conclusions

This paper presented a supplement to SMs based on FCMs. This decision aid mechanism proposes a new approach to supplementing current status analysis and objectives composition phases of typical strategy formulation projects, by supporting fuzzy cognitive modeling and "intelligent" reasoning of the anticipated impact of strategic change initiatives to business performance. The mechanism utilizes the fuzzy causal characteristics of FCMs as a new modeling technique to develop a causal representation of dynamic SM principles in order to generate a hierarchical network of linked performance indicators based on critical success factors.

This paper discussed the FCM approach in putting realistic and measurable objectives in strategic planning projects and presented sample maps with causal relationships. Preliminary experiments indicate that the mechanism does not provide fundamentally different estimates than expert decisions. Moreover, the decomposition of financial metrics into their constituent parts supported reasoning of the strategic performance roadmap. The main purpose of the mechanism is to drive strategic change activities rather than limit itself to qualitative simulations. Moreover, the proposed mechanism should not be seen as a "one-off" decision aid. It should be a means for setting a course for continuous improvement [48].

Future research will focus on conducting further real life experiments to test and promote the usability of the tool, but also to identify potential pitfalls. Furthermore, future research will focus on the automatic determination of appropriate fuzzy sets (e.g. utilizing pattern recognition, mass assignments, empirical data, etc) for the representation of linguistic variables to suit each particular project domain. Finally, further research will focus on implementing backward map traversal, a form of abductive reasoning [20]. This feature offers the functionality of determining the condition(s) $\mathbf{C_{ij}}$ that should hold in order to infer the desired $\mathbf{C_j}$ in the causal relationship $\mathbf{C_{ij}} \xrightarrow{\mathbf{w_{jk}}} \mathbf{C_k}$. Incorporating performance integrity constraints reduces the search space and eliminates combinatory search explosion. Backward reasoning has been tested extensively in other applications and its integration in the proposed methodology framework may prove beneficiary.

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Chapter 18
The Complex Nature of Migration at a Conceptual Level: An Overlook of the Internal Migration Experience of Gebze Through Fuzzy Cognitive Mapping Method

Tolga Tezcan

Abstract Turkey has experienced a major wave of migration since the early 1950s. Although many studies have tried to investigate how social dynamics and identities play a role in the migration phenomenon in urban areas, none of them have analysed this through a model that allows to present perception of migrants and the phenomenon of migration from the point of view of social groups at a conceptual and relational level. This study conducted in Gebze proposes to analyse FCMs based on modelling position and perception that shows how migrants locate one another in the city and the migration phenomenon. The findings of this study suggest that since experiences and perceptions differ according to social categories, social inequalities caused by and/or leading to migration become visible and more comprehensive from the perspective of different social categories of migrants.

Acronyms

FCM	Fuzzy cognitive mapping
CM	Cognitive mapping

1 Introduction

Migration is generally considered as a demographic event or presentation of problem patterns via reflections of urbanization. Although many studies have tried to investigate how social dynamics and identities play a role in the migration phenomenon in urban areas, none of them have analysed this through a model that allows to present

T. Tezcan (✉)
Scientific and Technological Research Council of Turkey (TUBITAK), Kocaeli, Turkey
e-mail: tolga.tezcan@tubitak.gov.tr

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a perception towards migrants and the phenomenon of migration from the point of view of social groups at a conceptual and relational level. The way migrants place themselves, one another and migration itself is not independent of historical experience and daily practices. In this study fuzzy cognitive mapping (FCM) approach is presented in order to understand historical experiences of migration that have reflections on daily practices and identify the causal charachteristics of the migration issue. In order to understand the migrants' perceptive positions in Gebze where 95 % of the population is placed on the scale of migrants, 300 face-to-face FCM interviews were conducted. This study proposes to analyse FCM based for modelling position and perception that how migrants locate one another in the city and the migration phenomenon. FCM, knowledge-perception based method suitable to model complex issues, can encode the most important factors necessary for understanding migration according to different social categories. This study also introduces FCM and proposes a theoretical framework for using it in social studies. The findings of this study suggest that since experiences and perceptions differ according to social categories, social inequalities caused by and/or lead to migration become visible and more comprehensive from the perspective of migrants.

The outline of this paper is as follows. Section 2 presents a short literature overview of internal migration experiences of Turkey and its theoretical background. Section 3 gives the main aspects of cognitive mapping (CM) and FCM theory, and steps of FCM analysis. Section 4 displays the resulting data; Sect. 5 displays data analysis. Results are shown in Sect. 6; discussion of the results is illustrated in Sect. 7. Finally, Sect. 8 contains a conclusion of the paper and brief directions for future research.

2 Internal Migration Experiences of Turkey

Gebze is a district of Kocaeli which is located on the northern bay of İzmit in the east of the Marmara region. Gebze, half way between Kocaeli and İstanbul, has an advanced industry with its 11 Organized Industrial Zones [12]. According to research carried out by the State Planning Organization, Gebze takes its place among the Primarily Developed Provinces [9]. However, the developed industry of Gebze has become a reason to ignore the factor of labour in almost all aspects and the inhabitants of Gebze who have experienced migration at all levels of difficulties in order to provide a labour force may not have been analyzed in detail. Even only in this respect, it is essential that the abstraction level of development be changed from industry to individual-urban relationship.

Turkey has experienced a major wave of migration since the early 1950s. In parallel with the mechanization of agriculture and attempts in urban industry, education and healthcare, which increase quality of life, are among the main reasons for migration that cities instigate. Cities where production is based on industry need the labour force as new financial areas and are centres of push factors with their varied living structures and areas. On the other hand, rural areas accommodate pull factors with the lack of facilities that are offered. However, it is not enough to explain migration around push and pull factors as stereotypes of traditional sociological explanations, which in turn gives the impression that a theoretical picture is forced upon the framework of migration, rather than showing the larger picture of the situation.[1] More importantly, it has been observed that perception of migrants about urban areas; city-dwellers about migrants, and migrants about other migrants, has been trivialized through analysis conducted on the reasons for migration. Beyond this, integration within cities is presented as an a *priori* category and in cases where this integration cannot be provided the migrant is defined as a subject of "crime" and the city and city-dweller as the victim. Although there is remarkable amount of accumulated knowledge on migration in Turkey, it is possible to assert that there has been an epistemological crisis in definition of the term of migration. Focussing on the reasons for and results of migration rather than evaluating migration as a process has deepened this crisis even more. There is the possibility of placing diversities of migration (internal, external, forced, voluntary, etc.) on unfounded grounds without analyzing migration processes. There are great number of results of migration, as well as the reasons for it, on the basis of the system where rural transformation dissolves social classes and reconstructs them, and where urbanization serves new life instructions, a nation-state model and modernity transform identities. Because of both its reasons and results, it also creates a process [15]. In this respect, migration should be defined through reason, result and process as well. Yalçın [61, p. 19], who has combined many definitions of migration, defined migration as

> aiming geographic, social and cultural relocation movement from one place to another for short-term, medium-term or long-term periods with the purpose of either returning or settling permanently because of financial, political, ecological and personal reasons.

This comprehensive definition is based on reasons and excludes the aspects of process and result. In addition to Yalçın's casual definition, migration, as an intention of relocation and rush to lead a better life, is defined by us as a movement of desire to move up to a higher class where personal and social identities are reconstructed, combined, conflicted and/or synthesized; work relations and class positions are changed; new formal or informal lines of business are created and all these social relationships are repeated by continuous transformation with attempts to create equality for periphery-core tension. It is beneficial to consider this way of thought, where the migration phenomenon is reduced to movement, along with Spinoza's "motion". According to Spinoza, each body is constantly in motion and their separation from each other, or being considered separately, depends on their capability of movement. The representation of mobility is formed according to other bodies' mobility or immobility [17]. Constructively, the essence of each movement depends on another movement and is meaningful within these two movements. What creates this essence is the mobility in itself. It should not be forgotten that each personal and social movement is meaningful within other mobility/immobility. Migration is generally considered as a demographic event or presentation of problem patterns via reflections of urbanization. However, this complicated process should be considered along with all its

[1] For push-pull factor conceptualization: Lee [30].

mobility and immobility and the complete process that has an effect on all social structures should not be ignored.

There are four different approaches to analyzing migration [56]. In the first approach, migration occurs in order to reduce social inequality and thus maintaining the social balance. If migration exists in a region, it should be regarded as a step taken to reduce inequality. It is assumed that once the inequality is solved, migration will end. If migration is still in progress, either there is not enough migration or inequality persists. In the second type of analysis, migration occurs as a one-way harmonious movement parallel to social changes. The most widely known example of this is the migration from rural to urban areas as a result of industrialization. Migration theories are defined as a movement generally from underdeveloped regions to developed ones. On another level, migration would occur from areas where labour was plentiful to areas where there is lack of labour and thus underdeveloped areas would develop quickly [23]. The third type of analysis emphasizes the fact that even though there is no social inequality, migration based on social role choices will always take place. The last approach places the political process at the centre. In this process either migration is encouraged or policies are developed to prevent migration. Migration analysis states that each individual has her/his own free will. However, as Kaya [21, p. 24] comments

> Almost all migrations, whether for financial, social, ethnic, religious reasons or because of terror or natural disasters, have a forced nature. Almost all migrations have inherent poverty, deprivation, social and political exclusion in themselves.

In the industrialization process, relocation from urban to rural areas is a structural process and cities are considered as factors responsible for the elimination, reduction or transformation of the reasons for migration. In addition, because of the populist policies of a multi-party system of Turkey, the migration movement which started in 1950s coincided with the era when cities were not prepared with their infrastructures and superstructures. In one sense urbanization in Turkey has not improved alongside the same development in developed countries. Thus, migration has been a process which developed under compulsory conditions and improved with political guidance.

One of the major areas which migration studies focusses on is the problem of the livelihood of migrants and locals, adjustment to “cultural harmony” and the “adaptation” of migrants to city life. The aspect which is different in Gebze, if there is a cultural conflict to be mentioned, is the conflict not between the locals and the migrants but among the migrants themselves. According to a survey conducted on family members in this research scope, only in 5 % of the population either the individual or any of the family members are not migrants. If we consider this 5 % populace as locals, the remaining 95 % is placed on the scale of migrants. When quantitative minority of locals is considered along with quantitative majority and diversity of the migrant population, locals not showing any kind of resistance is understandable. Parallel to this, according to research conducted in İstanbul, the competition within the city is not between the new settlers and the locals in İstanbul but between the new settler groups from the same cities [10]. In this respect, in this study we try to present how migrants locate one another in the city and the migration phenomenon by using FCM.

3 Fuzzy Cognitive Mapping Theory

FCM, which has been on the agenda of social sciences since the 1960s, is a tool in many disciplines. While psychology uses FCM to model social and and psychological processes [8, 57], political sciences utilise it to reveal conflict analysis [2]. It is also used for clarifying vague cognitive images by electronic systems [28]. Educational sciences create metaknowledge and explore hidden implications of learner's understanding through FCM [7]. In order to model business performance indicators, industrial management has used FCM [20]. Environmental sciences also use this method, through anthropology, political sciences, management and computer systems literature, in a social impact framework [26, 27, 37, 38, 40]. FCM has been successfully used for modelling and decision-making in medicine [42, 44–47].

Cognitive mapping (CM), introduced by Axelrod [2], is a representation of the causal relationship among concepts. FCM, introduced by Kosko [29] has been constituted as the extension of CM. CM could be generalized into FCMs by fuzzifying causality values [31]. For this reason, the clarification of CM theory will be beneficial to understand FCM. In this section, firstly theoretical background of CM will be clarified, secondly FCM will be discussed and finally the strengths and weaknesses of FCM will be argued.

The purpose of CM is to visualise the structure and process of people's perception and collect modes of thought on issues together with their causes under a single complete perspective in a holistic manner [11]. There are causal relations among concepts at different levels and a participant formulates a theory depending on her/his method of interpretation by associating the causal relations with the concepts in her/his mind. Furthermore, even concepts with no relation also have hidden relations. Kosko [29] claimed that it discovers the hidden relationships among concepts. In other words, the appearance of some concepts on maps in an unrelated way accounts for another form of relation. This method tries to perceive the subjective world instead of revealing the objective truth. In this respect, this method focusses on understanding the nature of complexity [34]. This method is unique, in that it not only focusses on the consensus of the group but also examines the roots which discrete thoughts draw on [18, 49].

Cole and Persichitte [7, p. 2] argued that defining FCM requires the basic understanding of the theoretical foundation of CM:

> FCM combines the strengths of cognitive maps with fuzzy logic.

Since FCM has been constructed upon CM, FCM contains theoretical background of it. FCM, a method for analyzing and depicting human perception of a given system, forms the typology of thought, knowledge, experience and political perspectives. [42] It is a method to construct models, behaviour of any system, based on participants' perception and experience.

> FCMs represent knowledge in a symbolic manner and relate states, processes, policies, events, values and inputs in an analogous manner [1, p. 27]

FCM

> describes different aspects in the behaviour of a complex system in terms of concepts; each concept represents a characteristic of the system and these concepts interact with each other, showing the dynamics of the system [33, p. 2].

On this issue, Papageorgiou and Kontogianni [43, p. 443] argued that

> FCM represents a system in a form that corresponds closely to the way human beings perceive it.

In a general view, FCM is used for structuring perceptional processes. Also it is a tool for creating metaknowledge and exploring hidden implications of the studied issues [7].

FCM has been used as a knowledge acquisition scheme [25]. It displays a thinking system through a graph showing a cause and effect. FCM allows graphical representation to make visible which concept influences other concepts by displaying interconnections between them [43]. FCM is based on causality; it is a method of symbolic representation for modelling of a system which covers domain-specific knowledge and experience [48]. At this point it can be asserted that the concepts, their mode of articulation and their relationships with other concepts in FCM based on causality reveal the positions in the system [39]. In this respect, FCM, a combination of fuzzy logic and neutral networks, allows the fuzzy causal relations among concepts to be identified and their effect to be constructed [31]. FCM has a capacity to represent unstructured knowledge through causalities [24]. Fuzzy logic claims that everything is a matter of degree:

> Instead of variables/answers in a system being either 'yes' or 'no' to some user-specified question, variables can be 'yes' and 'no' to some degree [16, p. 205].

The most crucial feature of FCM is that the model demonsrates which concept influences which other and to which degree [47]. In FCM, the edges take values in intervals $[-1, 1]$ representing the degree of causality. A value of -1 represents full negative, 1 full positive and 0 denotes no effect. Instead of using only sign (positive or negative), each edge is associated with a weight that determines the degree of the relationship in FCM [54].

The concern of CM is to analyse whether one of the concepts is perceived to have an influence on another with positive or negative links [32]. For Zhang et al. [62] CM has more general represantations than fuzzy relations. The main difference between FCM and CM is that while FCM models causality with fuzzy logic, the latter constructs a semantic relationship between concepts. In other words, FCM models causality, not merely semantic relationships [53]. CM has a limitation to quantify relationships among variables. Fuzzy logic is a solution to this weakness and enhances CM [5]. Since causal relationships are fuzzified, relationships among concepts do not only represent positive or negative causality, but also the degree of the relationships are identified [58]. FCM displaying type (positive or negative) and magnitude (degree) of influence is much more reliable due to its measurable and comparable features than CM.

On the basis of Kant's system of thought it can be observed that the ability of interpretation is dependent on time and space. The mind has prior forms of time and place and no other template is possible except for those. When external diversity, which is perceived in the form of time and space, starts to be conceptualized, categories of thought are involved in the process thus resulting in the rise of causality [19]. In addition to causality, meaning consists of paradoxes and comparisons which cannot be separated from context. A mode of articulation based on causality and comparison also reveals the systems of thought [4]. It is better to consider FCM method in a discursive content rather than as a positivist instrument. Text and discourse are the primary concepts that social sciences refer to. However, in general, discourses are turned into self-evident data by citing them outside the context. While presenting a problem based discourse analysis, it is essential that this framework is created through relationships within and among texts dependent on history and conjuncture [60]. As an analytically-contextualized method, FCM appears on the grounded theory range [13]. It is also possible to analyse FCM method in a phenomenological approach [14]. Phenomenology forms a counter position to positivism, which claims to be a scientific field in two main aspects. The first is the "comprehension reflex" to understand society through the laws of nature and the second is research methods of positivism [52]. Contrary to the assumption that reality is perceivable and always produces the same effect in all forms of time, place and culture as a law of nature, phenomenology creates subjectivity and interpretational strength in the researcher. However, FCM draws its interpretational strength from existentialist phenomenology based on participation rather than transcendental phenomenology separated from the mundane [50]. Each participant provides the researcher with the possibility of transition by conducting her/his own personal theory [22].

For Samarisinghe and Strickert [51], there are three advantage to using FCM. The first is that FCM is easy to build and give qualitative results. Secondly, FCM does not require expert knowledge, it can depend on simple observation by participations. Also according to Papageorgiou and Kontogianni [43] FCM models are easily understandable, even by a nonprofessional audience since each parameter has a perceivable meaning. Finally, FCM provides a summary of relationships among concepts that enhance both quantitative and qualitative predictions. FCM is a semi-qualitative method, in other words, it is a blend of qualitative and quantitative approach [43, 51]. FCM attempts to capture the holistic picture of the issue in both quantitative and qualitative meaning, for this reason, FCM could be evaluated as a mixed method.

The most commonly criticized aspect of FCM is its restrictive generalisation due to small sample size. Another criticism is the use of ungrounded assumptions. Although the first criticism is true to some extent, it is against qualitative methods in general meaning and the sample structure can be expanded by taking all the demographic elements into consideration. The second criticism is an attitude developed which opposes information gathering strategies free from the related method. This criticism can also be minimized by using different methods in the same research.

4 Research Data

4.1 Method

In order to understand the perceptive positions of the inhabitants of Gebze on migration, face-to-face FCM interviews were conducted. Gender, age, educational background, occupation and socio-economic status which form the sample quotas, were recorded. During the interviews, the participants were first shown a sample of FCM, which would not affect their perception of migration and the connotations of the concepts, and their relationships were explained. There are two structured elements in FCM interview. The first is the research question. According to the abstraction of research structure, the question designed for the research should not be manipulative and no other question should be directed to the participant during the interview. The second is the central concept, which the participants will correlate, which should be appropriate for the research question and be as brief and clear as possible. Participants should be able to relate to the concepts in three main ways; from the central concept to the periphery concepts; the periphery concepts to the central concept; and the periphery concepts to the periphery concepts. These relations can either be one-way or dual. These relations are graded by the participants on a scale of $+3$, $+2$, $+1$, -1, -2, -3; to show the strength of the relation. The scales are defined as follows (Table 1):

In the research, as a response to the question "Which concepts can come to mind when you think about migration? Would you please list and map these concepts?" the participants first produced their answers in monologues and then connected the other concepts to the central concept "migration" with values $[-3, 3]$. At this point, in order not to interfere with the participants' perceptions of migration, no additional questions were asked. To summarize the FCM interview process, participants firstly identify key concepts, secondly they identify the causal directions (positive or negative) among concepts and finally they estimate fuzzy values of the directions [41].

The participants were requested to clarify any ambiguous concepts in their speech. Upon completing the mapping, the participants were asked to perform a 3–5 min general presentation of their own maps and notes were taken by the researcher. Later on, the researcher contributed to the analysis by preparing reports on each map.

4.2 Sample

Initially, the aim of the research was to conduct interviews with 300 people but in the end a total of 330 people participated in it. When choosing the sample, the 31.12.2009 dated Address-based Population Registration System of Turkey was used. Three age groups of 15–24, 25–40, 41–60 and gender were classified according to the Address-based Population Registration System and socio-economic status

Table 1 FCM scales

[+3]	Considerable positive effect/considerable increase
[+2]	Medium positive effect/medium increase
[+1]	Slight positive effect/slight increase
[−1]	Slight negative effect/slight decrease
[−2]	Medium negative effect/medium decrease
[−3]	Considerable negative effect/considerable decrease

Table 2 Distribution of the sample

	Women					Men			
	AB	C	DE			AB	C	DE	
	7.4 %	40.4 %	52.2 %	Total		7.4 %	40.4 %	52.2 %	Total
15–24	3	16	20	39	15–24	3	15	19	37
25–40	5	25	33	63	25–40	5	28	35	68
41–60	3	18	23	44	41–60	4	20	25	49
Total	11	59	76	146	Total	12	63	79	154

(SES) groups according to DATA-SGT [59] data. Interviews with more than 10 % of each sample quota were held and on completion of the face-to-face surveys, more interviews were omitted randomly according to the SES group range in Gebze. In the sample, the SES group range of Gebze was used. A represents upper class, B upper-middle class, C1 middle class, C2 lower-middle class and DE lower class. In the study, A and B were combined as AB and C1 with C2 and categorized as C. The distribution of the 300 participants according to age, gender and SES is illustrated in Table 2.

4.3 Analysis

FCM analysis is made up of three stages.

4.3.1 Condensation and Numbering

The effective way to better understand the structure of complex individual FCMs is to condense them. It is a method of simplifying individual maps by grouping concepts in order to construct social (collective) map(s). Qualitative condensation (also known as aggregation) suggested by Özesmi [36] allows to combine concepts that are represented by a larger encompassing concept. In qualitative condensation, condensed concepts emerge from themes that have stated by the participants but also from their relevance to larger theoretical framework of studied issue [39]. For instance Özesmi and Özesmi [39] condensed 253 concepts into 17 condensed concepts in their research. Nukurama et al. [35] condensed 152 concepts into 16 condensed concepts; Kontogianni et al. [26] condensed 52 concepts into 26 condensed concepts. Because the sample is comprised of 300 participants and this study adopts a sociological approach to analyse similar and different perceptions towards migration issue, more condensed concepts were needed compared to referred researches. In this study 2304 concepts were condensed into 77 condensed concepts.

After all the maps are analyzed, condensed concept number, with a high abstracted level including all concepts, is set. To illustrate, concepts like "Education" and "School" are all grouped under the concept "Education Opportunities". Once the individual FCMs are drawn, they are aggregated in a qualitative way to produce social FCM. By doing so, the most central concepts with their weighted relationships are illustrated [43]. Since individual FCMs vary with respect to the number of concepts and connections, reducing the number of concepts by nesting them into upper level themes of similar concepts is required [51]. It is crucial that not only the concepts but also their relations should be examined. Otherwise, when concepts are examined free of their relations, a different connotation could be obtained. Condensed concepts also should preserve the essential dynamics of the system. A total condensed concept number was set, and these numbers are assigned to the concepts on the maps. Numbering is the stage that facilitates the data entrance process on the matrix.

4.3.2 Data Entrance on the Matrix

After numbering each concept on each map, pages equivalent to the number of interviews are opened on the matrix programme. All the relations on a map are entered as Table 3. FCMs are transformed into adjacency matrices where the condensed concepts are listed on both vertical and horizontal axes to form a square matrix.

Values (weights) are normalized to the interval $[-1, 1]$ that means relationships among concepts are true to some degree, neither wholly true nor false [7]. According to Bertolini [3] in order to describe the degree of the relationship between concepts, fuzzy linguistic terms, such as 'often', 'always', 'some', 'a lot' etc. can be used. Also it is suggested to use seven linguistic variables; very very low, very low, low, medium, high, very high, and very very high [43]. Value can be a fuzzy value within $[-1, 1]$ where -1 indicates a negative relationship and 1 a positive relationship. Values are converted as 3 to 1; 2 to 0, 5 and 1 to 0, 25.

At this stage, as a final step another page could be named as "all data" is opened on the matrix programme and all the relations of the maps are summed up. To analyse demographic groups such as "male", "female", "15–24 age group" etc., other pages could be opened.

Table 3 FCM matrix sample

	Migration (1)	Education opportunuties (2)	Health facilities (3)	Infrastructure problems (4)	Inequality (5)
Migration (1)		2	2	−2	3
Education opportunities (2)	3				−2
Health facilities (3)					
Infrastructure problems (4)					3
Inequality (5)	3	−3	−2		

5 Data Analysis

The file that contain all the relations of all the maps is copied onto the Matrix page of FCMappers Excel Macro[2] and analysis files are created following the appropriate instructions.

5.1 Centrality Analysis

The relation directed from concept A to concept B increases the "outdegree" value of concept A and "indegree" value of concept B. The total sum of outdegree and indegree value produces the "centrality" value. Kosko [29] describes centrality as a measure of determining the significance of concepts. Centrality is a sum of relationship values (indegree and outdegree). The centrality value of a concept represents the size of the correlation that the concept has in relation to other concepts. In other words, centrality illustrates the importance of concepts. A concept with a high centrality value reflects its importance in participants' perception. While the concept with a high outdegree value has active, effecting, inverter and altering aspects, the concept with a high indegree value indicates less active phenomenon and situations. In this respect, as well as the centrality value, the outdegree and indegree values of centrality values are also of importance as the active or the passive use of a concept is a trait that reflects the fictional style of thought. According to Papageorgiou and Kontogianni [43, p. 432],

> Centrality shows how connected the variable is to other variable and what the cumulative strength of these connection is.

[2] FCMappers Excel Macro could be downloaded from: http://www.fcmappers.net.

In order to form the centrality tables the “Calculate Indices” function on FCMapper Excel Micro was used. When creating centrality tables to compare the demographic structures/patterns, a certain level is set and any concept below this level is deleted. While the structures with the highest concept level are investigated, the concepts which do not appear on any of the tables are detected. The demographic structure that inhabits these marginal concepts becomes significant and these marginal concepts become specific to the demographic structure.

5.2 Cluster Analysis

Cluster analysis reveals which concepts appear on the same maps. Independent of whether the concepts have any relation or not, the concept clusters that are used together are shown. SPSS or MINITAB programmes can be used for cluster analysis. Since MINITAB allows graphical representation of concept clusters, MINITAB is suggested to use for cluster analysis of FCM.

5.3 Social Map

The social map is a means of collective presentation that shows the relation frequency between concept A and concept B rather than all the relations that are directed to and from concept A. A Social map is potentially stronger than an individual maps, since the perception/experience/knowledge are derived from a multiplicity of sources that makes point errors less likely. Also the social map includes all knowledge weighted by a measure of confidence in the source [55].

The file formed by “Make net file” function is opened with a Pajek program and the social map is produced. While the width of lines describes the strength of the relation, the interrupted lines reveal negative relations. Also each relation has a value could be named as “strength of the causal relation” (SCR). For instance if the SCR, directed from A to be, is 5, that means sum of the values of relations which are directed from A to B is 5. Higher SCR of the relation directed from A to B indicates that more relations are established between the related two concepts. In other words, each directed relation is associated with a value (weight) that quantifies the strength of the causal relation.

The reason why a concept with a high centrality value does not appear on the social map is that the correlated concept has a dispersed pattern. In other words, mentioned concepts with multiple relational structure affect different concepts or in turn are affected by them rather than affect the same or affected by them. To illustrate, while the relation between “Employment” and “Unemployment” reaches its peak, “Quality of life” is associated with many concepts and the relations are dispersed. This indicates that the concept “Quality of life” does not have a rooted correlation with another or other concepts and has abundant discursive structure. These types of concepts are candidates for a new research topic via FCM.

The social map is based on a semi-subjective decision. A scale which is supposed to represent all of the relations is set and the remainder is omitted from the map. The general tendency of the participants in mapping is to link centre concepts to periphery concepts and periphery concepts to centre concepts. Periphery to periphery relation is as significant as centre-periphery or periphery to centre relation as the relations surrounding the central concept enable the evaluation of the periphery concepts within each other. Generally, periphery to periphery relation values are lower than centre to periphery or periphery to centre relation values. In order to prevent data loss, a value representing the whole relation is set, while a lower value is designed for periphery to periphery relations.

The social map is produced in two stages. The first stage involves the proportional inclusion of the demographic structures in order that the sample group can represent the universe. In the second stage, the values are divided by the number of the participants in the stated demographic structure in order to provide a comparison of demographic structures within each other. To facilitate the comparison the values could be divided into a 1/10 scale, depending on the number of participants. On a larger scale sample, the division of values by the number of participants does not pose a problem for comparison.

6 Results

6.1 Social Maps and Centrality Tables Analysis

In this section, social map analysis and centrality tables of FCMs will be examined and demographic categories will be compared. In addition, in order to produce concept typologies, outputs of cluster analysis will be evaluated.

Young people think that "Education opportunities" increase migration most (SCR: 36). In addition to this, migration itself also affects "Education opportunities" in a positive way (SCR: 8). Migration, however, also increases the "Lack of education" (SCR: 5). While young people consider education as an opportunity in urban life, they think that education is not available for every migrant. "Employment" and "Unemployment" are two opposing concepts. The main cause of migration for young people is mainly "Unemployment" (SCR: 28) rather than "Employment" (SCR: 19). As a surprising outcome, migration itself is also a concept that increases "Unemployment" to a great extent (SCR: 14). It is better to consider this relation alongside "Population density". Migration increases the "Population density" (SCR: 12). Migration is not considered as the movement from one place to another but as a population group creating surplus in another place. On the one hand, migration proliferates "Shanty housing" (SCR: 4) and "Unplanned urbanization" (SCR: 7); on the other hand, it increases the "Adaptation problems" (SCR: 7). Therefore, "Shanty housing" is not considered as a place where inhabitants can adapt and prepare for city life. According to young people, shanty housing dwellers still do not appear on the urban dweller position.

The reason why two close concepts like “Cultural diversity” and “Cultural change” exist is because of the emphasis on the difference in participants’ statements. From the viewpoint which considers the state of being cosmopolitan as wealth and cultural cohesion collected around the concept “Cultural diversity”, negative references such as corruption, conflict and cultural disunity are put in the “Cultural change” concept. From the viewpoint of young people, migration leads to both “Cultural diversity” (SCR: 8) and “Cultural change” (SCR: 7). Consequently, there does not exist a single point of view on the cultural effect of migration. In addition to this, “Exclusion” (SCR: 6) and “Chaos” (SCR: 6) also increase with migration. Such interferences of urban life on culture are reflected in relationships with family/relatives and affect these relationships in a negative way (SCR: -5).

Relations directed towards the migration concept can be interpreted within the scope of reasons of migration. The most significant reasons for migration are “Education opportunities” (SCR: 36), “Unemployment” (SCR: 28), “Poverty/Financial problems” (SCR: 25), “Employment” (SCR: 19), “Health facilities” (SCR: 14) and “Norms / Blood feud” (SCR: 12). “Terror” is also a concept that appears on all maps and young people (Fig. 1) placed “Terror” on their FCMs (SCR: 10). Furthermore, “Quality of life” (SCR: 7), “Lure of the city” (SCR: 6), “Domestic violence/Pressure” (SCR: 5) and “Natural disasters” (SCR: 6) are also among the reasons for migration. “Cultural and social facilities” concept forms the most surprising relation unity. While migration occurs in order to take advantage of these opportunities (SCR: 7), it is considered that these facilities decrease after migration takes place (SCR: -4). Although the city is conceptualized as a utopia containing all these potentials, “Population density” (SCR: 12) creates an obstacle to obtaining these facilities and becomes a legal instrument based on numbers. It is observed in almost all maps that migration is a personal movement and is independent of state policies.

It is essential to analyze social maps with centrality tables. While social maps show strong relations directed from concept A to concept B, centrality tables reveal all the relations that concept A include, in forms of degree. Thus, concepts with rich content that have relations with many concepts do not appear on social maps or appear on maps with weak relations. Since “Migration” as the central concept was placed on the map in order to structure the associations, it has the highest centrality on all centrality tables. Table 4 displays the centrality table for the 15–24 age group participants.

Although “Grouping/Citizenship” appeared on a centrality table with a value of over 10, it did not appear on social maps. “Grouping/Citizenship” both with its outdegree value (OV:7) and indegree value (IV:6) points that it is not only an inverter but also susceptible factor. While “Grouping/Citizenship” appears on the centrality table of participants between the ages of 15 and 24, it does not appear on the centrality table of the participants between ages 25–40 (Table 5) and 41–60 (Table 6). “Grouping / Citizenship” is a concept that young adults react to and according to them is a significant obstacle for “Integration”. It is a concept that is unique to young people and

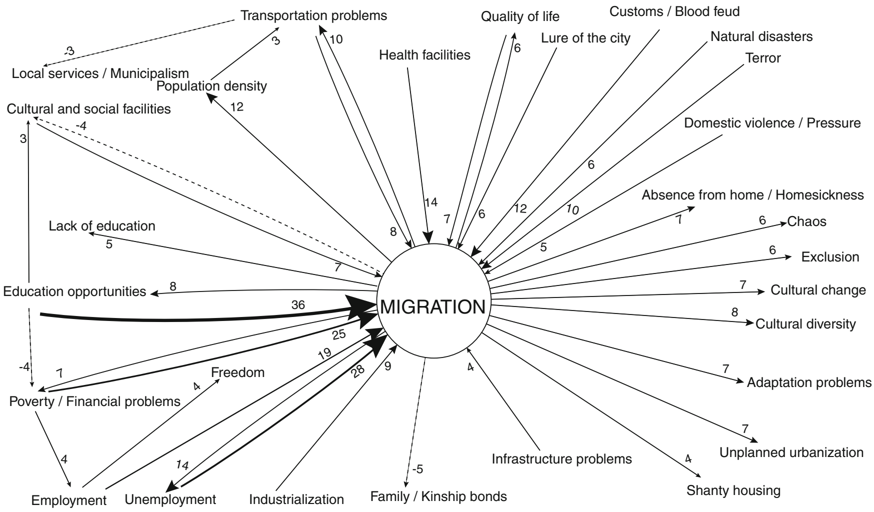

Fig. 1 Social map of 15–24 age group

has importance in terms of migration as citizenship institutions where foundations of citizenship are formed and produced institutionally are not preferred by young people. As the second generation of migration to Gebze, the young object to the formation of social bonds through citizenships. As well as not being a member of these institutions, the young also interpreted citizenship as a negative aspect of migration. “Voluntary migration”, “State policy”, “Housing shortage”, “Crime”, “Marriage”, “Geographical conditions” and “Investment opportunities” are also the concepts that did not appear on social maps but are of central importance. It is possible to draw a conclusion that by correlating with many concepts rather than correlating with a single one, these concepts have a complex and thus a strong effect on young people’s interpretations.

The concept that relates to migration most is “Education opportunities” (SCR: 21). “Education opportunities”, which can be interpreted as the survival of a child over parent-oriented approach, is a dominant statement both for the 15–24 (Fig. 1) and 25–40 (Fig. 2) age groups. However, as it would be analyzed later, “Poverty/Financial difficulties” are replaced by it between the ages of 41–60 (Fig. 3). This outcome is important as it reflects the priority of expectations. The conceptual and associational interpretation of migration is weaker than that of the participants between the ages of 15–24 and 41–60. There is no other concept on the social maps of the 25–40 age group than that of the 15–24 age group. All their concepts were correlated at lower values when compared to the 15–24 age group. This outcome brings about three different results which are exclusive to each other. The first one is that the participants between the ages of 25–40 do not consider the causes and outcomes of migration as relational as the other age groups do. On the basis of this, migration is an internalized movement for this category. The second result shows that the 25–40

Table 4 Centrality table of 15–24 age group

Concepts	OV	IV	CV	Concepts	OV	IV	CV
Migration	180	265	445	Chaos	3	13	16
Education opportunities	62	19	81	Exclusion	5	10	15
Poverty/Financial problems	50	20	70	Stress	3	13	15
Unemployment	38	23	61	Family/Kinship bonds	3	12	15
Employment	34	18	53	Freedom	4	10	13
Transportation problems	22	17	39	Grouping/Citizenship	7	6	13
Cultural and social facilities	14	18	33	Cultural diversity	3	10	13
Quality of life	14	18	32	Infrastructure problems	7	6	12
Population density	14	16	30	Local services/Municipalism	6	7	12
Health facilities	17	11	28	Shanty housing	4	8	12
Customs/Blood feud	20	8	28	Voluntary migration	7	5	12
Industrialization	17	9	26	State policy	9	2	11
Terror	16	9	26	Housing shortage	4	7	11
Adaptation problems	8	13	21	Crime	3	7	11
Absence from home/Homesickness	5	14	19	Marriage	6	4	10
Cultural change	6	13	19	Geographical conditions	8	2	10
Unplanned urbanization	5	13	18	Lure of the city	6	4	10
Lack of education	9	9	17	Investment/Opportunity	5	5	10
Domestic violence/Pressure	12	4	16				

OV: Outdegree value, IV: Indegree value, CV: Centrality value

Table 5 Centrality table of 25–40 age group

Concepts	OV	IV	CV	Concepts	OV	IV	CV
Migration	135	267	402	Crime	4	15	19
Unemployment	60	28	88	Customs/Blood feud	13	6	19
Poverty/Financial problems	65	22	87	Adaptation problems	8	10	17
Education opportunities	60	23	83	Cultural change	5	12	17
Terror	25	18	43	Unplanned urbanization	5	11	16
Employment	25	16	41	Lack of education	13	3	16
Population density	13	14	28	Chaos	4	11	15
Quality of life	8	19	27	Absence from home/Homesickness	1	11	12
Cultural and social facilities	11	15	26	Natural disasters	9	3	12
Transportation problems	10	14	24	Forced migration	7	5	12
Industrialization	19	4	23	Cultural diversity	2	9	11
Health facilities	13	8	22	Environmental problems	5	6	10
Lure of the city	13	8	21	Domestic violence/Pressure	7	3	10

age group is heterogeneous at concept level and age representation is not valid for this category. The third one asserts that the 25–40 age group has the reflex to perform dispersed relations through diverse experiences and historical. It is crucial that the centrality table based on the third reason should be examined.

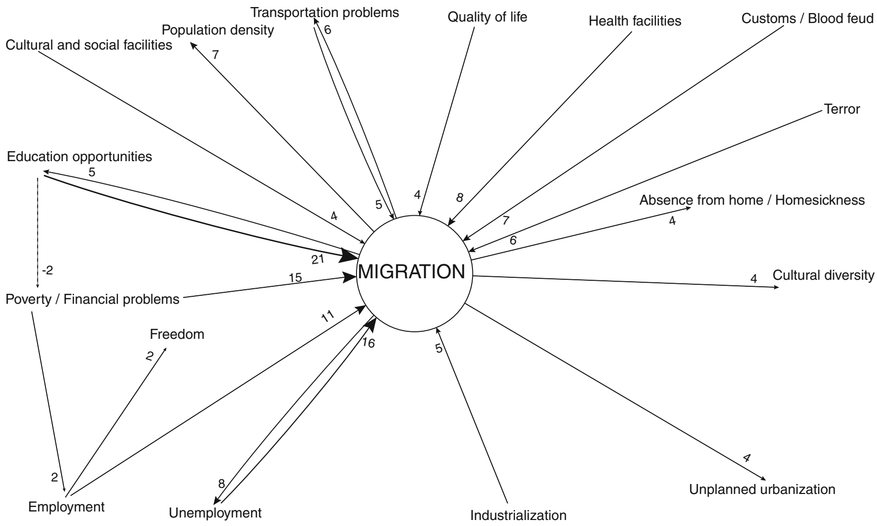

Fig. 2 Social map of 25–40 age group

Although the strongest relation observed on the social map is the one between "Education opportunities" and migration, the "Unemployment" concept takes priority in the 25–40 age group when the centrality values are taken into consideration. Even though "Cultural change" (CV: 17) has a higher centrality value than "Cultural diversity" (CV: 11), it does not appear on the social map (Fig. 2). Since cultural change includes normative thoughts such as conflict and corruption, this concept is not only in relation to migration but also with the causes and effects of migration. Also on many maps "Cultural change" is placed on a more important centre than migration and concepts are formed around it. In this respect, "Cultural change" is an effective concept in the in-terpretation of migration for the 25–40 age group. "Forced migration" (CV: 12) is another frequently mentioned concept but does not appear on the social map. This concept has an effecting factor; in other words, it has relations which lead to an alternate concept. Therefore, it focuses on the effects more than the causes of migration.

While the most frequent relation connected to migration is the "Education opportunities" for the age groups of 15–24 (Fig. 1) and 25–40 (Fig. 2), "Poverty/Financial problems" is the most frequent concept for the 41–60 age group. "Poverty/Financial problems", in itself, is observed as the central concept status of another FCM. "Poverty/Financial problems" proliferate "Crime" (SCR: 3) and is reduced with "Employment" (SCR: -3); it lowers the "Quality of life" (SCR: -6) and is dictated as the cause of "Terror" (SCR: 3). The interpretation of "Population density" as an obstacle on the map of the 41–60 age group is clarified by the decrease in "Education opportunities" (SCR: -3). The "Overcrowded family" concept, which does not appear among the other age groups, is another factor that increases migration (SCR: 5). The mechanization of agriculture and redundant young population forced

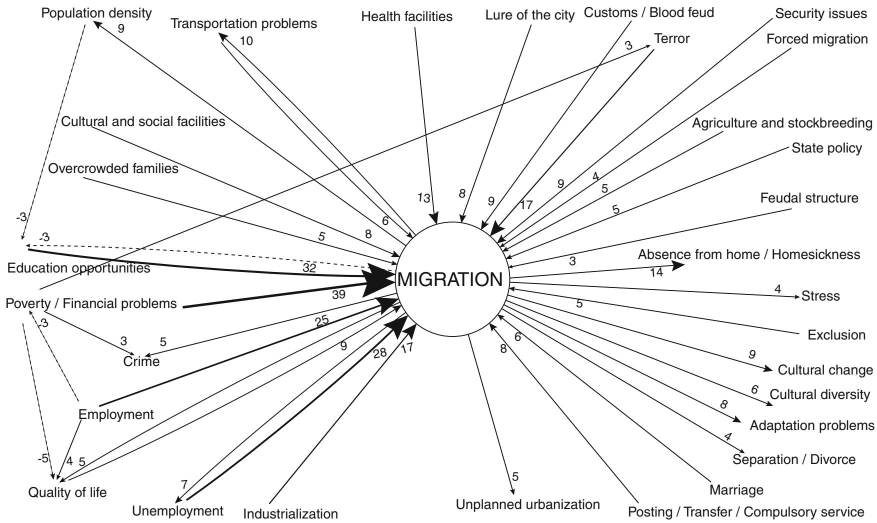

Fig. 3 Social map of 41–60 age group

to migrate to urban areas reveal themselves in this relation. Another relation that supports this outcome is that dissolution of the areas of "Agriculture and stockbreeding" increases migration (SCR: 4). the pressure of the "Feudal structure", that is pressure from landowners and clans increases migration also (SCR: 3).

The right top hand side of the social map represents the overview of old people as first generation migrants who were forced out of their own towns and villages. "Terror" (SCR: 17), "Security problems" (SCR: 9), "Forced migration" (SCR: 4) and "State policy" (SCR: 4) are the causes of migration that do not appear on other maps. "Absence from home/Homesickness" is a relatively strong cause of migration when compared to other maps (SCR: 14). The 41–60 age group as first generation migrants is still suffering from homesickness. The concepts "Marriage" (SCR: 6) and "Promotion/Transfers/Compulsory services" that do not appear on other maps are classified as causes of migration and "Separation/Divorce" (SCR: 4) the result of migration. The 41–60 age group relates "Cultural change" (SCR: 9) more frequently than any other age group and based on this, "Separation / Divorce" is a negative aspect of "Cultural change" for this age group. Finally, urban life is not seen as welfare but as a cause of "Stress" (SCR: 4) for the 41–60 age group. The centrality table of 41–60 age group is illustrated in Table 6.

There are three concepts on the 41–60 age group centrality table, which can be considered as an unique interpretation when compared to other age groups. 22 out of 28 centrality values of "Crime" are made up of the indegree value. The 41–60 age group thinks that "Crime" is the result of several factors. The factor that is reflected in the social map is "Poverty/Financial problems" (Fig. 3). "Security problems" also have a central significance (CV: 27) for the 41–60 age group, who migrated from the areas with displacement phenomena. "Concerns about the future" (CV: 15) concept

Table 6 Centrality table of 41–60 age group

Concepts	OV	IV	CV	Concepts	OV	IV	CV
Migration	158	311	469	Exclusion	10	7	17
Poverty/Financial problems	69	16	85	Lack of education	14	3	17
Education opportunities	53	25	79	Chaos	9	6	15
Employment	46	12	58	Voluntary migration	6	9	15
Unemployment	39	19	58	Concerns about the future	7	8	15
Terror	25	16	41	Lure of the city	10	4	15
Quality of life	12	23	35	State policy	10	4	14
Absence from home/Homesickness	8	27	34	Unplanned urbanization	5	9	14
Cultural and social facilities	18	14	32	Family/Kinship bonds	4	9	14
Transportation problems	14	18	32	Domestic violence/Pressure	6	5	12
Crime	6	22	28	Feudal structure	8	3	12
Security issues	16	11	27	Freedom	4	7	11
Industrialization	22	5	26	Agriculture and stockbreeding	7	4	11
Cultural change	5	21	26	Posting/Transfer/Compulsory service	8	3	11
Health facilities	19	6	26	Cultural diversity	4	7	11
Customs/Blood feud	13	11	24	Overcrowded families	9	1	10
Population density	10	9	20	Housing shortage	2	8	10
Adaptation problems	2	17	20				

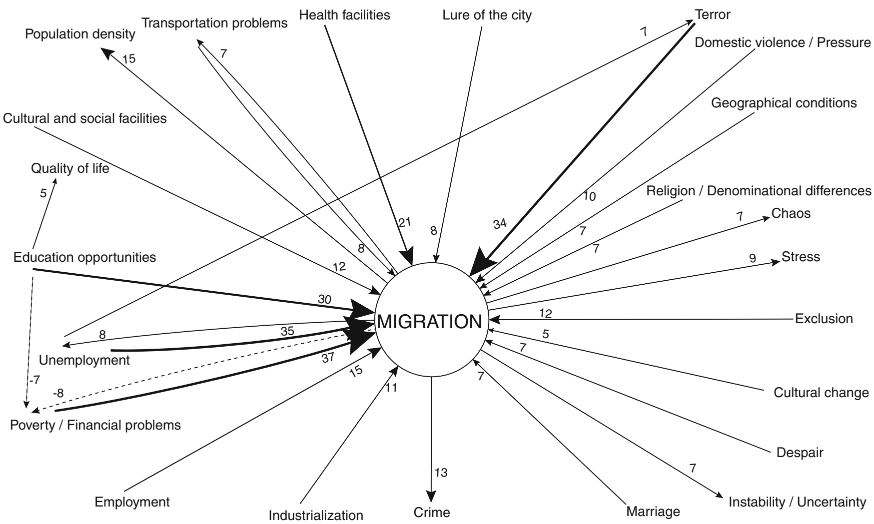

Fig. 4 Social map of AB SES group

show lines of fear. "Concerns about the future" of the 41–60 age group are directly related to their children's future (Fig. 3).

AB SES group establishes the most intensive relation between “Poverty/Financial problems” and migration (SCR: 37). “Unemployment” (SCR: 35) is listed as the second, “Terror” (SCR: 34) as the third; and “Education opportunities” (SCR: 30) as the fourth. For the AB SES group the way to deal with “Poverty/Financial problems” is to benefit “Education opportunities” (SCR: -7). Although this relation exists for the C (Fig. 5) and DE SES (Fig. 6) groups, its value is the highest in AB SES group (Fig. 4). While providing “Education opportunities” is one way of struggling with poverty in other groups, “Education opportunities” concept is considered as traits which increase the “Quality of life” only in the AB SES group (SCR: 5). However, the improvement in the “Quality of life” is based on “Employment” (SCR: 4) rather than “Education opportunities”. The relation between “Terror” and migration occur most in the AB SES group. The increase in “Terror”, however, can be explained by “Unemployment” (SCR: 7). Evaluating migration together with issues of security and terror could form the basis of how to approach migrants. One of the most common issues mentioned in the interviews is that people who migrate to urban areas because of terror actually cause terrorism themselves at different levels. What the social maps also reveal is that migration forms the basis of “Crime” (SCR: 13). The fact that migration increases “Instability/Unbalance” (SCR: 7) and “Religious/Denominational differences” (SCR: 7) are among the unique relations of the AB SES group. While “Exclusion” is the result of migration on many maps, the AB SES group thinks that “Exclusion” in the rural area increases migration (SCR: 12). “Population density” is also most commonly observed in the AB SES group than in any other SES group. With regards to the agenda of AB, AB removes migration from its perspective and experiences and reconciles it with other migrants’ perspectives and experiences, furthermore considers the city as an area knotted with problems. The centrality values of the AB concepts are shown in Table 7.

“Terror” is one of the most central concepts of AB. While the centrality value of “Terror” in AB group is 79, the closest value to it is 43 in C group (Table 8) and 27 in DE group (Table 9). “Terror” at indegree value of 32 is not only a deciding factor in the interpretation of AB group but it is also affected by others. “Religious/Denominational discrimination” (CV: 22) is an unique concept that does not appear on other SES groups’ social map. This factor described as Alewi/Sunni discrimination and religious pressure triggers migration.

The middle class (C SES group) forms the highest relation between migration and “Education opportunities” (SCR: 33). “Unemployment” (SCR: 33) becomes the second and “Poverty/Financial problems” (SCR: 29) the third. For the middle class, “Education opportunities” is an irreplaceable factor in the decrease of “Norms/Blood feud” (SCR: -4) and “Unemployment” (SCR: -7) and increase in “Employment” (SCR: 4). “Shanty housing” (SCR: 7) and “Unplanned urbanization” (SCR: 10) are a total result of migration and have the tendency to criticize space. “Grouping/Citizenship” (SCR: 5) is another concept that the middle class considers as a negative aspect of migration exactly as the 15–24 age group do. Even though these groups talk about the existence of “Adaptation problems” (SCR: 9), they agree that it cannot be solved through citizenship. “Investment/Opportunities” represent the desire of mobilizing of C SES group. Unlike the 41–60 group, the causes of “Terror”

Table 7 Centrality table of AB SES group

Concepts	OV	IV	CV	Concepts	OV	IV	CV
Migration	173	355	528	Religion/Denominational differences	17	4	22
Education opportunities	70	17	87	Chaos	7	13	20
Poverty/Financial problems	58	27	85	Industrialization	13	5	18
Terror	48	32	79	Customs/Blood feud	4	14	18
Unemployment	55	21	76	Stress	4	13	17
Employment	33	23	55	State policy	13	1	14
Cultural and social facilities	22	20	41	Investment/Opportunity	8	7	14
Cultural change	12	22	34	Adaptation problems	8	5	13
Population density	13	21	34	Despair	11	2	13
Quality of life	2	32	34	Freedom	10	2	12
Transportation problems	20	12	32	Family/Kinship bonds	2	9	11
Domestic violence/Pressure	18	11	29	Instability/Uncertainty	4	7	11
Health facilities	21	8	28	Lure of the city	8	3	11
Crime	12	16	28	Infrastructure problems	3	7	10
Security issues	16	11	27	Voluntary migration	8	2	10
Unplanned urbanization	17	8	25	Job security/Working conditions	9	1	10
Exclusion	16	7	23	Exile	3	7	10
Feudal structure	13	10	23				

for the C group is not "Poverty/Financial problems" but "Lack of education" (SCR: 3). While "Unemployment" is considered as a "potential threat factor", in the interpretation of the C SES group, illiterate people also share this factor. When considered that "Lack of education" (SCR: 4) increases migration, the increase both in "Terror" and migration clarifies the attitude towards "Lack of education". When it is taken into consideration that the majority of the C SES group in the sample are government workers, civil servants, it is meaningful that "Postings/Transfers/Compulsory postings" (SCR: 8) increase migration. They place their reasons for migration against the other migrants' reason as "Relative/Friend/Acquaintance invitation" (SCR: 6). While the AB SES group relate migration to "Cultural change", C SES group relates it to both "Cultural change" and "Cultural diversity" wealth. Besides migration increases "Cultural diversity" (SCR: 11) more when compared to "Cultural change" (SCR: 9). Therefore, whereas on the one hand, the middle class criticize migration on the basis of "Lack of education" and "Terror", on the other hand, they interpret the manifestation of migration in urban areas as wealth through political correctness. Table 8 presents concepts' outdegree, indegree and centrality values of the middle class.

Although "Cultural diversity" on C SES group social map is related to migration more than "Cultural change", the centrality value of "Cultural diversity" (CV: 17) is less than that of the "Cultural change" (CV: 29). Although the middle class equates migration to wealth in the gradient of political correctness, they use concepts like conflict, disorder and corruption more with other concepts in the cultural change gradient. The outdegree value of "Lack of education" (OV: 19), which is a common

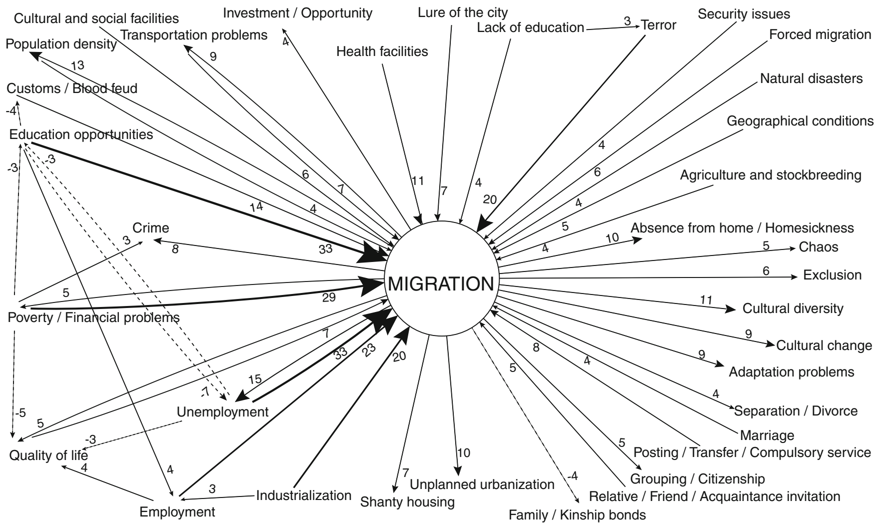

Fig. 5 Social map of C SES group

concept among the middle class, is much higher than the indegree value (IV: 5). Rather than associating "Lack of education" with various inequalities, the middle class is more interested in the effects of "Lack of education". The concept of "Easterners" (CV: 11) is prominent as a target cause of migration which the middle class consider as a negative aspect. Since the concept of "Easterners" does not only affect one concept but in fact many concepts and is affected by many as well, it does not appear on social maps.

DE SES group stands out as the most striking group that relates "Poverty/Financial problems" (SCR: 62) to migration in comparison with maps in all categories. It is possible to interpret this finding in terms of class differences in both pre-migration and post-migration periods. In this respect, concepts such as "Concerns about the future" (SCR: 4), "Job security/Working conditions" (SCR: 4); and "Regional inequality" (SCR: 3) specific to DE SES group are class-related. According to DE SES group, "Family/Kinship bonds" (SCR: -5) concept is one disadvantage of migration. What C group conceptualized as "Shanty housing", DE SES group interprets as a "Housing shortage" (SCR: 6). That migration provides "Freedom" (SCR: 4) becomes meaningful with DE's "Voluntary migration" (SCR: 4) concept. The "Quality of life" (SCR: 11) is related to migration more intensely in the DE group in comparison to all other maps. The fact that migration promises "Quality of life" and increases "Quality of life" (SCR: 6) results in the fact that "Quality of life" increases migration (SCR: 11) and thus forms a dual interaction. Migration resulting from "Overcrowded families" (SCR: 5) can also be observed on DE SES group maps as with the 41–60 age group. The centrality table of DE SES group is in Table 9.

According to the social map analysis (Fig. 6), unlike the C SES group, the DE SES group thinks that "Cultural change" (SCR: 8) is more prevalent than "Cultural

Table 8 Centrality table of C SES group

Concepts	OV	IV	CV	Concepts	OV	IV	CV
Migration	181	313	493	Unplanned urbanization	5	15	20
Education opportunities	71	25	96	Grouping/Citizenship	11	10	20
Unemployment	59	35	94	Shanty housing	7	13	19
Poverty/Financial problems	63	21	84	Cultural diversity	4	14	17
Employment	38	18	56	Lure of the city	13	5	17
Terror	28	15	43	Environmental problems	7	9	16
Quality of life	14	28	41	Security issues	7	9	16
Crime	8	28	36	Forced migration	10	5	15
Cultural and social facilities	16	19	35	Family/Kinship bonds	5	10	14
Population density	20	14	34	Investment/Opportunity	6	8	14
Industrialization	30	4	34	Freedom	4	9	13
Health facilities	19	15	34	Domestic violence/Pressure	9	3	12
Customs/Blood feud	20	12	32	Infrastructure problems	7	4	11
Transportation problems	14	18	32	Easterners	6	5	11
Adaptation problems	10	21	32	Posting/Transfer/Compulsory service	10	1	10
Cultural change	6	23	29	State policy	7	3	10
Chaos	10	15	25	Natural disasters	7	3	10
Lack of education	19	5	24	Agriculture and stockbreeding	8	2	10
Absence from home/Homesickness	5	18	23	Norms	5	5	10
Exclusion	8	13	21				

Table 9 Centrality table of DE SES group

Concepts	OV	IV	CV	Concepts	OV	IV	CV
Migration	125	241	366	Lure of the city	10	7	17
Poverty/Financial problems	65	17	82	Health facilities	13	4	17
Education opportunities	46	19	65	Customs/Blood feud	12	5	16
Unemployment	39	21	60	Industrialization	10	3	13
Employment	32	15	47	Cultural change	3	9	12
Terror	15	12	27	Voluntary migration	6	5	11
Quality of life	10	15	25	Stress	3	8	11
Transportation problems	12	10	22	Family/Kinship bonds	2	9	11
Absence from home/Homesickness	4	18	22	Security issues	5	5	10
Population density	10	12	22	Separation/Divorce	5	5	10
Cultural and social facilities	11	9	20	Unplanned urbanization	3	6	10

diversity" (SCR: 6). It is possible to obtain the same result from the centrality table. However, "Cultural diversity" appears neither on the social map nor the centrality table. For the DE SES group, the existence of different cultures in urban areas is regarded as a threat to their own culture (Fig. 6).

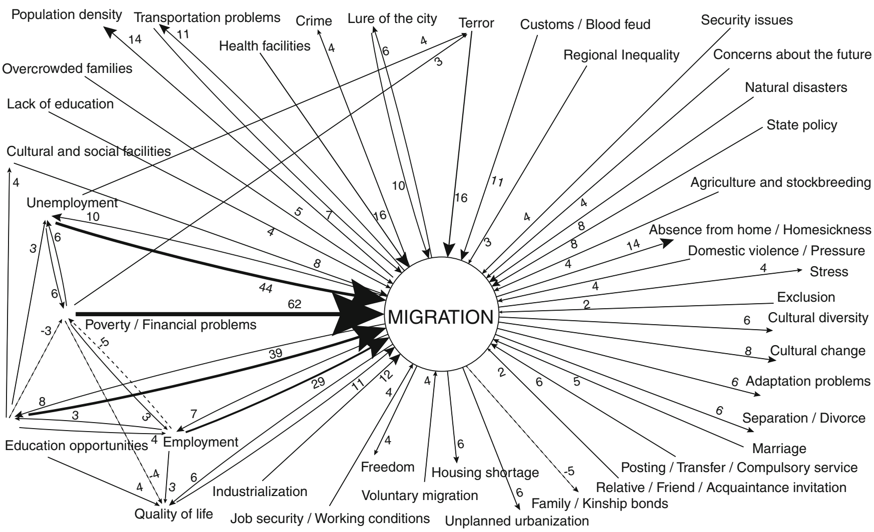

Fig. 6 Social map of DE SES group

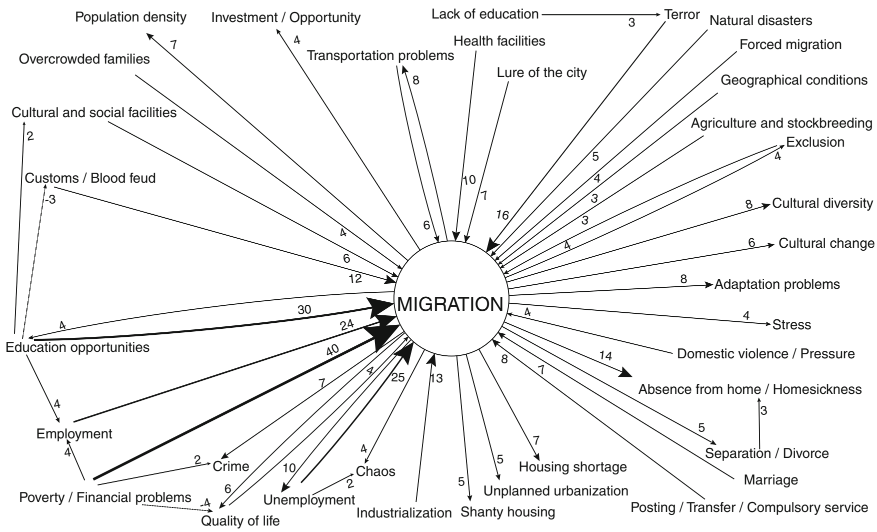

Fig. 7 Social map of women

"Poverty/Financial problems" (SCR: 40) is the strongest concept that women relate to migration (Fig. 7). However, men consider migration on the basis of "Unemployment" (SCR: 36) (Fig. 8). Since women are subjects existing in "Shanty housing" areas, "Shanty housing" (SCR: 5) appear only on women's maps. Citizenship institutions are a way in which men organize themselves as groups. In contrast to

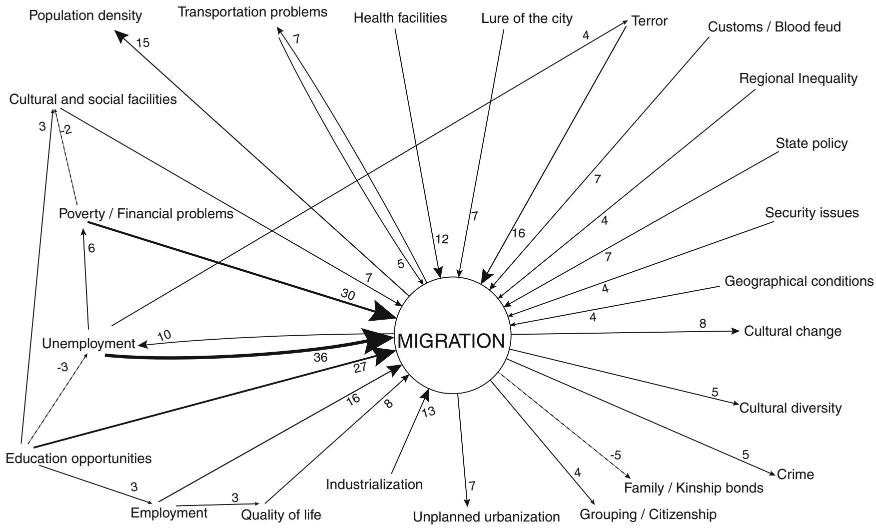

Fig. 8 Social map of men

the organization of men through "Grouping/Citizenship" (SCR: 4), the concept of "Shanty housing" appears on women's maps. From women's point of view, migration proliferates "Shanty housing" and "Grouping/Citizenship" is the reason from men's point of view. It can be observed that "Population density" (SCR: 15) is considered as an issue specific to men. It is not surprising when it is considered that urban areas and work life are dominated by men and that "Population density" increases competition in urban areas. Women consider population less of an issue (SCR: 7). While women relate migration to negative aspects such as "Adaptation problems" (SCR: 8), "Exclusion" (SCR: 4) and "Chaos" (SCR: 4), which are concepts not observed among men. There is also a difference in the concept of "Quality of life" in that men consider the "Quality of life" that the city promises to increase migration whereas women think that migration also increases the "Quality of life" (SCR: 6). Thus, "Quality of life" is a motivating factor in migration for men. However, men do not think that this expectation is fulfilled. Women mention that with the presence of "Infrastructure facilities" in urban areas their "Quality of life" increases when compared to domestic labour in the rural area. This finding demonstrates that the concept of "Quality of life" is not standardized and thus cannot be fully evaluated and it also reveals the gender inequality within the society. Hence, being far away from work life and the practicality of city life, what is obtained from the cities, that do not allow them to be a part, is limited to what they get in reality. For men, migration is associated with "Cultural change" (SCR: 8) and for women firstly it is associated with "Cultural diversity" (SCR: 8) and consequently "Cultural change" (SCR: 6). In the area of culture, men worry about keeping what they have and women are concerned about social cohesion. "Domestic violence/Pressure" (SCR: 4) that women suffer is

Table 10 Centrality table of women

Concepts	OV	IV	CV	Concepts	OV	IV	CV
Migration	167	292	459	Freedom	5	14	19
Poverty/Financial problems	72	11	83	Cultural change	6	12	18
Education opportunities	57	26	83	Exclusion	9	8	17
Unemployment	40	23	64	Domestic violence/Pressure	11	5	16
Employment	39	18	57	Lure of the city	10	6	15
Terror	23	13	36	Family/Kinship bonds	5	10	15
Quality of life	10	23	33	Unplanned urbanization	6	9	15
Customs/Blood feud	19	11	30	Marriage	10	4	14
Cultural and social facilities	16	14	30	Separation/Divorce	7	7	14
Absence from home/Homesickness	3	25	28	Cultural diversity	4	10	14
Crime	6	21	27	Housing shortage	3	11	13
Transportation problems	13	12	25	Posting/Transfer/Compulsory service	9	3	11
Industrialization	19	4	23	Forced migration	7	4	11
Health facilities	15	7	22	Security issues	3	7	11
Population density	12	10	22	Investment/Opportunity	3	7	11
Adaptation problems	6	15	21	Shanty housing	3	7	10
Chaos	9	12	21	Stress	2	8	10
Lack of education	14	5	19	Voluntary migration	4	6	10

Table 11 Centrality table of men

Concepts	OV	IV	CV	Concepts	OV	IV	CV
Migration	115	263	378	Cultural change	3	17	19
Unemployment	55	25	80	Lure of the city	12	5	18
Education opportunities	55	16	70	Unplanned urbanization	5	13	17
Poverty/Financial problems	50	18	68	Customs/Blood feud	9	5	14
Terror	23	18	40	Adaptation problems	5	9	14
Employment	29	9	38	Security issues	9	5	13
Population density	16	17	32	State policy	12	1	13
Quality of life	10	17	27	Crime	3	9	12
Transportation problems	11	15	26	Grouping/Citizenship	6	6	12
Industrialization	19	7	25	Cultural diversity	4	7	11
Health facilities	16	7	23	Stress	2	8	10
Cultural and social facilities	10	10	20				

included in migration together with "Marriage" (SCR: 8). The fact that these two concepts do not appear on men's maps make it a concept specific to women. The central tables of men and women are shown in Tables 10 and 11 respectively.

Both from the social maps and centrality tables' standpoints, it is possible to assert that women's world of concepts on migration is richer than that of the men. This finding is also parallel to the negative effects of migration. It is possible to see the

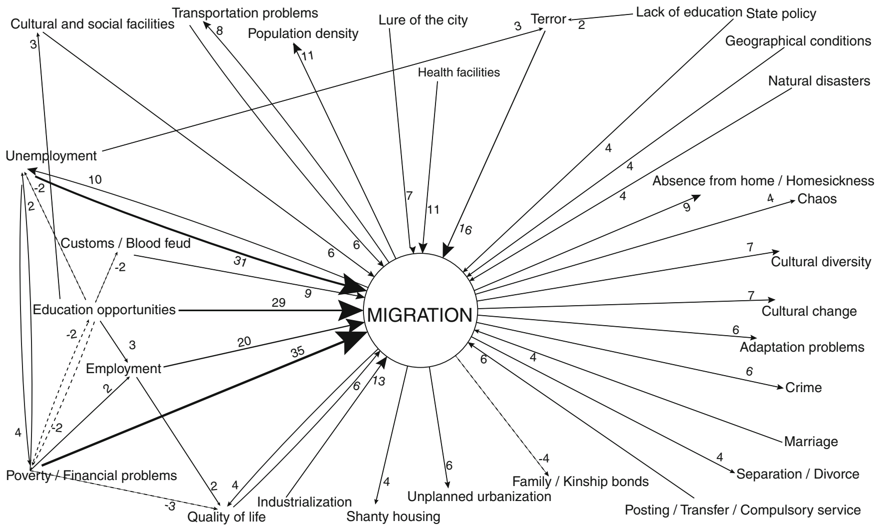

Fig. 9 Social map of all participants

reflection of "Population density" on centrality tables. The centrality value of "Population density" that causes competition in work and city life is higher among men (CV: 32) than women (CV: 22). However, "Absence from home/Homesickness" belongs to the world of women suffering from "Adaptation problems". The centrality value of "Absence from home/Homesickness" among women is 28 while it does not appear on the centrality tables of men (CV: 4). Since migration based on "Customs/Blood feud" is a reason which is kept hidden among men (CV: 14), consequently it can only be discussed by women (CV: 30). It appears on women's social map also. Although the concept of "Freedom" does not appear on either maps, the centrality value of this concept is high among women (CV: 19), whereas it is almost non-existent among man (CV: 1) The conflict with the "Quality of life" can also be observed in the concept of "Freedom". It is considered that women deprived of the benefits of city life and as the representatives of public areas men have different conceptualizations of freedom. Apart from what freedom means to these two categories would be a study topic for a new research study.

The social map of all participants (Fig. 9) reveals that "Poverty/Financial problems" (SCR: 35) is considered to be a major cause of migration. Being an industrial area it is inevitable for Gebze to be prone to migration due to unemployment; however, the increase in the unemployment rate on account of migration is an unexpected situation. It is essential to interpret that no more migrants are accepted in migrant-dominated Gebze from the relation of "Population density" (SCR: 11). "Education opportunities" are considered as a solution for all unsolvable problems in almost all spheres. In the development of these, education institutions are considered to be positive, however, individuals are the victims of "Lack of education". In this respect,

Table 12 Centrality table of all participants

Concepts	OV	IV	CV	Concepts	OV	IV	CV
Migration	134	274	408	Cultural change	4	15	19
Education opportunities	55	20	74	Adaptation problems	6	12	17
Poverty/Financial problems	60	14	74	Absence from home/Homesickness	2	15	16
Unemployment	48	24	71	Lure of the city	10	6	16
Employment	33	14	47	Chaos	5	10	15
Terror	22	15	37	Unplanned urbanization	4	10	14
Quality of life	10	18	28	Lack of education	11	2	13
Population density	12	13	25	Exclusion	6	7	13
Cultural and social facilities	13	12	25	Security issues	6	6	12
Transportation problems	12	13	25	Cultural diversity	3	8	11
Health facilities	16	7	22	Family/Kinship bonds	3	9	11
Customs/Blood feud	14	8	22	Stress	2	8	10
Industrialization	18	3	22	Domestic violence/Pressure	7	3	10
Crime	4	15	19	Freedom	3	7	10

education refers to the system as an opportunity and lack of education refers to individuals who cannot be educated, and thus have the potential to cause “trouble” in society. In addition to “Lack of education”, “Unemployment” based on overpopulation or indolence is also observed as a factor which intensifies “Terror”. In some maps “Terror” is conceptualized as the pressure received from terrorism and others as the movement of terrorism to urban areas. One surprising finding of the research is that migration due to “Security problems" is considered as the movement of terror.

The indegree value of migration is 274 and the outdegree value is 134 (Table 12). Migration is conceived as a concept which is influenced by other concepts and processes rather than a single factor. “Education opportunities”, “Poverty/Financial problems” and “Unemployment” are the three primary concepts. When education is considered as the fundamental strategy in the prevention of unemployment, “Education opportunities” can also be evaluated in terms of financial problems. The primary reason why Gebze had so many migrants is due to financial problems. “Customs/Blood feud” which is mostly discussed by women, reveals that migration is seen as a form of struggling with traditional structure. Finally, when “Cultural change” and “Cultural diversity” concepts were examined, it was understood that participants considered the area of culture in a negative aspect.

6.2 Cluster Analysis

Cluster analysis was used to produce concept typology of the concepts that exist on the same maps independent to their relations. Cluster analysis which is applied using the MINITAB 15.0 program is carried out on the basis of stating all the variables

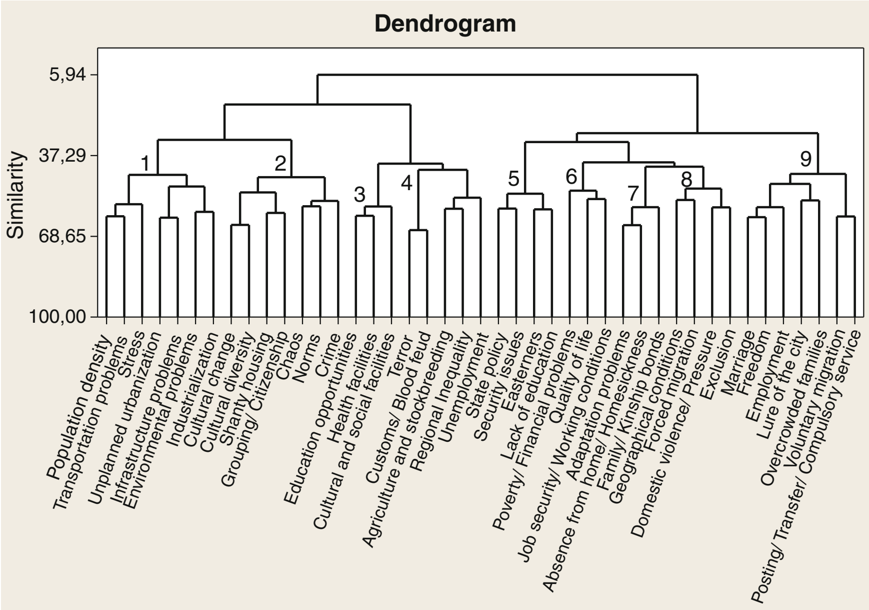

Fig. 10 Cluster analysis

together. In other words, when concept A is mentioned with concept B at the same time, concepts A and B form a cluster. After that, concepts A and B approach concepts C and D and can form new multi-conceptual clusters. The figures that start from 100 which appear on the left hand side of the visual called a "Dendrogram", which is a scale showing how close the concept cluster is. The shorter the branches of the cluster are, the closer the correlation is to 100 and the correlation of the elements of the cluster increase.

Social maps and centrality analysis are relation-based analysis methods. In other words, if a relation formed between two concepts, these two concepts become meaningful and discernible. However, some concepts may not be suitable for possessing relations because of their contents. To exemplify, the two concepts "Cultural change" and "Cultural diversity", representing a transformation in the area of culture, were used frequently by the participants. Although these two concepts are important in that they reveal two different approaches in the field of culture, analysis between these two concepts is limited as no relation appears between the two. In this respect, although the concepts which are used on the same maps have no relation to each other, they show the conceptual typologies of the participants with regards to migration (Fig. 10 and Table 13).

The first cluster which can be seen as a negative aspect of the city is result oriented. "Population density", increase in problems such as the traffic, "Unplanned urbanization" and increase in "Infrastructure problems" related to this and "Stress" due to urban problems are related to excessive migration. The relation of "Industrialization"

Table 13 Concept typologies of cluster analysis

1. Negative aspect of the city: Population density—transportation problems—stress—unplanned urbanization—infrastructure problems—environmental problems—Industrialization
2. Cultural field: Cultural change—cultural diversity—shanty housing—Grouping/Citizenship—chaos—norms—crime
3. Positive aspect of the city: Education opportunities—health facilities—cultural and social facilities
4. Problems of region under state of emergency: Terror—Customs/Blood feud—agriculture and stockbreeding—regional inequality—unemployment
5. Reflection of the problems of region under state of Emergency: State policy—security problems—Easterners - Lack of education
6. Economic Worries: Poverty/Financial problems—Quality of life—Job security/Working conditions
7. Tension Based on Absence from Home: Adaptation problems—Absence from home/Homesickness—Family/Kinship bonds
8. Forced Migration: Geographical conditions—Forced migration—Domestic violence/Pressure—Exclusion
9. Reasons for Migration: Marriage—Freedom—Employment—Lure of the city—Overcrowded families—Voluntary migration—Posting/Transfer/Compulsory service

and "Environmental problems" clustered under this group is also a negative aspect of the city. However, the second cluster, on the basis of wealth and corruption, indicates the area of culture with its reason, result and spaces. Citizenship and citizenship institutions considered as institutional obstacles to "Cultural change" and "Shanty housing" areas where differences are interpreted as "Cultural diversity"; the situation where all changes in culture do not abide by customs and the potential of "Crime" related to these the worries that the cluster problematizes. "Education opportunities", "Health facilities" and "Cultural and social facilities" are the fundamental expectations of a migrant to a city and for this reason, this cluster is referred to positive aspect of the city. The fourth and the fifth clusters have regional references. "Terror", "Customs/Blood feud", "Agriculture and stockbreeding", "Regional inequality" and "Unemployment" as a result of these in the fourth cluster are categorized as the problems of the region under a state of emergency and are the fundamental problems of state of emergency notion. The fifth cluster deals with regional problems at a more abstract level based on reason-result-subject. It can be stated that "uneducated" Easterners pose "risks" in cities through security issues experienced because of the state policy that the fifth cluster named "Reflection of the Problems of Region Under State of Emergency". The sixth cluster, indicating economic worries, re-veals the belief that the "Quality of life" that the city promises together with decent work can minimize "Poverty/Financial problems". The seventh cluster reflects the tension of migrants who think that "Family/Kinship bonds" were destroyed, who suffer from "Adaptation problems" and who are finally planning or dreaming of going back to their hometowns. In the eighth cluster, the participants form the perspective of forced migration with "Geographical conditions", "Domestic violence / Pressure" and the

"Exclusion" they suffer in their hometowns. The ninth cluster reveals the reasons for migration. In addition to the reasons for migration, where the decision where to migrate is not directly dependent on the migrant, in cases like "Marriage" and "Posting/Transfer/Compulsory service", "Mechanization in agriculture" and "Overcrowded families" which form surplus population, "Employment" opportunities and the desire of "Freedom" are considered as "Voluntary migration" by migrant.

7 Discussion of the Results

Even though migration is known as a concrete action of moving from one place to another, it constitutes a complex nature due to its effects, reasons and results. FCM is a unique method in the analysis of a process like migration where effects, reasons and results are interlaced. The way migrants place themselves, one another and migration itself is not independent of historical experience and daily practices. In this regard, effects/outcomes of migration become visible from the perspective of migrants as well as the social inequalities caused by and/or lead to migration.

It is possible to summarize these findings in nine points:

1. The primary reaction of urban inhabitants to migration is "Population density". Besides the increase in rents and decrease in salaries resulting from the "Population density" with the pressure of competition, "Unemployment" also increases due to migration. In other words, although "Unemployment" increases migration, migra-tion increases "Unemployment" in all social maps.
2. The assumption that the population of Gebze, considered as surplus in society, will interfere with the cultural area is the reaction of migrants towards other migrants. The meeting of differences in urban areas is stated as a conflict rather than wealth. Worries that "Separation/Divorce" in urban areas (which is depicted as an example of cultural change) will increase and thus family, one of the most sacred of in-stitutions in Turkey, will be solved are reactions that migrants have towards cities. The assumption that the same change affects "Family/Kinship bonds" is also a concern for migrants.
3. Even though the provisions of health, educational, cultural and social facilities are the primary expectations of migrants, it is interpreted from the relations that all these facilities still exist at an "expectation" level.
4. "Shanty housing" and "Unplanned urbanization" are the visible sides of urbanization. Because of this, migration level and the issues based on this are measured according to levels of "Shanty housing" and "Unplanned urbanization". This is one reason why "Shanty housing" areas are deemed to be problem areas by urban inhabitants' perception.
5. The interpretation of migration as semi-independent to state policies in almost all maps raises the issue that migrants are considered as "guilty of urban problems". In this respect, the use of "State policy" and "Security issues" together with "Lack of education" and the concept of "Easterners" are not unexpected.

Easterners, who cause “Population density” and increase in rents, seek employment opportunities and from a different cultural aspect create urbanized terror in the perception of participants. This outcome arises from the analysis of migration through security in almost all aspects and thus specifies the boundaries of attitudes towards migrants from the East.

6. “Citizenship/Grouping” as a concept is an institutional structure of solidarity which varies according to age and gender. According to young people and women, citizenship, accepted as an organizational form by men, has no necessary place in urban life. It is essential that this outcome is considered alongside the characteristics of demographic structures and the target populace of citizenship institutions.
7. “Unemployment”, “Poverty/Financial problems” and “Education opportunities” are the three concepts that are related most interchangeably in all demographic structures. The 15–24 age group, AB and C SES group correlated “Education opportunities”; the 25–40 age group and men “Unemployment”; and the 41–60 age group, DE SES group and women related “Poverty/Financial problems” the most. All these concepts have an economic basis. The 15–24 age group, AB and C SES groups are strategically thinking of dealing with the problem of “Unemployment” problem through education. 25–40 age group and men are social categories who are expected to seek job opportunities, consider “Unemployment” as the central concept. On the other hand, the DE SES group and women as disadvantaged groups in terms of job opportunities conceptualize their desperation as “Poverty/Financial problems”.
8. The unemployed group excluded from the rural production because of mechanization in agriculture is stated as overpopulation in the family by the 41-60 age group and DE SES group. “Overpopulated families” which do not appear on any other demographic structures is a reason for migration only specific to these two categories.
9. Men depicted as “representatives of public domain” are less satisfied with the quality of their life compared to women who are “imprisoned” in their houses. Men who shifted from rural production to industrial production feel disadvantaged compared to women who see improvement in the quality of household work when they compare the infrastructure facilities in rural and urban areas. The same is valid with regards to the concept of “Freedom”. Women feel freer in urban areas. As mentioned earlier, it is thought that these two categories have different conceptualizations of freedom.

8 Conclusion

This study has focused on the migration issue with its reasons, outcomes and processes through FCM. This study also has shown the key role of FCM on identifying the causal relationship between the dimensions of concepts related to migration. Since participants can graphically represent their experiences and reflections on migration issue, by using FCM, the development of causal representation of dynamic social life would be possible. On the one hand, it is extremely difficult to describe social system by concepts and their relations among each other; FCM is useful to represent the social system's behaviour in a graphical way.

Carvalho [6] argued that FCM development is increasingly moving FCM away from social sciences. Social sciences have majored on either qualitative or quantitative methods. However, FCM as a mixed method has a capacity to represent dynamic social systems and it could be used more in social sciences. Using FCM in social sciences, each concept represents the actors, entitites and social, political, economic systems, not just parameters. In this respect, each concept should be analysed within the social, political and economic conjunctures.

The results indicate some similarities and differences among social groups. These similarities and differences should be a starting point for further researches and social policies. FCM provides new strategies for detecting potential and apparent social problems in a complex system. Results of this study can be valuable output for generating social policies for migrants and space relation. The FCM approach will be enhanced in future works related to complex social issues. It is capable of providing information to policy makers. Future research will help to develop a more comprehensive picture of migration through FCM. Future research may be constructed for a longitudinal method in order to analyse transformed concepts and relationships. By doing so, sociological theories could be harmonized with time parameter. Also combination with other methods (questionnaire, interview etc.) to construct control-check the issue will be useful for in-depth analysis.

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Chapter 19
Understanding Public Participation and Perceptions of Stakeholders for a Better Management in Danube Delta Biosphere Reserve (Romania)

M. N. Văidianu, M. C. Adamescu, M. Wildenberg and C. Tetelea

Abstract Community needs ask for local management approaches as a response to the structure and evolution of a specific environment. The importance of managerial ethics in individualizing operational entities in terms of sustainable development of increasingly tense spaces stands for an efficient design of socio-ecological systems, such as Danube Delta Biosphere Reserve (DDBR). Such an approach helps people gain knowledge, values and the awareness they need to manage efficiently environmental resources and to take responsibility for maintaining environmental quality. This study examines the perceptions of local stakeholders in Sfantu Gheorghe, DDBR, Romania, with the aim of developing key concepts that will be used in future information and communication strategies regarding economic characteristics, sustainable development and biodiversity conservation in the area. For this 30 cognitive maps were developed together with stakeholders. Analysis reveals that DDBR Administration, county authorities and local authorities are substantially worried about the pollution and overfishing, while other social groups care more about touristic activities, accessibility degree, health system or financial resources. The

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M. N. Văidianu (✉)
CICADIT, University of Bucharest, 4-12 Regina Elisabeta Blv, 030018 Bucharest, Romania
e-mail: marianatasa.vaidianu@g.unibuc.ro

M. C. Adamescu
Department of Systems Ecology and Sustainability, University of Bucharest, Bucharest, Romania
e-mail: adacri@gmail.com

M. Wildenberg
Umweltforschungsinstitut, GLOBAL 2000, Neustiftgasse 36, 1070 Vienna, Austria
e-mail: martin.wildenberg@global2000.at

C. Tetelea
WWF Danube-Carpathian Programme Romania, Bucharest, Romania
e-mail: ctetelea@wwfdcp.ro

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lack of coordination and effective policies for the management of different sectors of activities were also identified as a common problem and have accentuated both environmental and socio-economic problems.

1 Introduction

Current trends in biodiversity conservation are moving from a restrictive centralized approach, based on strengthening legislation and the application of coercive measures, towards the participation of local communities in managing natural resources as stewards [8, 13].

Direct participation of local actors is fundamental for protecting biodiversity and application of conservation measures. Worldwide biosphere reserves are becoming increasingly people-oriented. Achieving conservation objectives is more and more based on achieving the "critical mass" of active and interested people and on harmonizing biodiversity conservation and sustainable development [29]. Danube Delta Biosphere Reserve is confronted with a range of conflicts. The main reasons for these conflicts reside on multiple requests of stakeholders interested in potential economic benefits on the one side and concerns about the carrying capacity of the natural environment on the other.

The proposal of local development projects and economic activities, contrary to the habitat conservation requirements, will continue if the benefits and values of the natural capital are not known and are not taken into consideration. The possible benefits brought by the usage of natural capital and conservation measures will still be considered inappropriate and worthless to most of the stakeholders. To facilitate the implementation of conservation measures, tangible examples of integrating the environmental requirements with economic analysis of different alternative local development plans must be presented.

Stakeholders should generally be involved in scenario development because scenarios deal with complex issues that require both analytical and intuitive understanding of socio-ecological systems. In the last years, many efforts have been made to help stakeholders better understand the responsibility of decision making using bottom-up approaches, like e.g. Fuzzy Cognitive Mapping (FCM) [7, 9–11, 15, 20, 21, 24, 28, 33].

Applying this approach offered detailed information and business opportunities to stakeholders in the Danube Delta mainly through the identification of other stakeholder's needs and interests, providing them with reconciliation prospects. However, the necessity to apply Fuzzy Cognitive Mapping (FCM) was in fact driven by the necessity to support the development of sustainable management and compliance procedures appropriate for the Danube Delta Biosphere Reserve (DDBR) management plan.

Involving stakeholders can provide information and traditional knowledge and can express concepts, perceptions, experiences, ideas and interests that allow understanding conflicts of interest. In our case this is especially true due to the framework imposed by DDBR regarding biodiversity and environmental protection. Opportunity to contribute to the model assumptions before the results are reported helps to integrate the outputs of the entire process based on a general agreement and will lead to better decisions with less conflicts and more success [34]. Managers of natural protected areas may be able to increase the resilience of natural protected areas by implementing compensatory management actions and evaluating their efficacy using active adaptive management. Since socio-economical systems and ecosystems change over time, the ideal way for a protected area manager to apply the fuzzy adaptive management approach is periodically. This method is proposed to determine the most preferred compensatory management actions for increasing the resilience of natural protected areas to future changes [27]. Implemented management actions have to be assessed to check if they have become ineffective in maintaining ecosystem consistency with social and ecological carrying capacities due to changes in internal or external forces [14].

This chapter reflects how Fuzzy Cognitive Mapping (FCM) can be applied as a tool in sustainable development and conservation of a protected area, respectively a biosphere reserve. The study seeks also to explore how different stakeholders perceive the problems and strengths of this area. The results are expected to contribute to improved sustainable livelihoods and stimulate a better participation in conservation programs.

The chapter is structured as follows: a first section provides background information and unravels the historical drivers behind the designation of this area as a biosphere reserve. In the second section, a brief methodology description of FCM and conducted interviews are considered. This is followed by the description of FCMs results. The final section presents the discussion and conclusions of the study.

2 Study Location and Background

The Danube Delta, located on the east part of Romania Fig. 1, covering a total area of 5,80,000 ha with an average altitude of 0–12 m above the sea level, was established in 1990 as a Biosphere Reserve, under UNESCO's Man and Biosphere Program (MAB).

Different cultural background is providing an attractive multi-ethnic atmosphere in the deltaic area. The Danube Delta is home to a rich mix of Romanian, Ukrainian, Russian, Lipovan Russians, Bulgarian, Moldavian, Turkish and Gagauz people, scattered around the delta in small villages [32]. Starting with the tenth Century Sulina town was developed. At the beginning of the fifteenth Century a new settlement, Caraorman was established by the Ottomans. Ukrainians and Lipovan Russians came during the eighteenth Century. Today the Delta has a population over 13,500, concentrated in one town (Sulina) and seven communes (24 villages).

The Danube Delta is one of Europe's most important wetland complexes with rich biodiversity and habitats for endangered bird species. Over the years, extensive alterations of ecological structures occurred: from works to improve the navigability on the Danube to works aimed at increased reed, agriculture and fishing productivity [32]. These hydro-technical works (e.g. the channels length was increased from 1,743

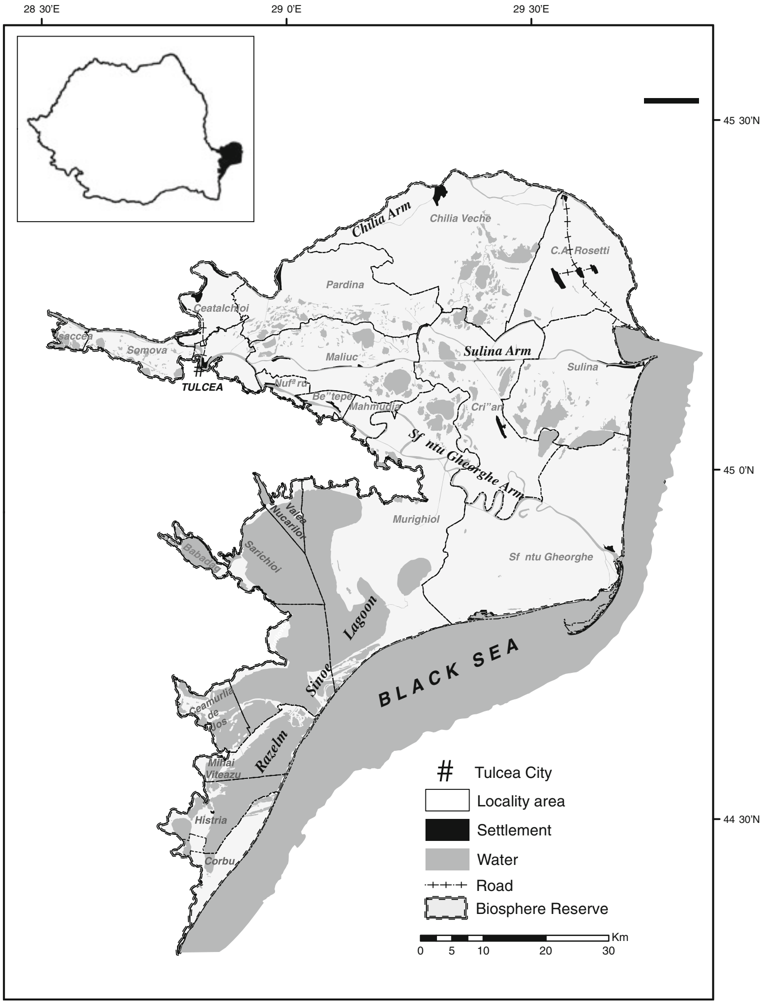

Fig. 1 Danube delta biosphere reserve—Study area map

to 3,496 km [4]) had a high and significant ecological impact. Major determinants of ecological and social carrying capacities [3] of DDBR include biophysical features, human use factors, and management actions. Human use that impacts on protected areas is evaluated using positive or negative indicators of ecosystem conditions [26]. Tourism is the new development trend, but its chaotic growth could increase environmental degradation [5]. According to statistical data about 70,000 tourists have visited the DDBR in 2011, but this activity provides only 2 for fishing and agriculture [16].

The main factors restricting the development of the area are the poverty of the local inhabitants, low level of education, lack of professional representatives and accessibility. Also lack of attractiveness due to the anthropic impacts during the communist period, when natural areas were transformed in agricultural land that is now abandoned or undergoing ecological restoration [25]. Using accessibility as an entry point gives us a better idea of what actually happened from the point of view of socio-economic development in many critical areas of Danube Delta. Major difficulties arise in addressing emergency medical cases and providing transport for education. Schedule and low frequency of transport vessels, and also the travel time are the main issues that negatively affect the living standards of local population [31]. Accessibility is also a factor important to conservationists because it is linked to pressures exercised on protected areas and biodiversity [23, 30].

After the delta's designation as biosphere reserve, activities are allowed in economical zones and buffer zones, under strict supervision of Danube Delta Biosphere Reserve Authority (DDBRA) only. No activity is allowed in the strictly protected areas or core zones. The potential conflicts are among the local people and concessioners, fishermen and birds (especially pelicans), hunters or sport fishermen and fishing companies/NGOs. They center on access rights like the right to exploit the different land use categories, the right to exploit the natural delta resources, and the access to different locations in the region. Other heavily debated issue are the duties and the responsibilities of different institutions, including the right of control and enforcement of legislation, and the purpose of taxes from exploitation of natural resources of the delta. The most important conflict is between the rights of the local population to use resources that the residents of deltaic villages were traditionally ascribed before that area was declared a biosphere reserve. The inequitable access to the ecosystems good and services generates most of the conflicts in which the local population is involved. Stakeholders from the outside have a variety of different interests and views, due to the multifunctional characteristic of the landscapes. The investors are only interested in recovering as quickly as possible their investments and often do not care about the connected costs to environment and society—as long as they are external to their business. Moreover they take the easy way using prohibited methods or tools. Sometimes locals turn against the investors because in their eyes they are just "outsiders" with a single purpose namely a material one. These challenges emerge by the lack of cooperation among different institution and stakeholders including the development of a clear responsibilities' frame.

A support from Government is yearly allocated for various actions in order to foster sustainable development. The most important objectives in the last strategic plans were: wetlands restoration, new habitats for the species in danger of extinction, renewing the delta's specific traditional activities (fishing, reed harvesting and ecotourism) and extending the natural habitats for reproduction, feeding and resting areas for fish and water bird species. Unfortunately these objectives did not contain a priority order of measures nor the necessary costs for solving each problem. Additionally communication strategies with stakeholders are missing and no direct involvement of stakeholders in this process was applied nor were the impacts of the suggested measures on the stakeholder evaluated. Therefore besides of all the inherent problems and conflicts between stakeholders already existing and blocking sustainable development paths new potential fields of conflict were created without strategies in place to manage them.

3 Assessing Stakeholder's Perceptions Using Fuzzy Cognitive Mapping

According to [28] cognitive maps are a useful complement to the semi-structured interviews: they help each interviewee to complete the factors relevant to the ecosystem and important to their activity; they prompt them to organize factors into a coherent view and to clearly state causal relationships among system components; they can be aggregated across people, and they provide a summary of the perception of a complex system within a group [28].

Axelrod, 1976 [1] was the first to use cognitive maps to arrive at a systems description by other stakeholders than researchers. Kosko [12] extended the idea of Axelrod's binary cognitive maps, by applying causal functions, adding fuzzy logic—so giving Fuzzy Cognitive Maps name. A cognitive map can be described as a qualitative model of how a given system operates and is based on defined variables and the causal relationships between these variables [18].

FCM applications and scientists' interest have increased during the last decade [22]. FCM have been used for modelling dynamic systems in different scientific areas such as political and social sciences, medicine, engineering, information technology, environmental management and history. FCM have found a good number of applications in the case of stakeholder's analysis for ecological modelling and environmental management [20]. Ozesmi and Ozesmi (2004) were the first who applied this method to environmental management. They captured stakeholders' involvement in the management of the Lake Uluabat by analyzing their perception [18]. FCM have been used in a wide variety of cases, in which social and biophysical aspects have to be combined. FCM, as used in this study, is based on the ideas of soft systems methodology [35]. It is capable of dealing with situations including uncertain descriptions using similar procedure such as human reasoning does [21]. For the analysis and depiction of the maps the software FCMappers was used (see appendix and accompanying material of this book and http://www.fcmappers.net).

FCMappers allowed us to analyze and to identify the cognitive maps of different stakeholder's perceptions of the DDBR. Causal mapping contributes to the goal of using peoples' knowledge of their environment to improve understanding of socio-ecological systems.

A number of 30 stakeholders were interviewed during August 2011 and qualitative data was obtained. The first step was to identify the right stakeholders to achieve the purpose of the study. The key stakeholders were identified as actors who have significant influence on the success of a development project. The discussions were held with the following groups of stakeholders: (i) local people; (ii) DDBR Authority representatives; (iii) NGO's; (iv) researchers; (v) fishermen; (vi) local authorities; (vii) county authorities; (viii) investors.

All interviews were carried out face-to-face, each group by the same interviewer using semi-qualitative interview techniques. There was no predefined list of concepts. A short introduction into the study and its objectives were given. The subject of the study was well received among stakeholders except for the DDBRA governor who refused to participate in the study. The refusal was explained by the inefficiency of this method or merely by a lack of time.

Each interview lasted between 40 and 90 minutes. The interviews started with an input to establish a relaxed atmosphere and to facilitate discussions. The interviewees were invited to speak of themselves and to identify the values and references that govern their perception. Every stakeholder group was asked to reflect on the following question: "What are the most important characteristics of the Danube Delta Biosphere Reserve"? Then we let stakeholders draw cause-effect networks starting with the concepts and their causal connections and then adding weights to indicate the strength of the causal influences for detailed descriptions of the approach see [6, 18, 35]. Then the causal networks were transcripted into adjacency matrices.

Based on the provided concepts and the developed matrix a number of indicators were calculated: outdegree, indegree, centrality and density. If the density of a map is high then the interviewee sees a large number of causal relationships among the variables. If in a map more connections are identified between concepts (high density), it indicates that the respondents see more options for changing the state of a system [18]. Outdegree is the row sum of absolute values of a variable in the adjacency matrix and shows how much a given variable influences other variables. Indegree is the column sum of absolute values of a variable and shows the cumulative strength of variables entering the unit. Centrality is the most important index summing the outdegree and indegree indicators. This shows how connected the variable is to other variables and what the cumulative strength of these connections is [18–21]. Centrality is also indicates how much importance a variable has in the perception of the interviewee. The first step in the analysis of cognitive maps is to describe variables, connections and structural indices. Description and tables are used to compare perceptions of different stakeholder groups. Using FCMapper software we have created net-files [2]. Pajek software helped us to visualize the matrices in the form of maps. Continuous lines represent the positive connections and dotted lines the negatives connections (see accompanying material of this book for matrices and net-files).

4 Results

The result of the FCM consists of 8 maps, one for each stakeholder group representing its collective understanding. As an intermediate step of creating useful visualizations of the maps, the concepts were classified into 10 categories: Social Aspects and Human factors, Nature, Economy, Tourism, Actors/Institution, Infrastructure, Agriculture, Resource use, Pollution and Management.

Analysis revealed that DDBRA, county authorities and local authorities are substantially worried about the pollution and overfishing, while other social groups care more about the economic activities: touristic activities, accessibility degree, health system or financial resources. The network statistics are shown in Table 1.

In the 8 maps shown in the analysis, the average number of variables was 23, with a minimum of 15 and maximum of 33. The average number of transmitter

Table 1 Matrices statistics of the cognitive interpretation diagrams

Sfantu Gheorghe case study	*Local people*	*DDBRA reps*	*Fishermen*	*Researchers*	*NGOs*	*Local authority*	*County authority*	*Investors*
Number of people/group	*5*	*3*	*5*	*4*	*3*	*4*	*4*	*4*
Factors/map	30	20	15	33	19	25	26	19
Connections/ map	40	23	23	49	26	32	31	22
Receivers/map	6	5	2	5	2	6	4	5
Transmitters/map	14	7	6	9	11	9	12	6
Ordinary variables/map	10	8	7	19	6	10	10	8
Density	0.0522	0.0575	0.1022	0.0449	0.072	0.0512	0.0458	0.609

Table 2 Variables with the highest centrality, indegree and outdegree

Stakeholder Group	Centrality	Indegree	Outdegree
Local people	Tourism	Tourism	Flooding
	Pollution	Fishing	Reserve
	Fishing	Income source	Old transport infrastructure
DDBRA reps	Financial resources	Financial resources	BR management
	BR management	Biodiversity	Tourism increasing
	Ecotourism	Nature degradation	Local administration
Fishermen	Biodiversity	Income	NGOs role
	Income	Biodiversity	Flooding
	Traditional fishing	Tourism income	Traditional fishing
Researchers	People	Water	Diluted perimeters
	Fish story	Accessibility	People
	Accessibility	Biodiversity	Administration
NGOs	Tourism	Tourism	Proper resource management
	Fishing	Fishing	Delta
	Biodiversity	Financial resources	Illegal fishing
Local authorities	Reserve	Tourism	Reserve
	Tourism	Fishing	Transport
	Fishing	Health	High taxes
County authorities	Concessioners	Treasure (gold pit)	Concessioners
	Fish	Income	Tourism
	Treasure (gold pit)	Fish	Fish
Investors	Tourism	Tourism	Reserve
	Reserve	Civilized tourism	Flooding/high groundwater
	Many cars	Land price	Many cars

variables was 9, the receiver variables 5 and 10 per map for the bidirectional (ordinary) variables. Maps had an average of 32 connections with an average density of 0.326. The objective of this study was to compare cognitive maps made by each stakeholder group and to outline similarities and differences in their perceptions, in order to develop communications strategies and to involve stakeholders in the preservation of protected areas. As expected the comparison of maps shows that stakeholder groups have diverging perceptions of the area and its associated problems. Different concepts observed among the maps indicate that for any strategy or project to be implemented it is important to build on the understanding of the diverse local desires and needs.

The most mentioned variables (concepts) are: *tourism*, *fishing*, *financial resources*, *biodiversity*, *reserve*, *reed*, *prohibited fishing*, *transport*, *pollution*, *flooding*, *development*, *disorganization*, and *health*. The variables with the highest centrality, indegree and outdegree of each stakeholder group are depicted in Table 2.

Tourism is the variable with the highest centrality in the Local people map, NGOs map and Investors map and the highest indegree in the Local people map, NGOs map, Local authorities map and Investors map. This reveals the recognition of the

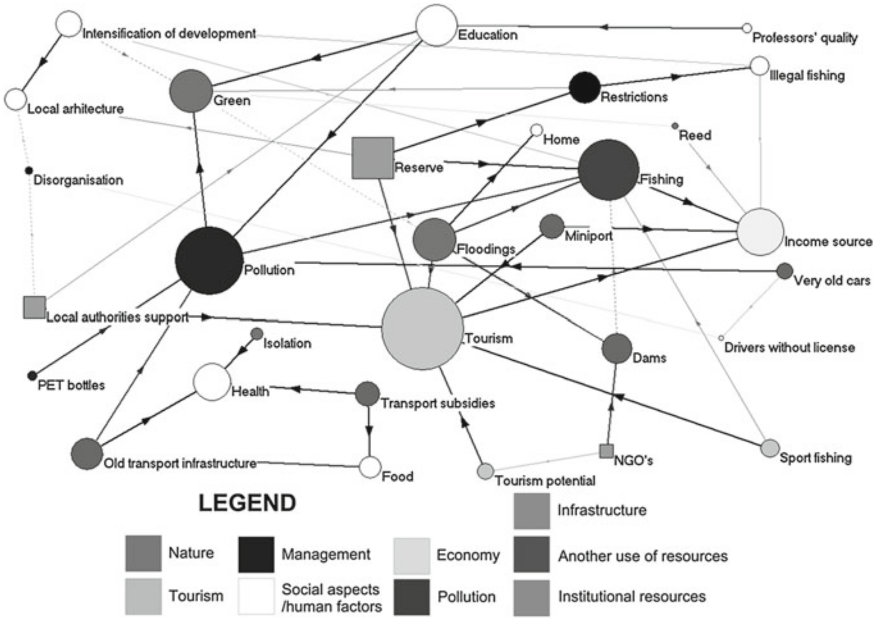

Fig. 2 Cognitive map of local people interviewed in Sfantu Gheorghe

importance of tourism and its impact on the socio-ecological system. The concept *reserve* has the highest outdegree in the Local authorities and Investors maps expressing their perception of the significant economic benefits and regulatory mechanisms connected to the *reserve* concept.

Comparing the number of variables shows us that local people have conceptual maps more complex than Authorities, Investors and Representatives of NGOs. This could be due to a deeper involvement and understanding of the systems interactions and components by the local people [18].

This analysis reveals that residents face important functions (transmitter variables) that they cannot control Fig. 2. They have developed ways to address these changing and difficult conditions, which is also reflected in their cognitive maps, which show a high degree of adaptation possibilities.

This is also a message for the officials and other competent bodies that the resident population is ready to change the existing system. For Local people, most variables are related to fishing, tourism, livestock, health and some to safety. Although these elements have a strong imprint on the lives of local people, they do not see possibilities to control or shape these forces. A causal relation depicted in the map shows that the local population is aware of the need to maintain the biodiversity drivers: *pollution*, *education*, *dams* or *development*.

Locals identified several variables linked to the wide spectrum of problems faced and the need for adaptability to the living conditions in the Danube Delta. Looking at the *income sources* variable, we see that it binds with variables such as *tourism*,

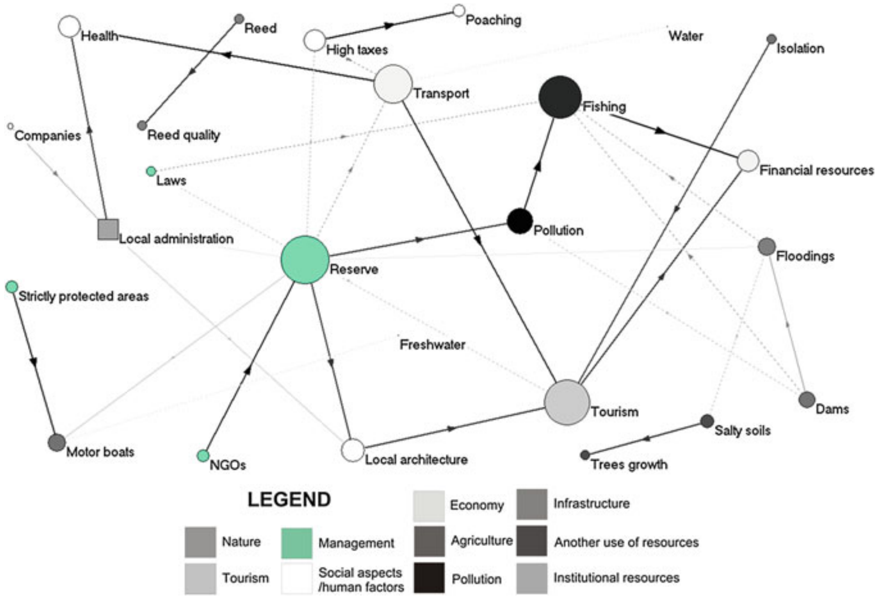

Fig. 3 Cognitive map of local authorities interviewed in Sfantu Gheorghe

fishing, *illegal fishing*, *reed* and *small harbour (miniport)*. They are also aware of the impact of pollution on biodiversity (*green*) and lack of education for conservation. A sign of conflict between local people and authorities, respectively DDBRA can be recorded by the concentration of negative value factors such as *transportation subsidies*, *disorganization* or *restrictions* with the *reserve* concept.

The Local authorities share with Local people some variables like *transport*, *health*, *flooding*, *isolation*, *restrictions* and *local architecture* and also some of the most important connections in the maps.

In their vision, *laws* factor translated through more enforcement, negatively affects both *tourism* and *fishing*. The concept of *reserve* on the other hand links positively to *local architecture* and *tourism* activity Fig. 3. The number of average connections in the maps of Local people's is higher, leading us to believe that their power of understanding of this system is more complex.

When analysing the variables expressed by officials, it can be noted that they are more comprehensive Fig. 4. They support the idea of the failure of protective agents (DDBRA representatives) in carrying out their duties and inadequate policies which don't contribute, in their views, to halt the trend of environmental degradation and loss of biodiversity in the Danube Delta.

They also suggest a solution for this namely to increase the number of DDBRA representatives (agents). They believe that there are external factors that degrade delta, which they cannot control, such as politics and political pressure, market

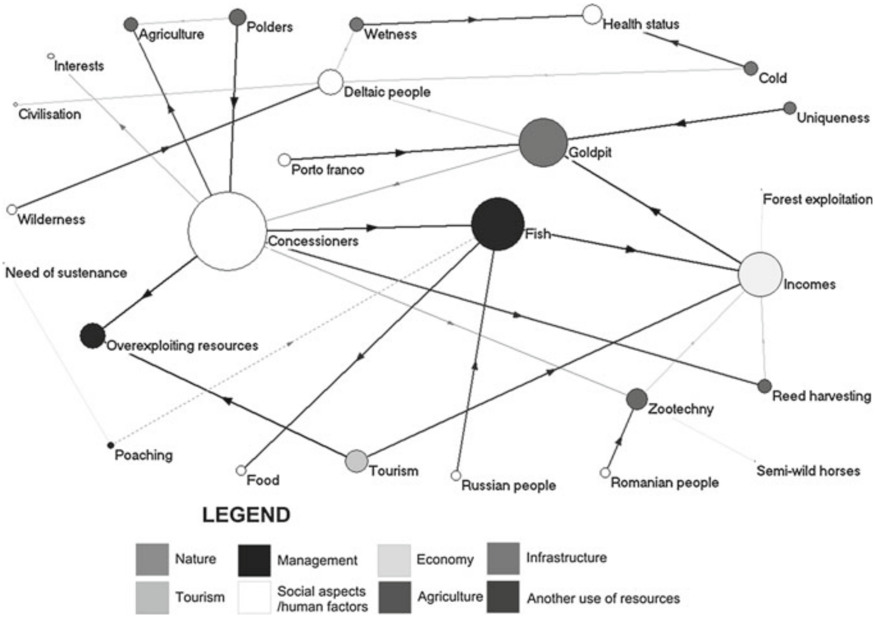

Fig. 4 Cognitive map of county authorities interviewed in Tulcea

forces, the application levels of laws, dams and pollution. Reed harvesting appears as a positive action, which cannot be improved.

The County authorities recognize that the institutions responsible for protecting the delta are not involved enough in fulfilling their duties. Highest centrality variable is represented by concessioners. Many areas of the delta are leased to concessioners for a long period of time, some even up to 99 years. The concern of the authorities is marked by concessioners disinterest in biodiversity conservation. They exploit the delta resources, such as fish, reeds, agricultural land, but focuses solely on profit. In their opinion mistakes were made when assigning on so long periods of time without a preliminary sustainable guide for resources use.

In terms of NGOs representatives, the main concepts that are used to describe the activities in this area are tourism, fishing, biodiversity and isolation Fig. 5. Authenticity of ethnic groups is emphasized as a specific feature and it is considered a positive variable in the socio-ecological deltaic system. Knowledge regarding key ecological processes was prominently drawn on the map. Specifically, *isolation* is dependent on *low accessibility*, while *management of resources* is dependent on *fishing* and *tourism* or *financial resources* through *biodiversity*.

Fishermen regard *income* and *biodiversity* (in the sense of the fish richness) as the most important features Fig. 6. Many have the impacts on their business most pressingly in their mind. They point out that *flooding* has a negative impact on *traditional fishing*, *health* and *tourism.* The variables and relationships are mostly

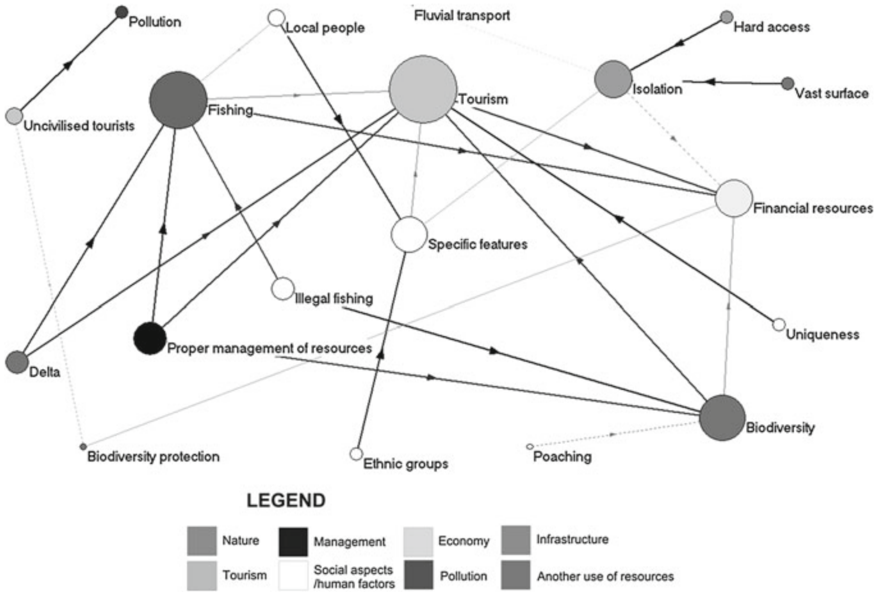

Fig. 5 Cognitive maps of NGO representatives

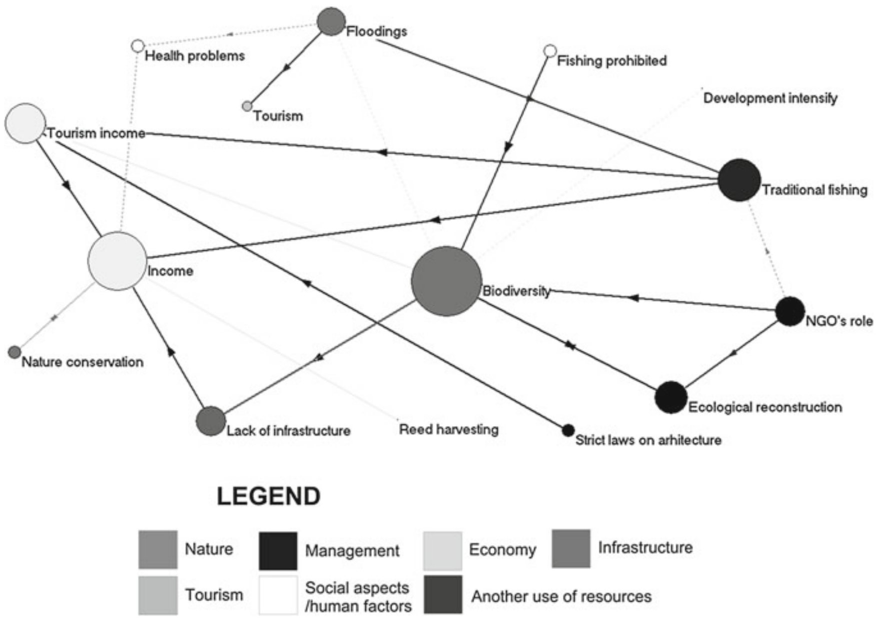

Fig. 6 Cognitive map of fishermen

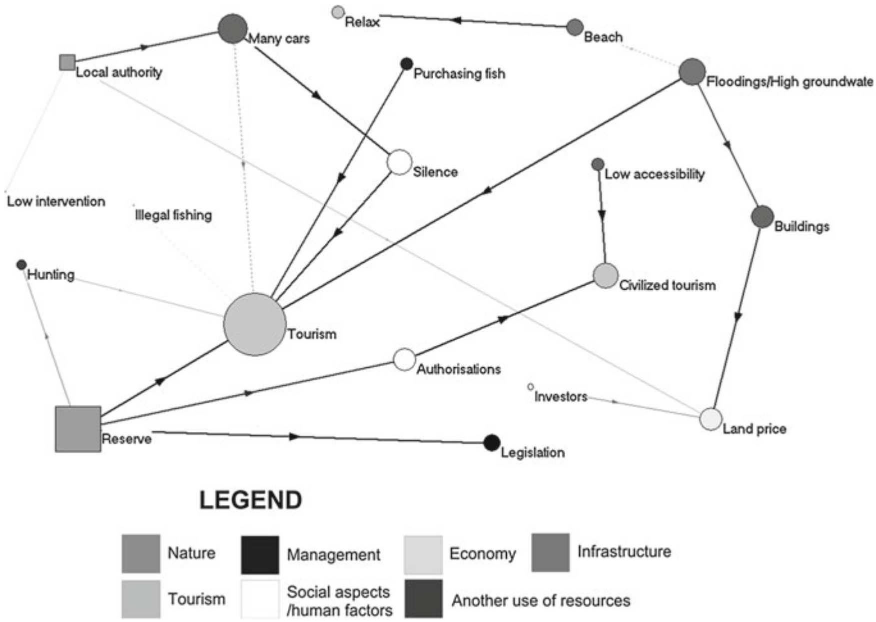

Fig. 7 Cognitive map of investors

related to their subsistence problems as a consequence for ensuring better living standard.

For Investors, the map reveals a strong importance of *tourism* sector Fig. 7. As variables with positive effects on management and sustainable development *silence* and *reserve* are mentioned, and with negative effects on tourist attraction the following: *many cars*, *hunting* and *flooding*.

From their point of view, *low accessibility* is an advantage to keep a selection of tourists with civilized behaviour. They also identified a difficulty in *purchasing fish* for visitors' food. In their opinion legislation and functional authority must have a proper application within the reserve.

DDBRA staff is the authority in charge to create and implement a proper management of this area. Although representatives of DDBRA also have a good knowledge of the delta, marked factors and connections represented by them are not too many in number Fig. 8.

In their view the factors like *financial resources* and *biosphere reserve management* positively influence *fishing*, *ecotourism* or *reconstruction*. DDBRA representatives' perceptions reveal that tourism increase generates positive value in the enhancement of *financial resources*. By linking these concepts to the other factors, they recognized the pressures of increasing number of visitors and financial resources on activities related to environment and sustainable development. Compared with other maps, the concepts that show the impact on the natural environment are relatively more pronounced.

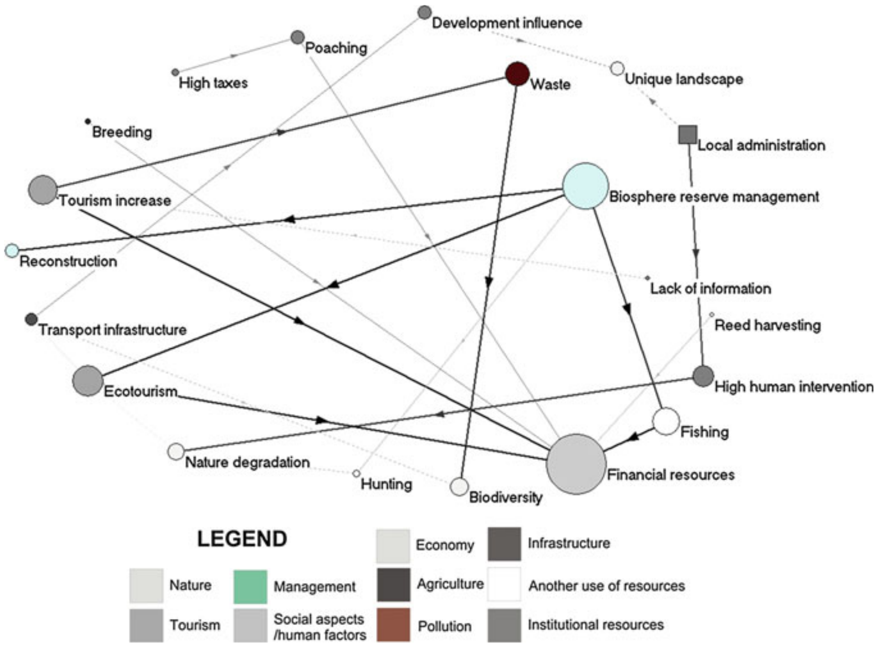

Fig. 8 Cognitive map of DDBRA representatives

The map with the most concepts is drawn by the Researchers Fig. 9. Because of the type of knowledge they hold and the education they received, they could describe the delta and its problems in a more detailed way. The concepts used reflect a great diversity. The research group is part of two research institutions Marine and Fluvial Research Station, University of Bucharest (located in Sfantu Gheorghe) and Danube Delta National Institute for Research and Development (located in Tulcea) and is composed of both natural and social scientists. They were the only ones that created a cognitive map where the concept *people* (used with the following sense: strong authenticity of these persons and their essential role in order to maintain the deltaic specificity) had the highest centrality.

Factors used in their description are clearly differentiated from the other stakeholder groups. *Climate change*, *adaptability* or *carbon emissions* are stated only in their map. Multiple impacts are specified as a consequence of *lack of communication*, *lack of functionality* or *disorganization* and general chaos, including uncertainty (*insecurity, diluted perimeters, lack of firm support point*), *high human intervention* or *pollution*. Looking at the overall map a complex degree of understanding the situations and worrying perception of the development process is noted.

Based on the results of Fuzzy Cognitive Mapping application, this approach was a useful tool capable to map and to make statements about the decision-processes in Danube Delta Biosphere Reserve.

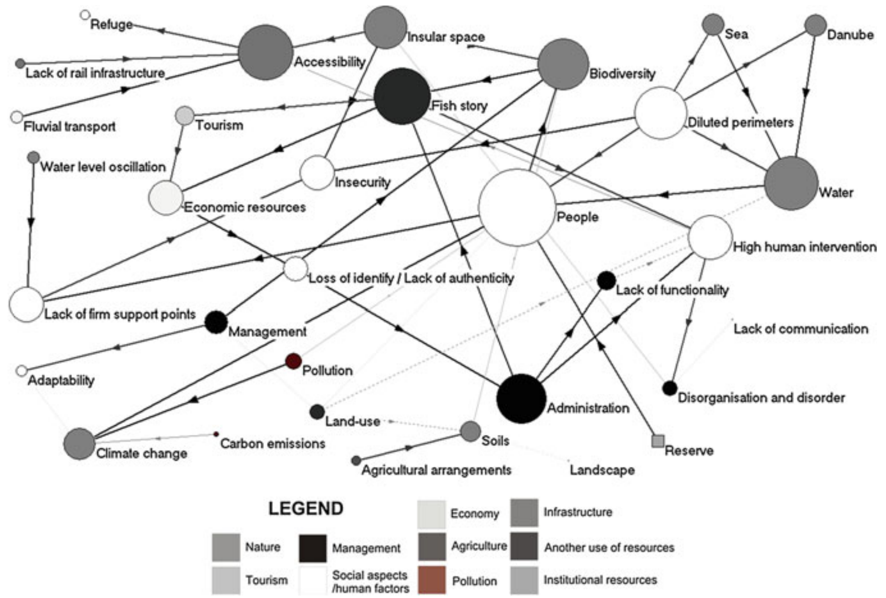

Fig. 9 Cognitive map of researchers interviewed in Sfantu Gheorghe and Tulcea

5 Discussion and Conclusions

During the interviews sessions the perceptions were different among the stakeholders. Almost the entire population of the villages depend on the biosphere reserve for a variety of resources, but rights and access to them have been curtailed. There is little or no consultation with local people about the management of the DDBR. The effects did not cease to appear mostly related to resource use conflicts. A solution for this is diversifying economic activities and trying to adapt to market forces. The FCM allowed us to identify also a negative perception of Local People and Fishermen groups regarding the DDBRA actions. The general perception is that local people are forced to follow the decisions made for them by the DDBRA. Many of the interviewed stakeholders pointed out the role of tourism in the area and the importance as source of income for the local people. Some of stakeholders identified that there are no strong interorganizational linkages among researchers, authorities, NGOs, investors and communities to make people aware of biosphere reserve management issues. Moreover they think that the authorities are in charge only to regulate their activities and resource access through high taxes or too small resource quotas. During the years, such measures worsened the situation and echoes from different fora and rapidly propagated. The main drivers behind the instability and conflicts in the Danube Delta are the inequitable access to resources and the lack of transparent and inclusive decision making process. The results show that the use of FCM is an efficient methodological tool for depicting people perceptions on environmental risks and conservation in a biosphere reserve. It is conceivable that more effective conservation could be achieved with less government enforcement if some forms of control are turned over to local villages. Moreover, empowering local people can improve efficient management of available resources through sustainable harvesting of products [33].

The perceptions of stakeholders show that they understand systems behaviour and different policy options and they could have a positive impact on the system. A future step will be to confront the stakeholders with their maps and the maps of the other groups. This approach provides a transparent way to access stakeholders' cooperation in ongoing projects and for further management issues. This will increase the local community's relationship with the environment and, in time, will decrease hostility of local people toward conservation due to the experience of top-down conservation programs in the last two decades.

Since researchers are aware of the problems described, their involvement in management plans formulation is essential. They could take into consideration the stakeholders interests through more involvement for awareness rising and finding solutions for a sustainable approach. Such actions can lead to positive changes in communication among groups as vital key elements to ensure long-term sustainability and help capacity building. Furthermore, it is important that the results to be presented in joint workshops, where each group of stakeholders can anticipate potential problems of the other groups. These different views should be taken into account when formulating the management plan of this area to achieve support and implications of the stakeholders.

FCM analysis was used with the aim of developing key concepts for future information and communication strategies regarding economic characteristics, sustainable development and biodiversity conservation in the area. The study highlights how the stakeholders use resources without knowing the impacts on biodiversity. This approach reveals that there are some similarities in the stakeholders understanding which can be used to reinforce common interests, on a win-win approach. A holistic management strategy could indeed provide a framework for sustainable development also in specific sectors, such as tourism, fishing, and so forth. FCM results show that for effective policy implementation, the relevance of biosphere reserve concept to every individual would thus need to be emphasized. It also needs to be ensured that all participants are suitably informed, motivated and that attention is given to their views. Better citizen engagement is needed for more effective conservation policies and to contribute to culturally driven behavioural changes towards a sense of community responsibility.

Besides the positive aspects of the method there are also some weaknesses connected to fuzzy cognitive mapping. A FCM requires a simplified representation of the elements in order to generate a model of the system under investigation. Sometimes the simplification could be imprecise, unidentified or not reflecting the reality, leading to incomplete cognitive maps, partly losing their meaning. It is however always important to look at the stories behind the relationships, as some differences might look bigger than they were intended by the different groups. Also the role of facilitator is very important during the interviews sessions. His/her influence on the process may heavily impact the quality of the results. A problem can be that the facilitator does not find the right balance between supporting the interviewees in creating the map and at the same time not exerting influence on them.

Implementing a properly prepared management plan, in which the interests of each stakeholder group are considered, can attract informed and transparent investors. If discussion and participation in joint projects is easy then a decreased impact on biodiversity could be forecasted. A true process of public participation seeks responsiveness to the views of those involved and must contain mechanisms to respond to differentiated opinions and to meet goals and objectives [26]. FCM should be seen as a tool that helps to better integrate different views coming from different stakeholders in the decision making process. This also makes it an interesting communication tool to work towards consensus. Hopefully future activities in the DDBR will be based on partnership between the diverse interest groups and lead to a sustainable development for people and nature.

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Chapter 20
Employing Fuzzy Cognitive Map for Periodontal Disease Assessment

Vijay Kumar Mago, Elpiniki I. Papageorgiou and Anjali Mago

Abstract Periodontal disease is a chronic bacterial infection that affects the gums and bone supporting the teeth. This research work aims to assess the severity level of periodontal disease in dental patients. The presence or absence of sign-symptoms and risk factors make it a complicated diagnostic task. Dentist usually relies on his knowledge, expertise and experiences to design the treatment(s). Therefore, it is found that there is a variation among treatments administered by different dentists. The methodology of Fuzzy Cognitive Maps (FCM) was used to model this problem and then to calculate the severity of the periodontal disease. The relationships between different sign-symptoms have been defined using easily understandable linguistic terms following the construction process of FCM and then converted to numeric values using Mamdani inference method. For convenience, a graphical interface of the system has been designed based on FCM modeling and reasoning.

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V. K. Mago (✉)
Faculty of Administrative Sciences, Fairleigh Dickinson University, Vancouver, BC, Canada
e-mail: vijay.mago@gmail.com

E. I. Papageorgiou
Department of Computer Engineering, Technological Educational Institute of Central Greece, 3rd Km Old National Road Lamia-Athens, 35100 Lamia, Greece
e-mail: epapageorgiou@teilam.gr

A. Mago
School of Population and Public Health, University of British Columbia, Vancouver, BC, Canada
e-mail: dranjalimago@gmail.com

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1 Introduction

Medical diagnosis is characterized as a complex process due to vague and imprecise values of signs and symptoms. The impact of a sign or symptom on diagnosis is usually not well defined. Conventional methods have a limited contribution in modelling the diagnostic or decision making systems. So, we design a decision making system based on Fuzzy Cognitive Maps (FCM) technique because of the capabilities of FCMs in handling such complex situations. The proposed system aims to be a front-end decision tool about periodontal disease severity level assessment for dentists.

Periodontal diseases refer to the diseases that affect periodontal tissues. Majority of the periodontal diseases are related to plaque-affected inflammatory tissues [15]. The range from uncomplicated gum inflammation to serious damage to the tissues and bone supporting teeth can lead to tooth loss. These diseases fall into two categories:

- Gingivitis, the breakdown of gum tissues supporting the tooth.
- Periodontitis, usually preceded by gingivitis, involves the breakdown of both, gum tissues as well as bone supporting the tooth.

Both of these diseases are caused by plaque. It is a colourless, bio-film of bacteria that sticks to the surface of teeth and gums. It does not get completely removed even by brushing and flossing. The toxins produced by bacteria in the plaque may injure the gums and supporting tissues [15]. Plaque hardens into a rough deposit called tartar or calculus. Tartar below the gum line causes inflammation and infection leading to periodontal diseases.

The symptoms of periodontal disease are tooth mobility, gum bleeding, continuous mild pain and swelling of the gums, and the main signs are the presence of plaque and periodontal pocket. Risk factors that cause periodontal disease include smoking, diabetes, hormonal changes etc. These symptoms and risk factors are crucial concepts for the prediction of disease and are taken under consideration for the construction process of the proposed system.

Depending on severity, periodontal diseases are classified into four stages [21]; Initial lesion, Early lesion, Established lesion, Advanced lesion. More details can be found in [1, 9, 21, 25]. FCM is a method for analysing and depicting human perception of a given system. The method produces a conceptual model which is not limited by exact values and measurements, and thus is well suited to represent relatively unstructured knowledge and causalities expressed in imprecise forms. FCM is a dynamic tool because cause-effects relations and feedback mechanisms are involved [8]. The advantageous modeling features of FCMs, such as simplicity, adaptability and capability of approximating abstractive structures encourage us to use them for complex problems [26]. FCMs have been used in many different scientific fields for modeling and decision making [3, 7, 18, 22, 23, 28].

A number of focused application works on FCMs in medical domain have been established. For example, Papageorgiou and her co-workers [19] applied the FCM approach with an active learning algorithm for treatment planning selection on a well known medical decision making problem pertaining to the problem of radiotherapy. Georgopoulos and Stylios [4, 5] used the case based reasoning technique to augment FCMs. Their system was applied in the speech pathology area to diagnose language impairments. Later on, Papageorgiou [16] and Papageorgiou et al. [17] presented the application of fuzzy computational intelligent approaches for medical decision making and for assessing pulmonary infections. Recently, Papageorgiou [20] developed a software tool based on FCM for treatment of uncomplicated Urinary Tract Infections. Interested readers may refer to recently designed applications of FCMs [6, 24]. Very recently, authors of [11] proposed an evolutionary technique based on FCM and Cellular Automata to understand the spread of Human Immunodeficiency Virus (HIV) among injection drug users who share paraphernalia.

2 Fuzzy Cognitive Maps

Fuzzy Cognitive Maps are fuzzy logic based graph structures for the representation of causal reasoning [8]. FCMs are applicable to soft knowledge domains as their structure helps systematic causal propagation. These graph structures describe the behaviour of an intelligent system using concepts, representing entities, states, variables or characteristics of the system. Each node in FCM represents a concept , where C is the set of concepts. Similarly, each arc (C_i, C_j) is directed as well as weighted, and represents causal link between concepts, showing how concept C_i causes concept C_j. The arc weights are associated with a weight value matrix E_n, which is $n \times n$ square matrix with each $E_{i,j}$ having values in $[-1, \ldots, 1]$. If $E_{i,j}$ takes on discrete values $\{-1, 0, 1\}$, the FCM is called *trivalent FCM* [29].

An FCM works in discrete steps. A strong positive correlation between the current (postsynaptic) concept and the presynaptic concept is indicated by a positive weighted arc. It is referred to as the former positively influences the latter. Similarly, a negative weighted arc is used to denote a negative correlation. Two conceptual nodes without a direct link are independent. The arc weights are used to represent either 'expert opinion', semi-quantitative or quantitative data on the relative degree to which one variable influences another. Figure 1 shows one such sample FCM structure.

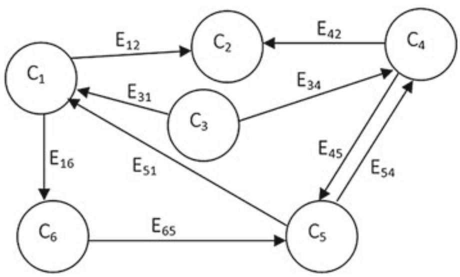

Fig. 1 Sample fuzzy cognitive map structure

FCM offers a more flexible and powerful framework for representing human knowledge and for reasoning, unlike traditional expert system that explicitly implement “IF-THEN” rules [8], it emphasizes the connections of concepts as basic units for storing knowledge, and the structure represents the significance of system. It may help describe the schematic structure, represents the causal relationships among the elements of a given decision environment, and the inference can be computed by numeric matrix operation. It is an advantageous tool for the design of the knowledge base and the modelling of complex systems.

Values of the concept C_i in time t is represented by the state vector $A_i(t)$, and the state of the whole fuzzy cognitive map can be described by the state vector $A(t) = [A_1(t), \ldots, A_n(t)]$, which represents a point within a fuzzy hypercube that system achieves at a certain point. The value A_i of each concept C_i in a moment $t + 1$ is calculated by the sum of the previous value of A_i in a precedent moment t with the product of the value A_j of the cause node C_j in precedent moment t and the value of the cause-effect link E_{ij}. The mathematical representation of FCMs has the following form:

$$A_i^{k+1} = f\left(A_i^k + \sum_{j \neq i, j=1}^{n} A_j^k \times E_{ji}\right) \tag{1}$$

where $A_i(k)$ is the value of concept C_i at step k, $A_j(k)$ is the value of concept C_j at step k, E_{ji} is the weight of the interconnection from concept C_j to concept C_i and f is the threshold function that squashes the result of the multiplication in the interval [0, 1]. The transformation function is used to reduce unbounded weighted sum to a certain range, which hinders quantitative analysis, but allows for qualitative comparisons between concepts. The activation function f is an unipolar sigmoid:

$$f(x) = 1/(1 + e^{-\lambda x}) \tag{2}$$

where $\lambda > 0$ is a parameter that determines its steepness in the area around zero. In our approach, diverse values of λ (lambda) were examined through the validation analysis to use the proper one. This function is selected since the values A_i of the concepts, by definition, must lie within [0, 1] [29]. Bueno and Salmeron [2] suggested that appropriate value of λ, used in sigmoid transformation function, be arrived during experimentation phase.

The main objective of this research work is to design a system that can assist dentist to assess the severity level of the periodontal disease. In our previous works [10, 12, 13], we used fuzzy logic to decide the treatment plan for mobile tooth and carious tooth. But, there have been no reports of using FCM technique to handle uncertainty in dentistry so far. This unique effort will be enhanced further to involve dental schools and professionals so that we can test the usefulness of the proposed system.

3 Construction of FCM Model for Periodontal Disease

Prediction of periodontal disease is a complex process with enough parameters, factors, different socio-economic status and life-style related conditions. The advantageous modelling features of FCMs, such as simplicity, adaptability and capability of approximating abstractive structures encourage us to use them for this complex problem. The origin of this work is based on the application of FCM methodology to assess uncertainty inherent in the medical domain thus deciding the severity of periodontal disease and the cause of the disease. This is particularly important because the treatment depends upon the severity of the disease. For instance, the presence of *trauma from occlusion* necessitates its rectification before any other treatment intervention. And its contribution in the severity of the disease is highlighted by the FCM model.

3.1 Determination of Concepts and Their Fuzzy Sets

The development and design of the appropriate FCM for the description of a decision support tool for specific disease requires the contribution of human knowledge. The dentists worked as experts to develop FCM model using an interactive procedure of presenting their knowledge on the operation and behavior of the system. A team of three professional dentists has been formed to define the number and type of sign-symptoms and other life-style related factors used in deciding the severity and presence of periodontal disease. The FCM model, consisting of 14 concepts-nodes, has been designed by the team after thorough deliberations. The 13 concepts are the symptoms and risks, taken under consideration for the decision on disease and are illustrated in Fig. 2. The central node **Periodontal Disease (PD)** is the basic decision concept. As it is shown in Fig. 2, the PD is the decision node gathering cause-effect interactions from all other input nodes.

There are 13 nodes that a dentist can observe or get to know after discussing with the patient. Hence these nodes are considered as observable nodes or input nodes. The impact of these nodes on PD is defined using five fuzzy values (Very Weak (VW), Weak (W), Medium (M), Strong (S), VeryStrong (VS)) following a positive or negative assignment. Each one observable node consists of three (Low (L), Nominal (N), High (H)) or five fuzzy values (Very Low (VL), Low (L), Nominal (N), High (H), Very High (VH)). These are shown in Figs. 3 and 4.

The membership functions (triangular and trapezoidal) for fuzzy variables having five fuzzy sets are described by Eqs. (3–8). Similarly, Eqs. (8–10) are the governing membership functions for fuzzy variables having three fuzzy sets.

$$\mu_{VW}(x) = max\left(min\left(0, \frac{0.232 - x}{0.232}\right), 0\right) \tag{3}$$

$$\mu_{W}(x) = max\left(min\left(\frac{x}{0.232}, \frac{0.464 - x}{0.464 - 0.232}\right), 0\right) \tag{4}$$

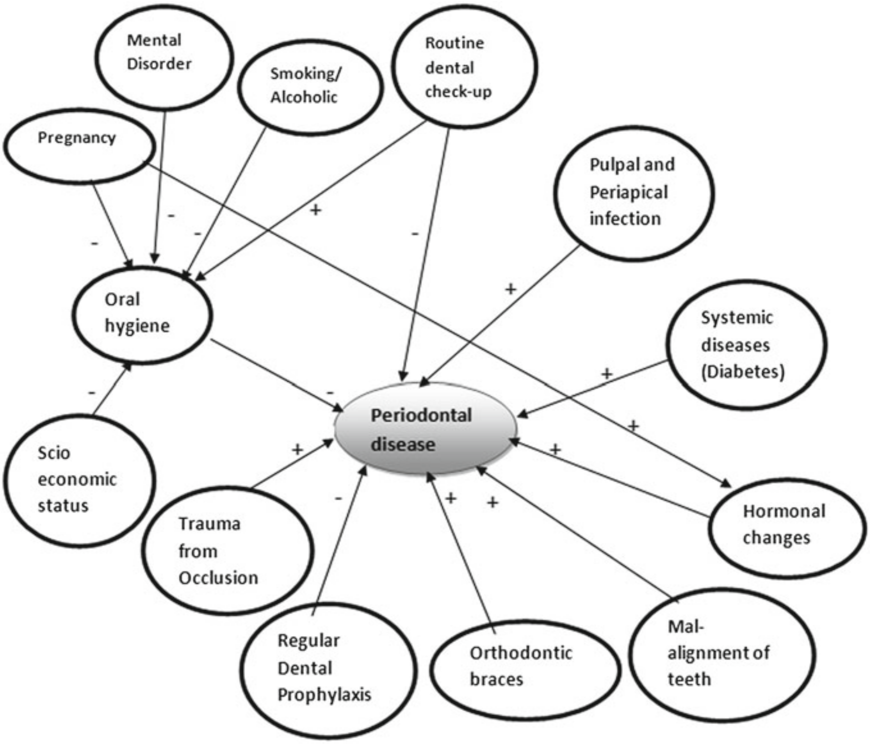

Fig. 2 FCM model for diagnosing the severity of periodontal disease

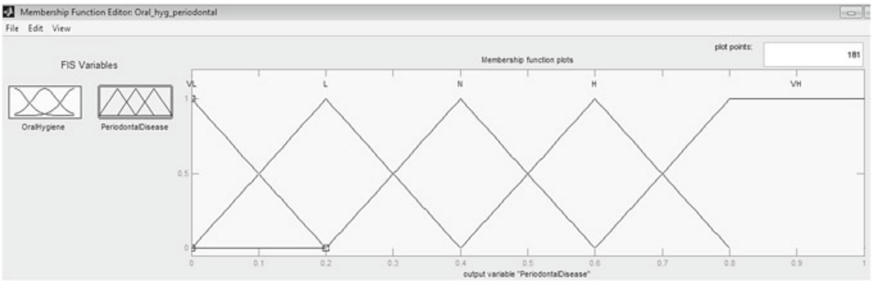

Fig. 3 Five fuzzy sets for the concept "Periodontal Disease"

$$\mu_M(x) = max\left(min\left(\frac{x - 0.232}{0.464 - 0.232}, \frac{0.696 - x}{0.696 - 0.464}\right), 0\right) \tag{5}$$

$$\mu_S(x) = max\left(min\left(\frac{x - 0.464}{0.696 - 0.464}, \frac{0.928 - x}{0.928 - 0.696}\right), 0\right) \tag{6}$$

$$\mu_{VS}(x) = max\left(min\left(\frac{x - 0.696}{0.928 - 0.696}, 1, 0\right), 0\right) \tag{7}$$

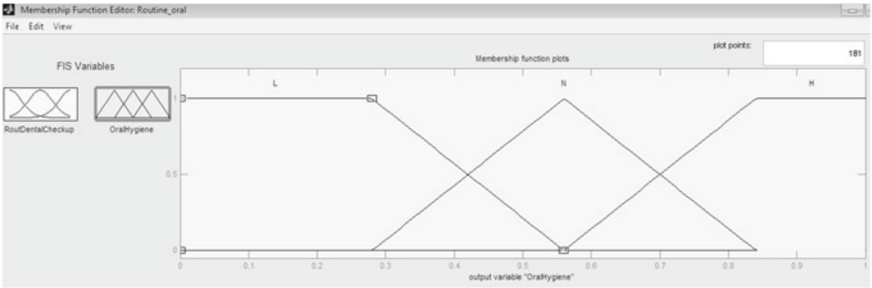

Fig. 4 Three fuzzy sets for concept "Oral Hygiene"

$$\mu_W(x) = max\left(min\left(0, 1, \frac{0.5 - x}{0.5 - 0.25}\right), 0\right) \tag{8}$$

$$\mu_M(x) = max\left(min\left(\frac{x - 0.25}{0.5 - 0.25}, \frac{0.75 - x}{0.75 - 0.5}\right), 0\right) \tag{9}$$

$$\mu_S(x) = max\left(min\left(\frac{x - 0.5}{0.75 - 0.5}, 1, 0\right), 0\right) \tag{10}$$

Each concept has a weighted impact on the decision node "Periodontal Disease" and in some situations; the node may have impact on other observable nodes. For instance, the concept node representing the symptom 'Routine Dental Check-up' is having impact on 'PD' as well as on 'Oral Hygiene'. In the next subsection, we describe the method adopted to calculate the weights on the FCM edges.

3.2 Determination of Fuzzy and Numerical Weights

After determining the fuzzy sets for each concept variable, all the three dentists were asked to define the degree of influence among the FCM concepts and to describe their causal influence using an "IF-THEN" rule, assuming the following form:

*IF value of concept C_i is **A** THEN value of concept C_j is **B**. Thus the linguistic weight E_{ij} is **D***

where **A**, **B** and **D** are linguistic variables and **D** is determined from the following prescribed membership functions in term set **T(influence)**.

T(influence) is usually suggested to comprise five linguistic variables, i.e., **T(influence) = very weak (VW), weak (W), medium (M), strong (S) and very strong (VS)** which are followed by a positive or negative sign of the relationship. Using these five variables, an expert can describe in detail the influence of one concept on another and can discern between different degrees of influence. Then, the linguistic variables **D** proposed by the experts for each interconnection are aggregated using the "max" method and so an overall linguistic weight is produced [27]. Finally, the Center of Area ("centroid") defuzzification method [8, 28] is used for the transformation of the linguistic weight to a numerical value within the range $[-1, 1]$. This methodology has the advantage that experts are not required to assign directly numerical values to causality relationships, but rather to describe qualitatively the degree of causality among the concepts. Thus, an initial matrix $E^{initial} = [E_{ij}], i, j = 1, \ldots, n$, with $E_{ii} = 0, i = 1, \ldots, n$, is obtained.

3.2.1 An Illustrative Example on Calculating Numerical Weights

The impact of concept *Good Oral Hygiene* on PD could be: VW, W, M, S, or VS. The opinions of three experts have been gathered in this context and are listed in column 5 of Table 1. Expert-1 opines that there is a **Very Strong (negative)** relationship between "Good Oral Hygine" and PD, while Expert-3 is of the opinion that there is a **Strong (negative)** relationship between these two concepts. Expert-2 goes with the opinion of Expert-1. The relationships between concepts are defined in the form of "IF-THEN" rules of fuzzy logic. For the above mentioned case, two rules are designed:

Rule 1 (1^{st} *and* 2^{nd} *Expert*): IF (Oral Hygine is ON) THEN PD is VH. Thus the influence of concept Oral Hygine on PD is negative VS (0.67)

Rule 2 (3^{rd} *Expert)*: IF (Oral Hygine is ON) THEN PD is H. Thus the influence of concept Oral Hygine on PD is negative S (0.33)

The first rule has been multiplied with a rule coefficient 0.67 because this reflects the opinion of two experts out of three. Similarly, the second rule is multiplied by 0.33. It is also worth noticing that the antecedent part of these rules is boolean here, as we defined the linguistic term ON as either present or absent.

Using the 'max' aggregation method, the 'centroid' defuzzification method and the Mamdani inference mechanism, crisp value (-0.791) is calculated for the mentioned relationship between these two concepts. Similar approach is employed to calculate all the weights of the FCM. A weight matrix E gathering the initially suggested weights of all interconnections among the concepts of the FCM model was constructed. This matrix E was formed from the column "Numeric Impact" in Table 1. It gathers all the dentists' suggestions to describe the strength of the connections among concepts.

To analyze the variations in the qualitative response of the dentists, we applied Mann-Whitney ranksum test [14] to understand how different the experts' opinions are. The null hypothesis is that the two experts' opinions are independent samples from identical continuous distributions with equal medians, against the alternative that they do not have equal medians. The $h = 0$ indicates a failure to reject the null hypothesis at the 5 % significance level. The results are summarized in the Table 2.

Clearly, the experts' opinions are not away from each other but they do differ in terms of magnitude of the influence of one concept on another. This section described the knowledge capturing mechanism and the usage of FCM in storing the information in a model.

Table 1 Concepts of FCM model and the relationships

Concept 1	Concept 2	Impact type	Impact levels	Expert opinion	Numeric impact
Oral hygiene	Periodontal disease	Negative	VW, W, M, S, VS	Exp1:VS, Exp2:VS, Exp3:S	−0.791
Socio economic status	Oral hygiene	Positive	W, M, S	Exp1:W, Exp2:W, Exp: W	0.192
Pregnancy	Oral hygiene	Negative	W, M, S	Exp1:S, Exp2:S, Exp3:M	−0.707
Pregnancy	Hormonal changes	Positive	W, M, S	Exp1:W, Exp2:W, Exp3:W	0.192
Routine dental check-up	Oral hygiene	Positive	W, M, S	Exp1:W, Exp2:W, Exp3:W	0.192
Routine dental check-up	Periodontal disease	Negative	VW, W, M, S, VS	Exp1:M, Exp2:S, Exp3:M	−0.472
Mental disorder	Oral hygiene	Negative	VW, W, M, S, VS	Exp1:M, Exp2:S, Exp3:S	−0.594
Smoking or alcoholic	Oral hygiene	Negative	VW, W, M, S, VS	Exp1:S, Exp2:S, Exp3:S	−0.808
Pulpal and peri-apical infection	Periodontal disease	Positive	VW, W, M, S, VS	Exp1:S, Exp2:M, Exp3:M	0.472
Systemic diseases (diabetes)	Periodontal disease	Positive	VW, W, M, S, VS	Exp1:VS, Exp2:VS, Exp3:S	0.791
Hormonal changes	Periodontal disease	Positive	VW, W, M, S, VS	Exp1:S, Exp2:S, Exp3:N	0.594
Mal-alignment of teeth	Periodontal disease	Positive	VW, W, M, S, VS	Exp1:VS, Exp2:S, Exp3:N	0.636
Orthodontic braces	Periodontal disease	Positive	VW, W, M, S, VS	Exp1:VS, Exp2:S, Exp3:S	0.724
Regular dental prophy-laxis	Periodontal disease	Negative	VW, W, M, S, VS	Exp1:S, Exp2:S, Exp3:VS	−0.724
Truma from occlusion	Periodontal disease	Positive	VW, W, M, S, VS	Exp1:VS, Exp2:VS, Exp3:VS	0.887

Table 2 Results of Mann-Whitney test applied to experts' opinions

Series 1	Series 2	p-value	h-value
Opinions of expert 1	Opinions of expert 2	0.6010	0
Opinions of expert 2	Opinions of expert 3	0.5048	0
Opinions of expert 1	Opinions of expert 3	0.3422	0

3.3 FCM Inference Process

In each of the patient cases, we have an initial vector A, illustrating the presented events at a given time of the process which constitutes the initial activated concepts, and a final vector A_{new}, representing the last state that can be arrived at. The algorithm used to obtain the final vector A_{new} is consisting on the following steps.

1. Input C_i, $1 \leq i \leq n$ as n input concepts or parameters.
2. Create a vector A with each single cell containing values within [0, 1] depending upon the fuzzy state of the concept, respectively, for each one of these n parameters.
3. Create a 2-dimensional array E storing numeric impact values where $E_{i,j}$ = impact of i^{th} concept on j^{th} concept as shown in the last column of Table 1.
4. Inference process:

The interaction of the FCM results after a few iterations in a steady state, where the values of the concepts are not modified further. Desired values of the output decision concepts of the FCM guarantee the proper operation of the simulated system. For the interpretation of the results, a rescaling for the calculated value of PD is needed. Thus, an average for the output value of the decision concept PD is computed according to the following criteria:

$$R(x) = \begin{cases} 0 \text{ if } x \leq 0.5 \\ (x - 0.5)/0.5 \times 100\,\% \text{ otherwise} \end{cases} \tag{11}$$

repeat
  $A_{current} \leftarrow A \times E + A$
  for $i = 1 \rightarrow n + 1$ **do**
    if $A_{current}(i) \neq 0$ **then**
      $A_{new} \leftarrow 1/(1 + e^{-\lambda \times A_{current}(i)})$
    else
      $A_{new} \leftarrow 0$
    end if
    if $A_{current}(i) < 0$ **then**
      $A_{new}(i) \leftarrow -A_{new}(i)$
    end if
  end for
  $A \leftarrow A_{new}$
until $\Sigma A_{new} \neq \Sigma A_{current}$
$R \leftarrow A_{new}(n + 1)$ **return** R

where 0 represents that the characteristic of the corresponding process represented by the concept x is null, and 1 represents that the characteristic of the process represented by the concept is present at 100 %. For the specific approach, the function $R(x)$ gives the severity degree of periodontal disease in percentage.

4 Simulation Results

It is imperative to test the accuracy of the predictions made by the proposed tool. The performance of the FCM-based proposed tool was compared with the dentists' judgements as they participate in our study as the "gold standard". The important part of the fuzzy inference map reasoning is to check that the obtained possibility of periodontal disease matches dentists' opinions. Since this work is concerned on the modelling of the experts' knowledge for decision making, we have considered the aggregated decisions of the three dentists (experts).

This research work uses the unipolar sigmoid activation function in (2) where the value of lambda is selected after experimentation using the existing data set to produce acceptable and reliable results. Throughout the experimental analysis, we decided to select 35 cases for the varing value of λ values, $\lambda = \{0.8, 0.7, 0.6, 0.5, 0.45, 0.4, 0.3\}$. It was observed that the predictions made by the system were most accurate with the value of λ being 0.7.

A number of scenarios have been examined, and it was observed that the predictions were satisfactory. Two test cases are discussed below.

4.1 First Test Case

A young, college going, girl visits the clinic with a complaint that she feels her gums are somewhat swollen and thinks that her mal-aligned teeth are the main contributory factor. The concerned dentist knows that she regularly visits her clinic for prophylaxis and there is less chance of her getting affected with periodontal disease. The dentist uses the system to provide inputs, as shown in Fig. 5. The dentist's assumption is well supported by this system, as shown in Fig. 6. The iterations showning the values of the concepts involved during FCM propogation for this case are depicted in Table 3.

4.2 Second Test Case

A middle-aged fellow complains that the gums around his lower front teeth are receding (Trauma from occlusion). He is concerned with his swollen and bleeding gums. His medical history shows that he is diabetic and has a habit of smoking. The patient has mal-aligned dentition too. All these factors are supplied by the

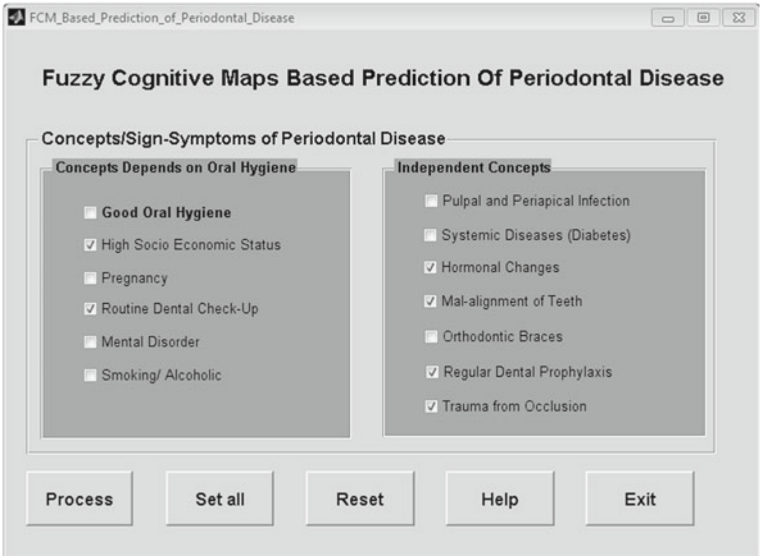

Fig. 5 The graphical user interface of the system

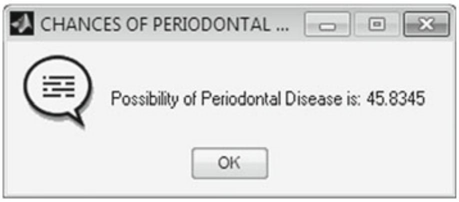

Fig. 6 The results for the first case

Table 3 The iterations showing the values of the concepts involved during FCM propagation for case 1

Concepts	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Iteration 6
Socio economic status/ routine dental check-up/ hormonal changes/ malaligned teeth/ trauma from occlusion	0.66	0.61	0.60	0.60	0.60	0.60
Regular dental prophylaxis	−0.33	−0.44	−0.42	−0.42	−0.42	−0.42
Periodontal disease	0.65	0.74	0.73	0.73	0.72	0.72
Probability of disease	0.31	0.48	0.46	0.46	0.45	**0.45**

Table 4 The iterations showing the values of the concepts involved during FCM propagation for case 2

Concepts	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Oral hygiene	0.63	0.65	0.66	0.67	0.67
Smoking/ alcoholic	−0.33	−0.44	−0.42	−0.42	−0.42
Systemic diseases (diabetes)/ malaligned teeth/ trauma from occlusion	0.66	0.61	0.60	0.60	0.60
Peridontal disease	0.83	0.88	0.87	0.87	0.87
Probability of disease	0.66	0.76	0.75	0.75	**0.75**

dentist to the proposed system that indicates that the patient is suffering from PD ($probability = 0.753984 > 0.5$). The iterations are summarized in Table 4.

From Fig. 1, it is observed that the concept *Oral Hygiene plays* a very crucial role in the FCM. It receives influences from five concepts and plays a pivotal role in the prediction of the disease. Hence, we have shown the values of this concept along with the values of PD in Table 4 that depicts five simulation steps to reach to the conclusion that the probability of the disease is 0.45. All values below 0.5 point to the absence of disease. Probability is calculated using the formula given in (11).

One strongest point of the methodology is the insight it can provide on the role of key feedbacks in the system. These feedbacks could remain hidden and might be uncovered by applying a tool such FCM. Also, FCM is capable to represent a system in a form that corresponds closely to the way humans perceive it. Therefore, the model is easily understandable, even by a non-technical audience and each parameter has a perceivable meaning. The model could be easily altered to incorporate new phenomena, and if its behavior is different from expected, it is usually easy to find which factor should be modified and how. Thus, the authors seek help from experts-physicians in enhancing the proposed FCM model by adding more concepts and potential cause-effect relationships among them. The authors would also like to test the system on real data which will be collected from a dental clinic. In order to tune the system to match the predictions made by the dentists, the authors intend to use different types of membership functions.

This work mainly elaborates with the development of the knowledge-based system, using FCM modelling approach for periodontal disease, and with the development of a software tool for supporting dentists in making decisions. We selected to develop a software tool with an easy to use Graphical User Interface (GUI) for dentists (end users). The tool can also benefit the non-specialized dentists in decision making in their daily practice. The proposed system is functional and could be also available to interested dentists.

5 Conclusion

The objective of this work was to model and predict efficiently the severity of periodontal disease, considering the inherent uncertainty in the complex problem. This research goal was achieved by using the soft computing technique of FCMs. The proposed approach for making predictions in periodontal disease was established as an alternative knowledge-based system inheriting the advantages of simplicity, flexibility, transparency and easiness of use. With this methodology, it becomes feasible for dentists to automate (or support, at least) their decision processes. Moreover, it is believed that one system cannot contain all medical knowledge. In upcoming work, the FCM approach will be extended to include more features, conditions and observations for the diagnosis management of periodontal disease, and more clinical trials will be accomplished to justify or improve the present results.

Acknowledgments The authors would like to thank Dr. Nistha Madan, Nitin Bhatia, Lakwinder Kaur and Reetu Salaria for their initial help during the construction of FCM model and later during the simulation and verification of the results.

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Appendix

List of Resources (Codes, Software, Demos) Included in CDROM

File name and description

1. **Chapter01_EPapageorgiou**

   Description. A code which implements the **hybrid learning algorithm of Non Linear Hebbian and Differential Evolution (NHL-DE) for Fuzzy Cognitive Maps** applied to adaptation and optimization of a real world process control problem.

   The code is written in Matlab.

   Name of the subfolder containing the code: **NHL-DE-FCM**

2. **Chapter03_Motlagh et al.**

   Description. An example code of FCM for Relationship Modeling of Systems for learning a simple 4-Bar linkage. The code is written in Matlab.

   Name of the code: **FourBar.m**

3. **Chapter04_Tsadiras_Basileiadis**

   Description. An FCM simulation system written in RuleML and running in Prolog. Prolog is used for the FCM representation and RuleML is used for FCM modeling and simulation of systems.

   Name of the tool: **RuleML-FCM Simulation**

4. **Chapter07_Froelich_Papageorgiou**

   Description. A Java application concerning an Extended Evolutionary Learning Algorithm of Fuzzy Cognitive Maps for the Prediction of Multivariate Time-Series. The implemented experiment runs the extended algorithm of evolutionary learning of FCM using the exemplary data of 5 patients. The code is written in Java.

   Name of the code: **FCMLEARN**

E. I. Papageorgiou (ed.), *Fuzzy Cognitive Maps for Applied Sciences and Engineering*, Intelligent Systems Reference Library 54, DOI: 10.1007/978-3-642-39739-4,

5. **Chapter08_Yasterbov_Piotrowska**

Description. An algorithm for multi-step learning of Fuzzy Cognitive Maps which runs using the ISEMK tool. A demo of the ISEMK- Intelligent Expert System based on Cognitive Maps is given. A dataset of Parkinson's patients was used for the FCM learning.
Name of the code: **multi-step-learning-code**

6. **Chapter09_Slon_Yasterbov**

Description. An application tool, namely RFCM, for creating and testing a structure of the Relational Fuzzy Cognitive Map (RFCM). (run RFCM.exe)
Name of the software: **RFCM**

7. **Chapter10_Mendonca et al.**

Description. Two algorithms concerning the modeling and simulation of dynamic fuzzy cognitive maps (D-FCMs). A simulation environment with 2-D animation was developed to test and validate the navigation system. It is applied to a mobile robot. The code is written in Matlab.
Names of the codes: **code1.m, code2.m**

8. **Chapter11_Yesil et al.**

Description. An **FCM-GUI toolbox** providing design, simulation and learning for Fuzzy Cognitive Maps using Big Bang-Big Crunch algorithm (written in Matlab)
Name of the software: **FCM-GUI**

9. **Chapter12_Franciscis_JFCM**

Description. A java package for designing and simulating FCMs (written in java).
Name of the software: **JFCM**

10. **Chapter13_Wildenberg et al.**

Description. FCMappers: Software in Excel for designing and simulating FCMs.
Name of the software: **FCMappers** (FCMapper.xls)

11. **Chapter14_Salmeron_Papageorgiou**

Description. An example code for Fuzzy Grey Cognitive Maps to model and analyze a chemical process control problem (written in Python and run in Eclipse).
Name of the code: **FGCM**

12. **Chapter15_Vascak_Reyes**

Description. A demo of FCM in navigation of a robocar.
Name of the demo: **Demo-robocar navigation**

13. **Chapter19_Vaidianu et al.**

Description. A weight matrix for modeling Perceptions of Stakeholders' for Management in Danube Delta Biosphere Reserve (Romania) and the produced .net files.

Name of the example case study: **Example-FCMappers-Romania**

14. **Chapter20_Mago_Papageorgiou**

Description. An FCM-GUI for periodontal disease prediction (written in Matlab)

Name of the software/tool: **fcm_based_prediction.exe**

Editor Biography

Elpiniki I. Papageorgiou is a Lecturer at the Department of Informatics and Computer Technology of TEI LAMIAS. She received her B.Sc. degree in Physics in 1997 from the University of Patras, Greece, with honor. In September 2004, she received her Ph.D. degree in Computer Science from the Dept. of Electrical and Computer Engineering, from the same University. From 2004 she was a postdoctoral researcher at Dept. of Electrical and Computer Engineering and her research was related with the development of novel cognitive models and algorithms based on soft computing techniques for complex decision making and control systems. She has been involved in several research projects (European funded research projects, IST, GROWTH, IMS as well as in national research projects) related with the development of novel methodologies based on uncertainty-aware intelligent/cognitive methods for complex systems and decision support, and expert systems for diverse applications.

Her broad research interests span the areas of Fuzzy Cognitive Maps, Expert Systems, Intelligent Systems, Learning Algorithms, Decision Support Systems, Data Mining and Knowledge Management in Software Engineering. She is author and co-author of more than 112 journals, conference papers and book chapters (ISI Web Science) and she has more than 782 citations (h-index=12 in scopus). Recent publications appeared in the following journals: *IEEE Transactions on Fuzzy Systems, IEEE Transactions on SMC (part c), Knowledge-based Systems, Neurocomputing, Applied Soft Computing, IEEE Transactions on Information Technology in Biomedicine*, to name a few.

E. I. Papageorgiou (ed.), *Fuzzy Cognitive Maps for Applied Sciences and Engineering*, Intelligent Systems Reference Library 54, DOI: 10.1007/978-3-642-39739-4,