From Prognostics and Health Systems Management

to Predictive Maintenance 2

Reliability of Multiphysical Systems Set

coordinated by
Abdelkhalak El Hami

Volume 7

From Prognostics and Health Systems Management to Predictive Maintenance 2

Knowledge, Traceability and Decision

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iSTE

WILEY

First published 2017 in Great Britain and the United States by ISTE Ltd and John Wiley & Sons, Inc.

ISTE Ltd
27-37 St George's Road
London SW19 4EU
UK

www.iste.co.uk

John Wiley & Sons, Inc.
111 River Street
Hoboken, NJ 07030
USA

www.wiley.com

Library of Congress Control Number: 2017942387

British Library Cataloguing-in-Publication Data
A CIP record for this book is available from the British Library
ISBN 978-1-84821-938-0

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Introduction

Intelligent Maintenance

Due to the evolution of technology, IT, and organizational approaches, industrial equipment is becoming more and more complex and automated. This complexity is a source of various incidents and faults that cause considerable damage to items, the environment and people. Obviously, the reliability of the equipment has an impact on the safety of items and people and, when maintenance is neglected, it can lead to incidents involving prohibitive costs, stemming from interruption of production, replacing items, etc. A lack of maintenance and its impact on the reliability of the equipment can lead to catastrophic consequences for the environment in cases of contamination. This can entail evacuation operations and environmental cleaning without, nevertheless, being able to completely remove the pollution in the area.

In order to prevent risks, companies must use reliable equipment, which should be well maintained by an efficient and well-organized maintenance system. Correct maintenance extends the lifetime of the equipment while contributing to better global performance. For this reason, maintenance has a strategic role in industry, and today it represents an essential task within a production system.

Sustainable process

An effective maintenance policy provides technical, economic and social advantages. It is coherent with the idea of sustainable development and makes it possible, on the one hand, to increase the availability of industrial systems and, on the other hand, to lengthen their lifecycle. From the point of view of economics, it reduces the cost of failures and, as a result, increases the profit of the product. The emergence of predictive maintenance, based on fault prognostics and, more generally, on PHM (Prognostics and Health Management) enables:

1) the anticipation of faults in systems' critical elements;

2) the prevention of industrial risks (in nuclear plants, oil platforms, etc.);

3) and the safety of people and items to be maintained.

Predictive maintenance

Classical maintenance strategies such as corrective, preventive and predictive maintenance are composed of business processes such as the upkeep, repair, or monitoring of an equipment's health state, its monitoring, fault detection, failure diagnostics or fault prognostics. Although these processes can be studied separately, it is wiser to integrate them into a PHM cycle, which can be considered as an adaptation of the OSA-CBM architecture. This cycle is described in part 1 of the book *From Prognostics and Health Systems Management to Predictive Maintenance 1: Monitoring and Prognostics* [GOU 16], starting from data acquisition, its processing by means of different modules of the cycle (data processing, detection, diagnostics, prognostics, decision and human machine interface (HMI)) and finishing with the decision and its presentation via suitable HMI interfaces for maintenance operators. This part is dedicated to the first modules of the cycle, from data acquisition to prognostics, proposing different monitoring and prognostic methods.

The purpose of the present book, which follows [GOU 16], is to tackle the other phases of PHM. These include the traceability of data, information and knowledge (first part of the book), and the ability to make decisions accordingly (second part of the book).

Maintenance implementation requires qualifications and contributes to the development of maintenance technicians. Our work, within a context of quality policy advocating for the continuous improvement of practices, is in line with a present challenge for a company, which is to provide the employees with the right information at the right moment, in order to allow them to work in the best conditions, and therefore to improve their skills. To maintain the items in a well-functioning state and to anticipate any failure, the maintenance operators need to be able to access all kinds of support services related to different maintenance strategies.

Companies should progress by transforming their activities through the development of a learning culture, which is the only alternative for maintaining a permanent state of innovation. Learning culture means sharing knowledge and cooperative work among members of a company. As a result, knowledge is considered to be the driving force of productivity and economic growth. An emergence of the knowledge management problem is taking place. Creating, capitalizing and sharing knowledge thus become a challenge that any company faces.

In this book, we address the expert maintenance knowledge of a maintenance company, the formalization and the manipulation of this knowledge. The maintenance operations, combined with technical advancements and new information and communication technology, have entailed an evolution of maintenance systems towards systems that integrate smart modules, which communicate and collaborate among each other. It is in this industrial and scientific context that the works described in the first three chapters are entirely situated. A knowledge management approach has been implemented in order to analyze the maintenance processes used by a maintenance company, with the goal of making an overview of support systems to be developed, and of being able to make them available as maintenance support services for the company's employees.

Actually, timely access to information concerning a product or a piece of equipment provides a better monitoring of the latter and allows us, for example, in the case of dangerous products, a better handling of this product, thus improving safety.

Information traceability

Information traceability is a vital element for ensuring the monitoring of a product or equipment in time, during its whole lifecycle. Over the last few years, Product Lifecycle Management (PLM) systems have been increasingly used to manage business operations and data generated by events and actions that involve the product[1].

Lifecycle refers to a set of phases that can be identified as the different stages of life of a product, from its creation to dismantlement. It is composed of three main phases:

– *Beginning Of Life (BOL)*, which includes the design and the manufacturing of the product.

– *Middle Of Life (MOL)*, which is related to the distribution, the usage and the maintenance operations.

– *End Of Life (EOL)*, which concerns the moment when the product ends its usage phase and is retrieved within the company in order to be recycled or eliminated.

The PLM concept is much more than an issue of visualizing and transforming data. It includes processes (the flow of data among the operators and the flow of resources according to competency) and methods (practices and techniques established along the process by using product data generated during each life stage of the product). This translates into three fundamental elements that constitute the basis of the PLM concept: ICT managing remote information systems, the processes and the methodology, which evolve along the lifecycle phases of a product (Figure I.1).

PLM services based on the Web, contrarily to PDM (Product Data Management) systems, do not limit themselves to facilitating the exchange of information regarding the product among heterogeneous product data management systems [GUN 08], but they can be a platform of collaborative development with the integration of data originated at scattered locations. PLM widens the field of application of PDM systems in order to provide a large company with more information concerning their product.

The availability of information during each phase of a product's lifecycle enables the sharing of information among the players of different cycle stages

1 CIMData: Product Lifecycle Management (PLM) Definition. Available online at: http://www.cimdata.com/PLM/plm.htmls

and the exploitation of this knowledge to improve the decisions to be made with respect to the product.

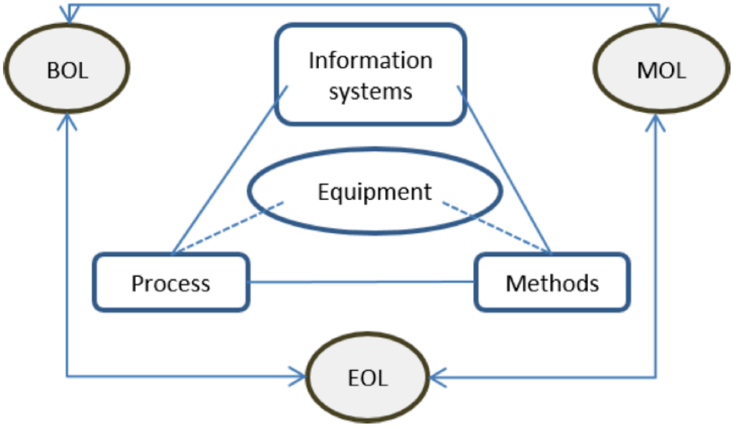

Figure I.1. *Elements of the PLM concept*

During the management phase of the product's middle of life, or MOL, a lot of data is gathered on the field for monitoring and controlling the product's life state and for keeping a record. Information issued from the product's beginning of life, BOL, is necessary for analyzing the product's structure and for understanding its behavior.

Within the context of safety of items and people, standards and laws are imposed in order to be able to trace the history of each product with the aim of ensuring a reliable, safe and traceable supply, and enabling the recovery of information required to understand post-mortem any anomalous event, whichever its seriousness.

Decision and strategy of maintenance

The second part of the book focuses on the concept of decisions based on expert knowledge of the system and on estimations provided by prognostics.

Indeed, sharing information regarding the product and its lifecycle process is vital for ensuring its durability. Knowledge of the product's history sheds light on this management, and it can provide information regarding the implemented maintenance policy, which has a non-negligible effect on the product's operating state. Actually, an effective maintenance policy yields technical, economic and social advantages:

– from a technical point of view, it allows an increase of the useful lifespan, availability and durability performance of a product;

– from an economic point of view, it reduces the cost of failures and, consequently, increases the profit of the product;

– finally, from a social point of view, it reduces to a minimum the number of incidents and risky situations.

Today, technological evolution enables the equipment to communicate and to provide information regarding the different ongoing events related to it. Therefore, it is possible to trace its operation and malfunctioning during its lifecycle. One of the key features of PLM systems is the availability of information, which can be easily accessed by the operators related to the product, and the intelligence integrated in their lifecycle. The idea is to propose a set-up of a so-called intelligent equipment, as in McFarlane's definition, which facilitates access to embedded and remote information.

In this book, we address the product's middle of life and, in particular, the implemented maintenance policy, as well as its impact on the other lifecycle phases. In fact, information issued from the MOL phase can be used:

– to evolve, within the BOL phase, the product's design by improving the product with respect to its usage, as in [STA 15];

– to define, within the MOL phase, the different kinds of decision (tactical, operational or strategic) in the best way possible. According to the monitoring problem, the decisions can be automatic or controlling decisions, decisions of online scheduling of diagnostics, or those of re-configuration of tasks or maintenance intervention planning;

– to improve the recycling procedure within the EOL phase of a component according to its health state and to the maintenance policy implemented on the product. Without information, decisions are made with respect to an approximate inspection, which is insufficient if the safety of people is at stake [PAR 04].

Chapter 1 illustrates a smart tracing system and its architecture connected to a remote maintenance platform. An infrastructure of smart products is proposed, which enables the equipment to be connected and capable of knowledge capitalization based on maintenance ontology.

Chapter 2 proposes a maintenance platform with a particular attention to knowledge, in order to guarantee the traceability of information along its lifecycle, and thus to be able to implement decision support systems.

An application of this intelligent traceability has been implemented on a ski lift and its brief description is given in Chapter 3.

Chapter 4 illustrates a bibliographic overview of different decision-making approaches in the context of PHM. The aspects of scalability of this decision phase (temporal granularity and description degree) are illustrated as well. This chapter is an opportunity to show the importance of decisions within the PHM process.

A first implementation of decisions is the object of Chapter 5. It adds a new strategic dimension to maintenance by means of the anticipation which it enables. Therefore, we speak of predictive maintenance. This chapter illustrates an example of optimization of predictive maintenance starting from information that is issued from the prognostic phase of PHM. This optimization consists of reducing the maintenance related costs via appropriate planning.

Finally, Chapter 6 develops an original approach for involving production resources with respect to demand. A further dimension is added to the planning phase by varying the utilization conditions of each piece of equipment with respect to its health state, with the aim of lengthening the production lifespan of the whole system before maintenance.

The book concludes with a summary analysis and perspectives regarding this emerging domain, since without traceability, knowledge and decision, any prediction of the health state of a system cannot be exploited.

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PART 1

Traceability of Information and Knowledge Management

1

Intelligent Traceability of Equipment

1.1. Introduction

Over the last few decades, the business awareness of companies has been based on their intangible capital, the knowledge and expertise of their employees. Many works have been dedicated to creating, sharing and capitalizing on this expert knowledge.

However, just like expertise and practical skills, data also contributes to the intangible capital of companies and it is carefully recorded. Banks jealously guard their databases. Companies distrust the cloud due to security issues related to data, which may fall into the wrong hands and be exploited by competitors or harm data owners. In the age of connected objects, of easy data harvesting and instantaneous remote access, it is evident that well-exploited data represents a gold mine. Indeed, data is becoming a resource which can be exploited by the economy. Data must be secured and exploited and this is the basis of informed decision-making within a domain.

The process of knowledge capitalization corresponds to the notion of knowledge management, which was defined by Davenport as the process of collecting, distributing and effectively using knowledge [DAV 94], an approach developed by [DUH 98]. Traceability is an essential element of the capitalization of knowledge related to different stages of a product's evolution [BIS 08]. Several works have highlighted the notion of the growth of products' lifecycle management as one of knowledge management [AME 05] and [STA 15]. In fact, the research consortium of the project FP6 IP 507 100

From Prognostics and Health Systems Management to Predictive Maintenance 2: Knowledge, Traceability and Decision, First Edition.
Brigitte Chebel-Morello, Jean-Marc Nicod and Christophe Varnier.

PROMISE (PROduct lifecycle Management and Information tracking using Smart Embedded systems) has remarked that traditional PLM systems lack product knowledge and visibility in the two MOL and EOL phases, and has recommended developing traceability and knowledge capitalization during the lifecycle.

The aim of our work is to design and develop a solution for processing and capitalizing knowledge related to industrial equipment throughout its lifecycle and for making it available for operators to easily access this equipment in an understandable way and at the required moment.

New PLM possibilities [RAN 11] are being introduced, thanks to continuous developments in the domain of information systems regarding radio-frequency identification (RFID), sensor network technology and, more generally, in product embedded information devices (PEID). A new generation of products called smart or intelligent products is being developed [KIR 11]. According to [YAN 09], it makes the information easily accessible for designers, users or disassemblers of the product or equipment. However, although these intelligent products are capable of gathering data during their lifecycle, they lack the means of extracting information and acquiring knowledge from this data. To reach this goal, we have tackled three challenges:

– Creation of a so-called intelligent product which allows users access to reliable information capable of being read or manipulated, as well as an available deduction related to the current health state of the product;

– Transformation of data in knowledge in a memory that stores all the information concerning the product during its lifecycle and which can be accessed from the product;

– Proposition for decision support services, online prognostics and monitoring of the health state of equipment and support services for maintenance and recycling of products. These services should be available via an information system which can be easily accessed through the product.

We will address these challenges in three stages: (i) after having defined what intelligent equipment is and having considered the work in this domain, we will orient ourselves toward the data exchange infrastructure CL2M, featuring RFID tags connected to an e-maintenance platform and equipped with deduction tools. (ii) We have developed a knowledge capitalization process that stores the knowledge in an operating memory which is distributed on the equipment and the e-maintenance platform. The knowledge is formalized according to the maintenance ontology IMAMO_RFID and made is available by means of an intelligent product infrastructure that ensures knowledge sharing. (iii) We have developed web services that require the availability of information regarding the state of (mal)functioning of the equipment along its lifecycle. In this way, we propose different decision support services:

– a support service for recycling components (products), in which data is indispensable in order to provide such a service [SIM 00];

– a support service for the monitoring and prognostic processes of the health state of the component;

– a support service for maintenance action planning.

As a result, this chapter will begin by outlining some state-of-the-art intelligent products followed in section 1.3 by a presentation of a knowledge capitalization process that monitors a component's health state along its lifecycle, and the proposition of an ontology called IMAMO_RFID, defined for intelligent products. Section 1.4 will be dedicated to the infrastructure of an intelligent product with the exchange of data and information and the implementation of decision support services.

1.2. State-of-the-art intelligent products

1.2.1. *Definition of intelligent products*

In order to monitor a product during its MOL phase, this product has to be intelligent in McFarlane's sense. [MCF 03] defines the product via a physical and informational representation stored in a database, which is associated with an intelligence provided by a decision support agent. An intelligent product is characterized by five main properties: possession of a unique identify, a capability to communicate effectively with its environment, ability to retain or store data about itself, and a potential to participating in or making decisions relevant to its own destiny. Other definitions of intelligent products exist [MEY 09, MCF 03] as listed [KIR 11] by Kiritsis, who synthesized them by defining an intelligent product as a system containing sensing, memory, data processing, reasoning and communication capabilities. He listed four intelligence levels ranging from a physical product without any embedded system to products with product embedded information devices (PIED).

1.2.2. *Research on intelligent products*

Research on intelligent products suggests integrating the product within an infrastructure of processed data sharing and lifecycle management. Ranasinghe *et al.* [RAN 11] have studied three Product Lifecycle Information Management architectures (PLIM) for collecting and accessing product data, both industrial and academic ones: (i) the EPC network architecture (Electronic Product Code), (ii) the DIALOG system (Distributed Information Architectures for collaborative logistics) and (iii) the WWAI network (World Wide Article Information). These architectures show some weaknesses regarding data synchronization when network disturbances occur. In other words, without a network connection there is no access to databases and the update cannot take place. Xiaoyu [YAN 09] remarks that the intelligent product should have some kind of mechanism that could use the collected lifecycle data to provide services. He suggests that an intelligent product should contain at least three fundamental elements: (i) an intelligent data unit (IDU), (ii) an access service and (iii) a communication infrastructure (CSI).

Z.Y. Wu *et al.* [WU 14] provide a software platform for lifecycle knowledge management that allows systematic assistance for the development of a product, in particular for new heating valves in nuclear power plants. For this purpose, record data has been exploited in order to support the design of the products (fault types, causes and recommendations regarding the actions to be undertaken).

Kiritsis proposes a closed-loop infrastructure for product lifecycle management, the CL2M (Closed-Loop Product Lifecycle Management), which was developed during the European project PROMISE [KIR 11]. The available technology (such as wireless sensors, telecommunications and product identification technology) makes it possible to connect the intelligent products with other information systems during an exchange request for information regarding the lifecycle. This closed-loop architecture enables the inclusion of the different users of the product in the information sharing, ranging from the designer to the constructors and the maintenance operators.

In this way, the designers are able to access real-time data of the product that they have designed, they can observe its usage conditions during the MOL phase and even have a look at recycling data (EOL phase). This is an important step for improving the product design. Furthermore, it enables collaborative tasks to be performed among the users, together with the analysis of information gathered during the lifecycle in order to extract new knowledge about the products. Moreover, Sylvain Kubler *et al.* [KUB 15] propose associating the CL2M concept with a new kind of hardware capable of communicating (for example, an RFID tag), which would make the component capable of undergoing physical transformations without losing either its ability to communicate or its stored data.

1.2.3. *Infrastructure of an intelligent product and RFID*

Recently, several different studies focusing on the usage of RFID technology within the domain of lifecycle management have been undertaken [KIR 03, MOT 11, MOT 13, WAN 10]. RFID technology uses radio waves for the automatic collection of data and is used for storing and transmitting information as well as identifying objects in several domains such as healthcare, military logistics, transport, clothing, food, construction, maintenance, and the logistics of the cold chain [ZAC 11, KAN 12].

Today, thanks to the existence of the RFID tag, intelligent products can provide a network oriented to the creation both of databases and decision support software services [RAN 11] 8 [MEY 09] 19 and [MCF 13].

Sylvain Kubler *et al.* [KUB 14] propose an information diffusion process in order to select information that is relevant to the usage context of the product: this information is stored directly on the product thanks to the RFID tag.

Sarac [SAR 10] underlines the fact that RFID improves both the traceability and the visibility of the products and processes information with accuracy. Mohamed *et al.* [MOT 11] use tags placed on the product to share lifecycle information. They illustrate twelve lifecycle stages such as production, installation and reuse/recycling/dismantlement. An information model is proposed for interacting with the different users along the different lifecycle phases and for providing them with access to data. The authors highlight the limited memory of the tags. Wang *et al.* [WAN 10] propose a usage of RFID technology for supporting disassembly decisions for products at their end of life, and they suggest a model for planning the dismantlement and sequencing based on fuzzy logic.

Kiritsis *et al.* [KIR 03] propose using RFID technology to implement a closed-loop system for PLM systems. The authors illustrate as well a concept for the e-transformation of information into knowledge. However, a lack of formal comprehension about the way of constructing lifecycle information still persists.

These works inspire us to present a piece of intelligent equipment implemented by a CL2M architecture that uses the RFID technology based on an e-maintenance platform. Our contribution concerns the transformation of data into knowledge and, in particular, the formalization of the knowledge that will be capitalized by a distributed memory. This formalization will be obtained from a knowledge capitalization process based on the maintenance ontology adapted for the lifecycle, which we shall call IMAMO_RFID.

1.3. Knowledge management approach

1.3.1. *Knowledge capitalization process*

In order to ensure information traceability during the whole lifecycle of the equipment, we have used a knowledge capitalization approach developed by our team [RAS 08]. It is based on the four phases of the Grundstein capitalization cycle [GRU 96, GRU 00]: the detection of strategic information, preservation of knowledge, its capitalization and its actualization (see Figure 1.1).

1) The detection of strategic information is done via an analysis of maintenance strategies developed in a company by observing the maintenance actions performed at each event. The events may be caused by failures, diagnostic tasks or systematic maintenance planning. This may concern the monitoring of the equipment's operating state, detection of the fault mode and prognostics of its state.

2) Knowledge preservation is achieved through the construction of an operational memory, which can be done via three existing approaches: bottom-up (collection of verbal data), top-down (model-driven) or mixed approach. We have chosen the top-down approach to formalize knowledge via

a maintenance ontology based on IMAMO [NEZ 06], which we have adapted to the intelligent product IMAMO_RFID.

3) Knowledge exploitation is implemented thanks to the infrastructure of the intelligent product and to an e-maintenance platform hosting the IMAMO_RFID ontology which ensures the exchange and diffusion of knowledge.

4) The actualization of knowledge is done via decision support services provided to the equipment's users. These web services can be of different kinds, depending on the information and knowledge data, its traceability, exploitation and maintenance support services.

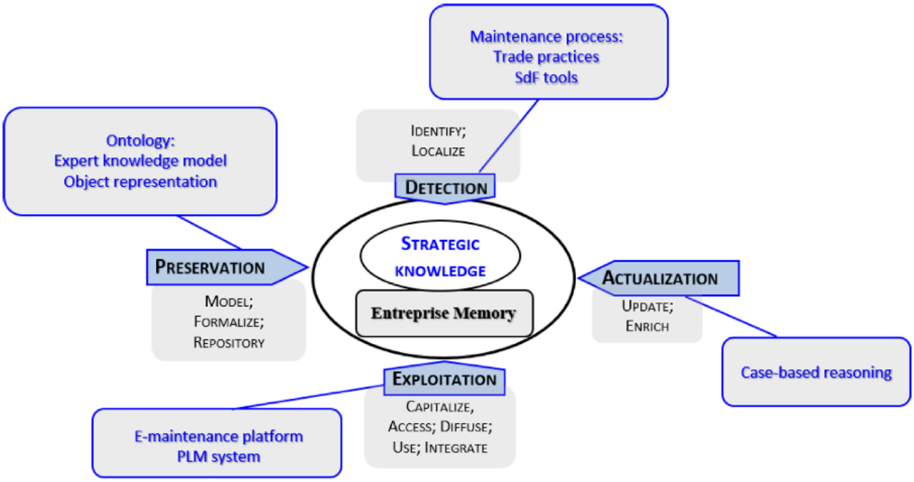

Figure 1.1. *Knowledge capitalization cycle*

We dedicate section 1.3.2 to a survey of the ontologies developed in PLM in order to propose an IMAMO_RFID in this work.

1.3.2. *PLM ontologies*

Ontology-based approaches are being developed to facilitate the communication and the exchange of information among various systems. This reasoning allows an inductive way of solving problems.

Several works regarding PLM ontologies exist. An ontology related to assembly (OAM - Open Assembly Model) is proposed in [FIO 07] and it is integrated into the models of existing products. In the BOL phase, design support ontologies have been developed in a unique environment [SUH 08] and in a distributed design environment [ZHA 08], as well as for the purposes of sharing product knowledge on a network [LEE 07].

An ontology dedicated to engineers working with knowledge management in design processes and implemented in a comprehensible way is proposed in [BRA 08]. Borsato proposes an ontology that is related to the data of the product and its process in terms of durability through semantic links.

Matsokis and Kiritsis [MAT 10] transformed the semantic object model of the European project Promise (PROMISE_SOM (Semantic Object Model)) into an ontology by adding temporal events. Karray proposed a first version of a maintenance ontology [KAR 10] and Matsokitis and Karray combined their ontologies to propose the SMAC (Semantic Maintenance and Lifecycle) model [MAT 10], which takes into account maintenance and different PLM phases. Karray created the IMAMO ontology by bringing together the models of MIMOSA CRIS (reference of the maintenance domain), the SMAC model and PROMISE-SMO. IMAMO incorporates the concepts of the SMAC model, which are related to the equipment's lifecycle in such a way as to take into account: (1) the lifetime, starting from the design phase; (2) the life environment, by monitoring all the events and the health states of the equipment; (3) the end of life, by calculating indicators that support the decisions of reuse and disassembly.

1.3.3. *Proposition of IMAMO_RFID*

In this work, we propose an ontology called IMAMO-RFID. We have created an evolution of the IMAMO ontology [KAR 10] with the purpose of managing the RFID tags associated with an equipment and their content. We have integrated the concept of distributed memory and determined the minimal necessary knowledge that has to be stored in an e-maintenance platform in order to guarantee the monitoring of an equipment during its whole lifecycle.

This package of memory card management, the “LifeRecordManagement” package, ensures the monitoring of the equipment during its whole exploitation phase.

The memory card management model ensures the monitoring of the equipment during its whole exploitation phase. It creates indicators that represent the equipment’s health state. These indicators, mainly statistical ones, are calculated from the stored record of data regarding the various operating state modes of the equipment, the sensor measurements and of different interventions performed on the equipment.

This ontology associates a memory card with each component or piece of equipment by using the LifeRecord management system, “the LifeRecordManagement package”. This package is directly linked to five other packages:

– InterventionManagement: a package that allows the usage and storage of data originating in maintenance interventions, both from systematic preventive and corrective interventions and/or palliative ones;

– MaintenanceStrategy: a package that includes technical indicators calculated via the function “Generate indicator” and the function “Validate control” which updates the counter indicator of the control operations that are performed or generated by prognostic functions;

– EquipmentManagement: a package that stores the equipment’s characteristics;

– MonitoringManagement: a package that allows the acquisition of data from sensors. It stores the collected data in a technical database created according to the notion of measure. This information model will be implemented in an intelligent product;

– RFIDManagement: management of the RFID tag, a new package in IMAMO. It enables reading and writing onto the RFID memory by using an RFID reader.

The class diagram in Figure 1.2 illustrates the objects of the various packages that define the links with the different classes associated with the distributed memory, which is composed of the LifeRecord and the RFID tag. We will describe only those classes that are involved in the management of this distributed memory.

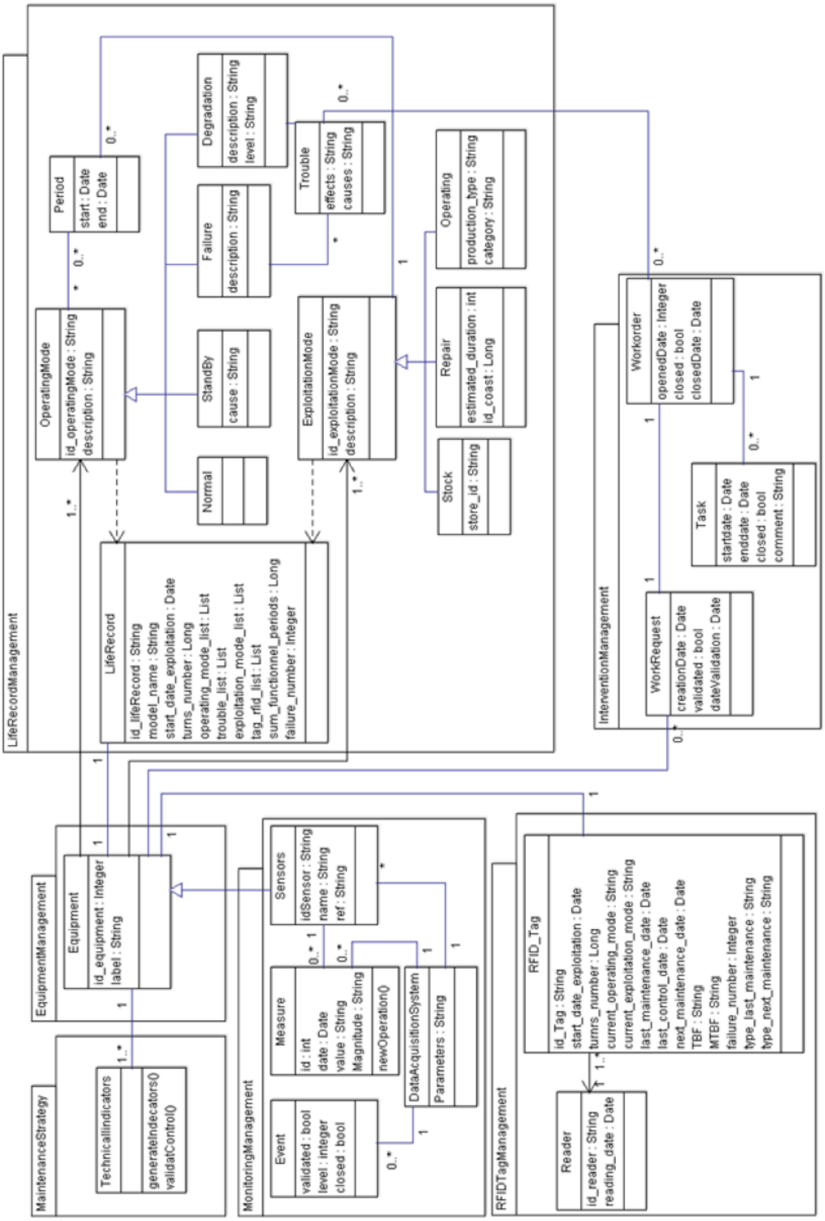

Figure 1.2. *Class diagram of the memory concept*

The latter comprises a set of operating and exploitation modes which are related to intervals of time defined by a start and an end date. Data regarding the equipment's usage has to be put in relation with the operation and exploitation modes, in order to guarantee the monitoring of the equipment during its whole lifecycle.

The operating mode (OperatingMode class in Figure 1.2) is related to the location of the component. It is quite important to be able to localize the component at any moment. We take into consideration the component's location, which is directly related to its operating state. For example, in the case of a component, the exploitation mode can be in stock (the location during a temporary suspension) or in repair in a maintenance workshop. Three exploitation modes are defined:

– Operational: in this case, besides the production duration, it is necessary to indicate the location of the equipment in order to localize its operating place;

– Stock: the component is in a normal state, ready to be used, although it is temporarily unused. It is placed in a storage location. For example, ski cabins are not used all the time. They can be parked in an appropriate place when they are not used;

– Repair: the component can be located in a workshop during the repair.

The operating mode of the equipment can be defined as the ability to perform a required function in particular conditions at a given moment or during an interval of time, supposing that the required exterior results are provided. The different possible modes are normal, degraded and failure states.

LifeRecord is a virtual memory that records data about the equipment's lifecycle. This data is synthetic, being composed of maintenance indicators calculated from the data record. These indicators, mainly statistical ones, may include (i) a reliability coefficient such as the MTBF (Mean Time Between Failures), which represents the average duration of correct operations between consecutive failures, (ii) a maintainability coefficient, MTTR (Mean Time To Repair), which is the average repair duration, (iii) the availability rate of the equipment, which is the ratio between the actual time of availability and the required time, and (iv) a health state indicator modeled by prognostic methods.

The variation over time of these indicators constitutes a characterization of the operating state of the component or equipment.

The RFID tag contains the minimal memory used for data storage associated with the component or equipment during its whole lifecycle. The equipment has several operating and exploitation modes during the MOL phase of its lifecycle. An operating mode involves several components, which are involved in the operating mode during a certain amount of time. A malfunction is associated with each fault or degradation. For a given malfunction, several interventions are possible.

1.4. Intelligent product: data flow and distributed memory

1.4.1. *Architecture of an intelligent product*

The proposed infrastructure is a closed-loop model of product lifecycle management (CL2M), shown in Figure 1.3.

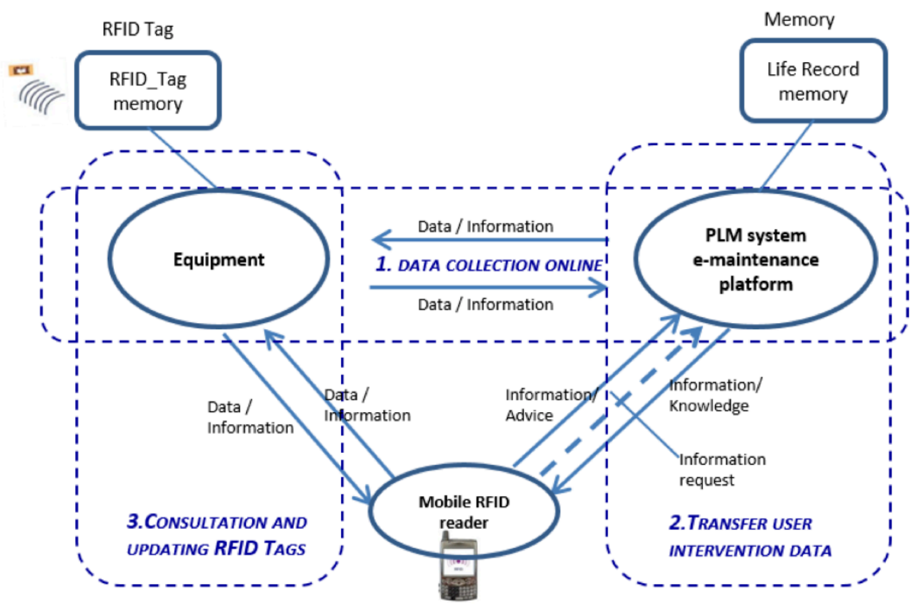

Figure 1.3. *CL2M infrastructure of an intelligent product*

To each critical component of a monitored equipment, we associate:

– an RFID tag with a unique identifier containing enough memory to record essential data and to communicate between the component and the PLM system;

– an additional feature consisting in the identification and communication capabilities that are now added to the product characteristics, thanks to RFID and NFC (near-field communication) technology;

– access via a mobile agent (mobile RFID reader) to the PLM system and to the memory, which we shall call the “vital card”;

– a PLM system that controls the knowledge capitalization.

1.4.2. *Stream of data and information in the MOL phase*

There exist three types of data transfer related to the various kinds of maintenance:

1) Online data collection that allows the acquisition of maintenance data via a remote platform and makes predictive maintenance possible. In fact, conditional maintenance planning is done depending on the wear state, which is controlled by the sensors, and the predictive maintenance monitors the variation of the sensors’ indicators via experimental measurements. The monitoring service is provided by the platform;

2) Transmission of data related to systematic maintenance, which schedules periodic interventions as a function of time or consumed units, and corrective maintenance, which focuses on an effective repair or replacement of the component or equipment after the failure occurs. Different kinds of services can be provided by the platform;

3) Information consultation and/or updates by the operator requesting information about the component’s health. The platform offers a decision support service regarding recycling or maintenance actions according to the component’s health state.

1.4.3. *Distributed memory: RFID tag and LIFE RECORD*

In order to gather knowledge about the health state of a component or piece of equipment during its lifecycle and to make this knowledge available, we propose to create a corporate memory of a company specialized in maintenance services. This memory is constructed by means of a knowledge capitalization process and it evolves during the lifecycle.

The corporate memory consists of two distributed memories:

– an RFID tag, which can be read with a mobile reader thanks to the NFC technology; we can thus read locally the tag identifier and the content of its memory, a "short term memory". The equipment is capable of providing a minimum of information about its health state: for example, if the information regarding its maintenance plan is updated, then the dates of its last and next maintenance are automatically updated. This memory is equivalent to a health record for this equipment;

– LIFE RECORD: we can access this remote memory, located in an e-maintenance platform, at a later step. Thus, it is possible to obtain all the information concerning the equipment model, its failures, effective usage time, degradation and past interventions.

1.4.4. *Stream of information during the MOL phase*

Data transmission during the whole lifecycle of the equipment is implemented by means of an e-maintenance platform. Information is collected, capitalized and stored in a memory. Figure 1.4 describes the data flow between the equipment and the platform. It corresponds to loop number 1 in Figure 1.3, "data collection online", whereas Figure 1.5 corresponds to loop number 2, "transfer of systematic maintenance data". The transmission of the intervention data corresponds to the data flow between the tag reader and the platform, which is related to control operations (systematic maintenance) and corrective maintenance.

Figure 1.4 shows that the sensor data originating on the component or equipment is collected (data acquisition, DAS) at regular intervals of time by means of events.

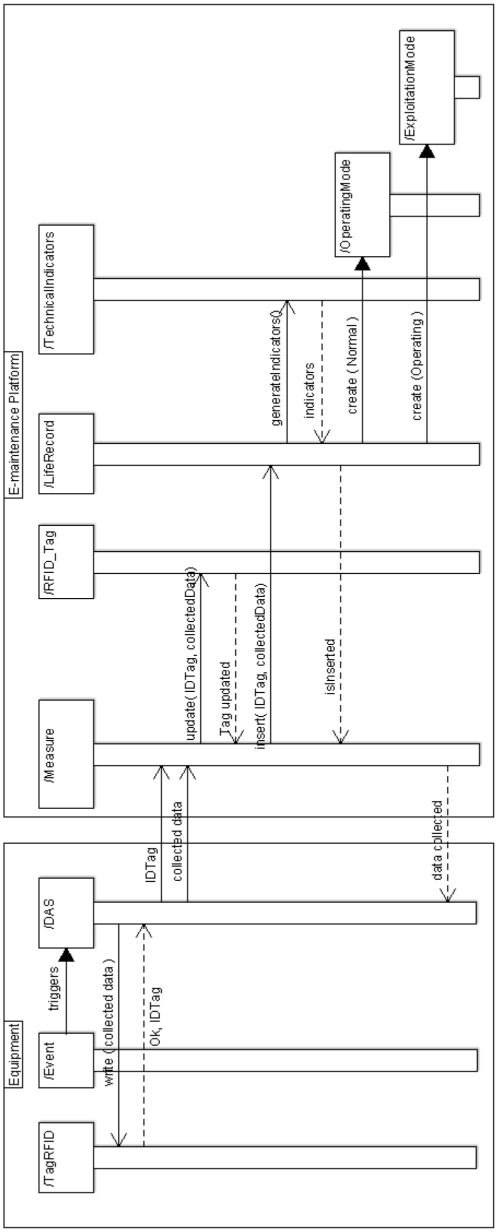

Figure 1.4. *Data flow during the transfer of intervention data*

The */Event* command prompts the data acquisition system, DAS, to collect data and to send it to the platform. A web service sends a message to the platform with one or more measurements. This message is recorded in the technical database. The data is stored in the RFID tag that contains the most recent data and in the LifeRecord in order to keep a record of all the measurements. From this record, the function "Generate indicators" calculates the indicators and updates the health state according to the lifecycle data. As long as data is collected, the equipment is in a normal "OperatingMode" and it is working.

This data stream is used to detect the occurrence of a fault and to generate an event concerning the control operations to be performed during the systematic maintenance. In the case of a failure, the platform creates a "failure mode" in cooperation with the associated perturbation. In the case of a control operation, the platform validates the control of the equipment via the function "validateControl" of the "TechnicalIndicators", then the function "GenerateIndicator()" of the "Class TechnicalIndicators" is called.

This approach allows the creation and transmission of indicators to the RFID tag, as represented in Figure 1.5. When an equipment failure is detected on the site, the maintenance operator uses an RFID reader to scan the tag that is associated with the faulty component, thus retrieving the maintenance data stored in the component, so that this data is eventually modified and updated. This data is used to describe the health state of the equipment, as well as its operation and its (mal)functioning modes. After the maintenance operator has updated the data within the tag, the mobile reader sends its content to the platform via a web service. The characteristics of the equipment are identified by means of the tag identifier.

The operational mode changes to "Failure" mode. This entails the creation of a "WorkRequest", validated by a maintenance supervisor who plans a "WorkOrder" that contains all the tasks to be performed during an intervention on this equipment. The timestamped data recovered via the web service will be inserted into the "LifeRecord". From the content of the "LifeRecord", the function "GenerateIndicators" of the Maintenance Strategy package of the "TechnicalIndicator" class calculates a set of indicators that are associated with this equipment, such as the number of failures, its MTBF, TBF and the type of the most recent maintenance (control, systematic upkeep or corrective) and sends them to the "RFIDTag".

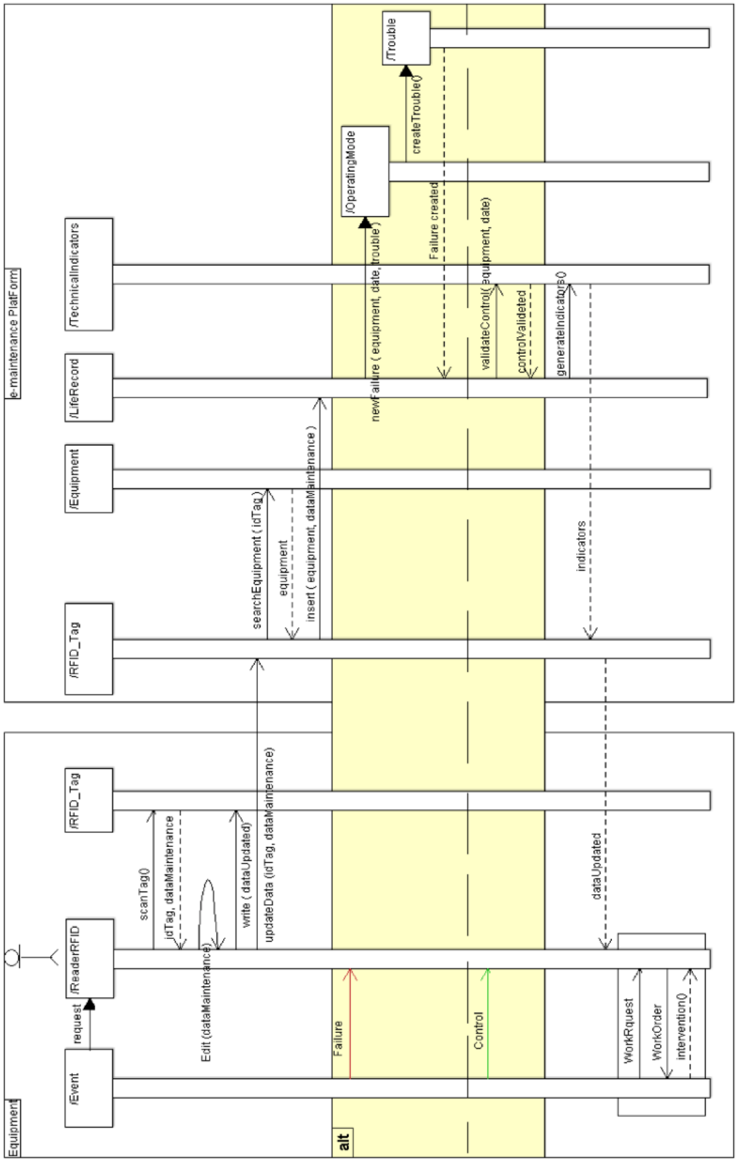

Figure 1.5. *Data stream during the transmission of intervention data*

1.5. Support service for component's recycling

The usage of the IMAMO_RFID ontology provides us with an access to all the information about the critical component or equipment. The indicators of correct operation rate calculation and of the number of failures undergone by this item are updated at each data collection interval. Thanks to these indicators, which synthesize the component's behavior and health state, it is possible to make decisions regarding the possibility of recycling the component.

We will identify these states by using specific scores, which are obtained from the calculation of the indicators and are updated during the whole lifecycle of the component. These indicators are stored in the memory of the RFID tag and they can be accessed without a prior connection to the platform.

If the number of failures N is greater than a default threshold $N_{threshold}$, the equipment is scrapped. In the opposite case, we consider the score defined as $score = MTBF * TM$.

The interval of time measurement is defined by $S \pm \Delta S$, where S $=$ threshold of MTBF, ΔS $=$ measurement error, and MTBF $=$ Mean time between failures.

If ($score < S \pm \Delta S$), then the equipment can be reused.

For the systematic maintenance, we calculate:

$$TM = \frac{\text{number of performed systematic maintenance interventions}}{\text{number of planned systematic maintenance interventions}}.$$

In this way, we take into account the maintenance performed on this equipment. If this rate is not good enough, MTBF can be penalized by multiplying it by the maintenance ratio. This may lead to a rejection of reuse for this equipment.

If the obtained score value is within the interval, LifeRecord has to be consulted.

On the other hand, if the score is slightly lower than the limit value, the component can be connected to the platform and its complete record can be consulted in order to access the characteristics of the component, on which basis the expert can make decisions.

1.5.1. *Implementation of an intelligent equipment and decision support service*

In order to create an intelligent system, we have implemented a closed-loop model architecture shown in Figure 1.4. The techniques employed, various components and some new intelligent services are described. These services allow knowledge capitalization during the MOL phase of the lifecycle and the calculation of indicators for decision support regarding the possible reuse of the component.

Component:

1) The e-maintenance platform provides some maintenance applications. It is based on J2EE specifications. The client is a light browser enabling access to the platform. The application server is a JBOSS server. The persistence level uses PostgreSQL as an object-relational database management system (ORDBMS);

2) The RFID tag has a unique identifier and contains a small memory which allows the storage of vital information and communication between the component and the PLM system;

3) The RFID reader: a smartphone or a tablet with applications developed under Android. It allows, on the one hand, reading and writing in the RFID tag by using the NFC technology and, on the other hand, communication with the platform via web services;

4) Web service: the communication is performed by means of the web service technology, which is a widely used technology for implementing service-oriented architectures (SOA). These architectures simplify the interoperability and the integration of applications on the platform;

5) NFC protocol: in order to ensure the equipment's monitoring, the RFID (Radio Frequency IDentification) tag technology is used and the NFC technology facilitates the reading and writing of information in the RFID tag.

1.6. Conclusion

Sharing information about a product and its lifecycle processes is vital to ensure its durability. The new possibilities of PLM afforded by technological advancements enable the creation of a new generation of intelligent products, which is the subject of this chapter. We proposed an approach that makes a product intelligent; in other words, we integrated the product in CL2M, a closed-loop infrastructure for data exchange equipped with an RFID tag.

To endow this equipment with the capabilities to manage the knowledge that concerns it, we developed a knowledge capitalization process that records the knowledge concerning the whole product's lifecycle in a corporate memory. This memory is distributed in two memories, one embedded on the product in an RFID tag (capable of identifying the product) and another that stores remotely all the events undergone by the product.

The implemented CL2M architecture allows the connection of the product to a remote maintenance platform that ensures the product's health state monitoring. This monitoring is performed using three types of data transfer: (i) online data collection via an acquisition system, with a transfer to the platform via a web service, (ii) local reading of the RFID tag embedded on the product via the NFC technology (its usage facilitates reading and writing within the RFID tag) and (iii) the acquisition of data related to user interventions by means of a questionnaire on a mobile RFID reader, which thus sends information to the tag and to the platform where the information is capitalized.

The knowledge capitalization approach, which we proposed and implemented, is based on the construction of IMAMO-RFID, an ontology from the maintenance domain adapted for intelligent equipment. This ontology stems from different ontologies within this domain, combining the concepts of maintenance, lifecycle and distributed corporate memories. This model associated with the intelligent equipment offers different services such as (i) making the product's lifecycle information available at any moment, (ii) allowing the decision of whether the product can be recycled or not according to a calculation of indicators performed on reliable information and (iii) proposing decision support systems based on constructed indicators such as MTBF or RUL and the information available thanks to the integration of the detection, diagnostic and prognostic applications in the maintenance platform.

This intelligent product can provide different services by means of its CL2M architecture, ranging from local or remote information retrieval to support services for traditional maintenance, such as systematic, corrective and conditional maintenance, and for predictive maintenance, which anticipates the failures. Some examples of these services will be described in Chapter 3.

2

A Knowledge-oriented Maintenance Platform

2.1. Introduction

In Chapter 1, we defined the architecture of so-called intelligent equipment, which consists of a distributed s-maintenance platform. This platform ensures the monitoring and maintenance of equipment in order to guarantee its reliability and right operating state. Correct maintenance allows the lengthening of the equipment's lifetime while contributing to a better global performance.

Maintenance's role is strategic in the industrial environment, and it arouses a lot of interest even today. Maintenance functions have been evolving continuously within companies. Many generations of maintenance systems have appeared, ranging from local systems to integrated computerized maintenance management systems (CMMS) initially and current systems that integrate intelligent modules that communicate with each other. Thanks to new information and communication technologies (NICT), and the emergence of web technology and the Internet network, the implementation of maintenance and control services can be done automatically, remotely, and with the support of different computerized systems set up within companies. At the same time, the CMMS tools have evolved to propose potential connections with other applications or systems, as for example, the "readers of measured values", mobile devices, external catalogs, computer-aided design (CAD) tools or websites.

From Prognostics and Health Systems Management to Predictive Maintenance 2: Knowledge, Traceability and Decision, First Edition.
Brigitte Chebel-Morello, Jean-Marc Nicod and Christophe Varnier.

The new CMMS generation present on the market can be thought of as decision support systems with the goal of controlling the maintenance and intervention costs, optimization of human and technical resources (such as the spare parts stock and tools), description of technical installations and related documentation, and measurements of the efficiency of maintenance activities (maintenance indicators).

Furthermore, several projects have addressed the concerns of integrating all these applications into a distributed information system while ensuring the interoperability among these applications. These maintenance systems propose to their users (maintenance operators) a computerized management of a set of basic activities of the maintenance process (such as intervention, planning, diagnostics, etc.).

The variety and the nature of different existing information systems and their evolution within the domain of industrial maintenance spurred us to review various generations of maintenance support systems [CHE 10]. The most sophisticated generation provides e-maintenance platforms, which have been developed mostly in large projects.

These maintenance systems propose to their users (maintenance operators) a computerized management of a set of basic activities of the maintenance process, such as the diagnostics, and provide a decision support for a set of predefined indicators about the equipment, interventions and related costs. Hence emerges the concept of services offered via maintenance architectures, which can vary from autonomous systems to integrated systems, where cooperation and collaboration are essential for any operation [RAS 07]. Some technologies, such as web services, have definitely contributed to this approach [BAN 04]. Remote maintenance and e-maintenance form concepts that are developed and applied in industry [MUL 08].

The e-maintenance concept, widely used in industry, has been addressed in a large number of works and has gathered a multitude of definitions, summarized in the CIM data Product Lifecycle Management (PLM) definition[1], starting from which we will define the concept of e-maintenance in section 1.3. However, the services proposed by e-maintenance systems are defined during the design phase, in compliance with the user's needs at a

1 http://www.cimdata.com/PLM/plm.html

given moment; therefore, they are not flexible enough to adapt to the user's demands and to evolve in accordance with new constraints and contexts. The challenge we give ourselves is to evolve the e-maintenance systems into systems that change following the users' requirements. The foreseen path consists of defining a knowledge-oriented system that would allow the definition of services according to demands. In fact, most current research on information systems is focused on knowledge [ERM 00], and this leads the researchers from various domains (i) to solve different types of problems, in particular those of semantic interoperability, (ii) to develop applications from a composition of web services using knowledge models as a support and (iii) to implement self-maintenance methods [LAB 06]. The latter applications of self-maintenance use rule-based reasoning methods or fuzzy inductive reasoning coupled with reasoning methods based on the situation. Consequently, we propose a new generation of maintenance information system by taking into account not only the current evolution in the ICT domain regarding business-oriented information systems, but also knowledge-oriented systems. We propose the first version of a knowledge-oriented system that uses web services. The heart of this system is a knowledge management system capable of inferring new knowledge and providing maintenance services on demand.

In section 2.2, we will focus on existing maintenance platforms and their software architecture depending on the kind of information exchanged and on the complexity of relations that link the various systems and applications that are integrated in these architectures. A classification of these architectures will be presented. An extrapolation of the features of e-maintenance systems will allow the definition of the characteristics of a new platform generation, a knowledge-oriented platform that we shall call an s-maintenance platform, where s stands for semantic.

In order to contextualize the s-maintenance concept with respect to that of e-maintenance, we carried out an overview of the state-of-the-art works about e-maintenance. As it turned out, there exists a wide range of definitions of e-maintenance, and the concept of s-maintenance is pioneering. We set out to give a general definition of e-maintenance basing ourselves on the works in this domain, and to frame the concept of s-maintenance with respect to this definition.

2.2. Software architectures of maintenance support systems

A brief reminder is required in order to be able to classify the software architectures with respect to the type of information exchanged and to the relations between systems.

2.2.1. *Exchanged data, information, knowledge and competence*

Many definitions of knowledge management exist; they have been reviewed by Rasovska in Chapter 2 of her thesis. The definition proposed by Jarboe [JAR 01] explains that organizations gather and communicate "resources, perspectives, and possibilities, implied and explicit, data, information, knowledge, and even competence". This definition leads us to characterize the different kinds of "information" or "knowledge" depending on their complexity, mutual relation, and comprehension level. Figure 2.2. illustrates the relation between these different entities. We adopted the definitions according to several references in this domain, such as [JAR 01, PRA 97].

– Data is a basic element that can be used to represent some information, such as a measurement or a characteristic, in a database. Two kinds of data are distinguished: raw data and structured data, which can be transferred remotely via an information system. An example of data might be a temperature $= 100°C$.

– Information is interpreted data that represents a real fact. It is the data that has been completed by a description indicating its context: what kind of measure is this, when, where and by whom it was taken, etc. In our example, it is the temperature of an engine's water measured in a piece of equipment.

– Knowledge is information that has been integrated, refined and synthesized with respect to a specific context. It is information that has been interpreted and contextualized, that has a sense and a meaning (why and how this measurement was taken, and the whole context of this measurement, often organized for exploitation needs). In our example, the water temperature of 100 °C in an engine is too high and is a symptom of a failure.

– Competence, in this case, is organized knowledge that can be exploited directly by the users in order to execute a certain task or action. It represents "the knowledge within the action", in other words, a solution to a problem which, following this action, is validated or actualized for an experience feedback.

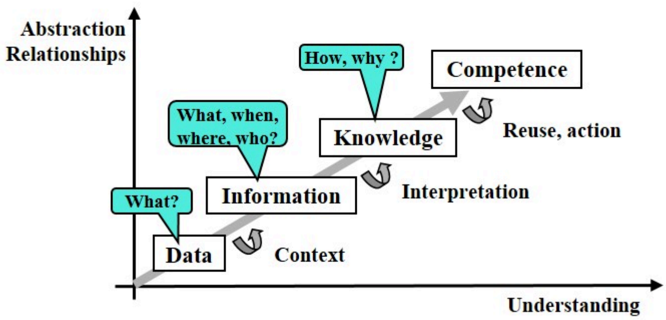

Figure 2.1. *Classification of different types of information*

2.2.2. *Relations between information systems*

The integration of applications into the same information system and the emergence of new management policies (RCM, MCO, etc.) related to the expansion of the Internet to companies were the precursors of so-called "intelligent maintenance". These information systems, initially independent and autonomous, started to communicate, or even to cooperate by exchanging and sharing information. More recently, ICTs have allowed the migration of these different autonomous systems to an integrated system, where cooperation and collaboration are essential for any operation (see Figure 2.2).

– The autonomy relation represents a framework in which a system has the maximum management capabilities and is independent from all the other systems and elements. There is neither data exchange nor communication between this system and the others, and it has to be self-sufficient with regard to the required information.

– The communication relation is a link between two or more systems that allows data transfers or exchanges. The information transmitted during the communication is not limited to alphanumerical characters anymore, and it also includes images, sound and video sequences. Within a certain context, the term communication is often used as a synonym of telecommunication.

– The cooperation relation represents cooperative work that is carried out by dividing tasks, in which each participant is responsible for a part of the problem's solution. In our context, we refer mostly to technological and industrial cooperation; therefore, a cooperation agreement is made between independent systems that commit to executing common projects to produce maintenance services.

– The collaboration relation represents a strategic partnership that combines competences, suppliers or various products. Collaboration implies a mutual commitment of the participants to a coordinated effort of solving a problem together, by sharing resources, information and competences in order to better adapt the organizations to their environment.

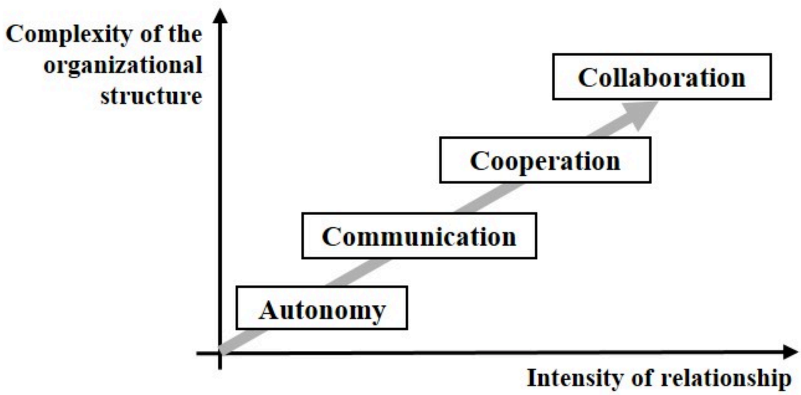

Figure 2.2. *Relations between systems*

2.2.3. *Characterization of maintenance systems*

We classified the different architectures of existing maintenance information systems according to two criteria: the evolution of the employed information and the relations between the systems that are integrated in the architecture. Four general architectures were identified: maintenance, telemaintenance, e-maintenance and s-maintenance (Figure 2.3). The maintenance architectures are arranged on an exponential function curve since the collaboration between these systems is achieved sooner than the shared competence level. The volume of information that is handled automatically is represented by the area of each system's block, and it increases with the collaboration intensity and the complexity of information shared [RAS 07].

– A maintenance system consists of a single information system, which is located at the production site and is used on the maintenance site. This is an autonomous system, without any exchange of data with other systems. In comparison with the classification of companies, it corresponds to a traditional company; therefore, we are referring to a traditional information system architecture.

– A telemaintenance system comprises at least two information systems: a transmitter and a receiver of data and information which communicate remotely. According to the AFNOR's definition, telemaintenance is "the maintenance of an item performed without physical access to the item by the staff". We talk of distributed architecture based on the notion of distance that allows data transfer via a radio, a telephone line, or through a local network.

– Thanks to the Internet's expansion, telemaintenance systems are moving towards the concept of e-maintenance. An e-maintenance system is implemented on a cooperative distributed platform that integrates various maintenance systems and applications. This platform requires the support of the Internet global network (hence the term e-maintenance), and the web technology makes it possible to exchange, share and distribute data and information, as well as to create knowledge together. In this case, the concept of intelligent maintenance can be exploited, and proactive and cooperative maintenance strategies are implemented.

– By means of an extrapolation along the two axes in Figure 2.3, we propose an architecture that improves the performance of e-maintenance in terms of communication and data exchange between the systems, and that allows the semantics of data processed by the applications to be taken into account: s-maintenance (where "s" means semantics). We propose a new concept based on web semantics [RAS 06], which was formalized in [KAR 12].

Consequently, the new generation of information systems for maintenance has to take into account not only the current evolution in the ITC domain regarding information systems oriented towards business and users, but also the evolution in the field of knowledge, which will be the cornerstone of a new generation of maintenance systems. For this purpose, we propose new knowledge-oriented systems with an exploitation of web services, based on ontologic engineering and the expertise of the maintenance domain [KAR 10, CHE 10]. These systems are able to generate new knowledge and provide services on demand [TOG 08].

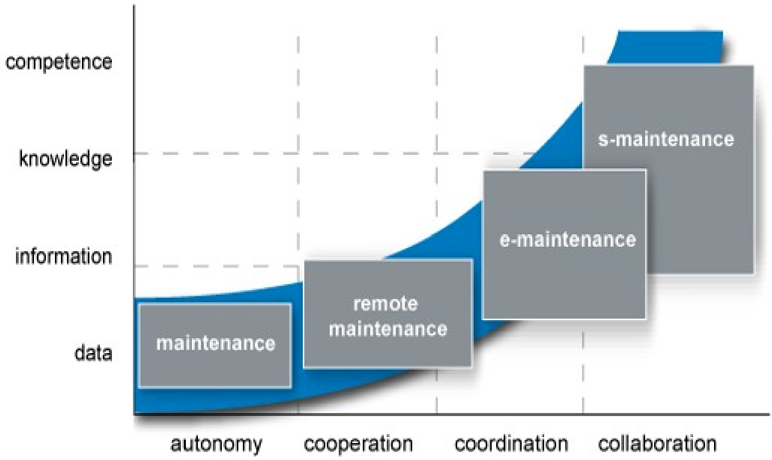

Figure 2.3. *Intensity of relation*

2.3. Projects and works on e-maintenance

Numerous works and large projects have focused on e-maintenance systems. Several e-maintenance platforms have been developed over the past few years, and many are still operational today; they can be divided into two large categories: the platforms from international or European projects led by industrial and university partners, and academic platforms created by academia and groups of researchers in [KAR 12]. We briefly review the main projects that produced e-maintenance platforms. According to the four criteria that are specific to s-maintenance, we will evaluate the operational platforms together with the platforms defined by the six most famous academic projects in the context of a university or a research center. Most of the platforms proposed remain at a theoretical proposition stage without a concrete implementation, with the exception of IMS-WATCHDOG in D2BTM. We analyzed the six most well-known platforms according to four features specific to s-maintenance with respect to existing e-maintenance platforms.

2.3.1. *Projects and works on e-maintenance*

Seven important projects on e-maintenance are reviewed: the international project MIMOSA, the European projects ESPRIT-REMAFEX, PROTEUS, PROMISE, SAMMART and DYNAMITE, and finally, a Swedish e-maintenance project 247_NFFP4.

For the MIMOSA project, a functional architecture OSA/CBM (Open System Architecture for Condition-Based Maintenance) was developed [THU 01a]. It is dedicated to the development of conditional or predictive maintenance strategies [THU 01a].

Within the project ESPRIT-REMAFEX, Yu *et al.* propose an e-maintenance system called the "Problem-Oriented Multi-Agent based E-Service System (POMAESS)". This multi-agent system offers a decision support system by means of case-based reasoning [YU 03]. Each expert agent is a problem-solving agent dedicated to the diagnostics with specific local, non-shared knowledge, localized at various sites. Within the European project PROTEUS, the first e-maintenance was developed that provides web services [BAN 04]. One of the purposes of PROTEUS is to integrate all the tools and applications on the subject of maintenance, and it is one of the rare projects that covers the entire maintenance process.

The goal of the European project PROMISE (PROduct lifecycle Management and Information tracking using Smart Embedded systems) is the management of the product lifecycle (PLC) with the integration of new technologies, such as RFID and computer networks. The PROMISE's architecture was designed to fulfill the specific requirements of PLM (product lifecycle management), to allow the recovery and updating of information about the products during their whole lifecycle, and to transform it into exploitable knowledge [KIR 04].

The European project SMMART (System for Mobile Maintenance and Accessible in Real Time) aims to provide tags with new intelligent technology. This system monitors the usage and maintenance data during the lifecycle of the critical parts. The architecture proposed in this project is based on the RFID technology, used for the traceability of logistic units and for the management of the configuration engine, which serves to recover the configuration data of critical components. Following the continuity of European projects, the

DYNAMITE (Dynamic Decisions in Maintenance) project had the objective of creating an infrastructure for mobile monitoring technologies and creating new intelligent devices or instruments. In this context, the maintenance platform DynaWeb was developed [ARN 07], and it designates an architecture based on web services and communication software that exploit the advanced maintenance functions related to the diagnostics, prognostics and CBM. Within the framework of a research program (NFFP4) supported by "Saab Aerotech" and the Swedish National Air Force Agency, "Wing F21", the project eMM (eMaintenance Management Framework) proposed a software work environment for e-maintenance management based on a service-oriented architecture [CAN 09]. This software environment comprises:

1) an e-Maintenance Management Model (eMMM);

2) an e-Maintenance Platform (eMP).

2.3.2. *Overview of state-of-the-art e-maintenance systems and platforms*

An e-maintenance platform is characterized mainly by the cooperation and the integration of intelligent software support components, whereas an s-maintenance platform is based on the collaboration and integration of autonomous functions (self-learning and self-management of the maintenance process).

In order to implement an s-maintenance platform, we desire to review the e-maintenance platforms with features that may be sought after in an s-maintenance platform. The common key points in these two kinds of platforms are the integration, the synchronization and the consideration of the entire maintenance process. The state-of-the-art overview that we present about existing e-maintenance platforms, whether these be theoretical or industrial systems, is performed according to four characteristics directly related to the definition of the s-maintenance concept, which are:

1) the type of maintenance addressed (CBM, diagnostics, entire process, etc.);

2) the interoperability among the platform's applications;

3) the dynamic services and knowledge engineering at the heart of the platform;

4) the degree of integration (mono-system, synchronous system, cooperation, collaboration).

2.3.3. *Project platforms*

We observed that PROTEUS is one of the rare projects that presents a complete vision of the maintenance process. However, with regard to knowledge exploitation, despite the integration of knowledge engineering into the diagnostic application, knowledge is not exploited at the heart of the platform (i.e. this platform is not a knowledge-oriented system), and this does not allow the platform to offer dynamic services.

The PROMISE platform is based on a so-called semantic data model. In fact, the purpose of this model is to provide generic comprehension to the final users of this platform. Nevertheless, this model is not exploited by the applications and services that are integrated in the platform, and consequently, it does not provide any reasoning (a fundamental aspect required in an s-maintenance platform).

2.3.4. *Academic platforms*

WSDF: Hung *et al.* proposed in [HUN 03] an e-diagnostics framework based on web services (WSDF: Web-Services-based e-Diagnostics framework) aiming to improve diagnostic systems remotely by providing the function of diagnostic information's integration automatically by means of the Internet.

IIEMD: Cao *et al.* [CAO 08] developed a cooperative and distributed intelligent maintenance platform IIEMD (Integrated Intelligent Equipment Maintenance Decision) which offers a set of decision support tools for various maintenance activities. IIEMD is a hybrid system, supported by an ontology in which two types of reasoning coexist, RBR (rule-based reasoning) and CBR (case-based reasoning). The IIEMD platform is one of the closest to an s-maintenance platform. It is based on knowledge engineering (ontology and inference engine) and emphasizes the cooperative aspect. However, it does not focus on dynamic and autonomous services. Furthermore, IIEMD handles only decision support services for repair, which is an approach oriented towards the final user (the technician), and which does not develop the notion of services generated at request for the various kinds of platform users (all the maintenance operators). EMAST (E-Maintenance Architecture to Support onsite Teams): Ribiero *et al.* propose an e-maintenance architecture to support maintenance teams on the production site [RIB 08]. Each module of this architecture performs self-monitoring and self-diagnostics, hence its capability of using the related information for generating alarms of predictive maintenance in addition to the time-based alarms of preventive maintenance. The whole documentation (technical manuals, plans, repair or maintenance procedures, etc.) is stored locally, at the site. The EMAST platform is based on an ontology of the domain and exploits knowledge engineering. However, this platform's architecture does not provide any details about the usage of this ontology nor about its exploitation with respect to semantic interoperability and to the services offered to the users.

The D2BTM platform implements intelligent services of self-learning dedicated to prognostics, which affects the robustness of predictive maintenance and not the self-learning of the platform and the experience feedback of all the maintenance applications. The user will not benefit from this feedback in the platform's on-demand services.

The agent-oriented platform (AOP) has some aspects in common with s-maintenance in terms of semantic interoperability and knowledge engineering exploitation. However, this exploitation of knowledge is performed locally via an agent, and it is not shared or reused by all the maintenance support applications that are integrated in the platform. Furthermore, the agents do not provide any dynamic service.

Overall, our study allows us to observe that there are only three platforms (PROMISE, AOP and IIEMD) among all those analyzed that deal with the problem of semantic interoperability, whereas the others are limited to a syntactic level of interoperability. Concerning the complete maintenance process, only the PROTEUS platform and the web platform address it in its entirety. The eMM and IIEMD platforms address a set of activities of this process to a certain extent, without focusing on a single activity or a single maintenance strategy as most other platforms do (for example, MIMOSA, DYNAMITE, WSDF). Regarding knowledge exploitation, we observe that various platforms take an advantage of knowledge and ontological engineering as in the case of EMAST, PROTEUS and IIEMD. However, in most cases, this exploitation is restricted to a part of maintenance: prognostics in the case of DEBTM, repair support in IIEMD, or an exploitation limited to a small number of applications as in the case of PROTEUS, in which the knowledge database is a module external to the platform's kernel. We also observe that the majority of these platforms are split between cooperation and collaboration. The MIMOSA, PROTEUS, D2BTM, POMAESS and AOPs are classified as cooperative platforms. On the other hand, platforms described as collaborative are PROMISE, DYNAMITE, WEB platform, EMAST and IIEMD.

2.3.5. *Summary*

In light of the above-mentioned platforms, we see that a difference exists in terms of features and goals of each platform. Furthermore, the majority of these platforms have some characteristics that are not consistent with the s-maintenance criteria. Nonetheless, we note that some of these characteristics are taken into consideration in a partial way. Our analysis leads us to identify the platforms that are the closest to an s-maintenance platform, such as the IIEMD platform and AOP, which focus on sharing and exploitation of knowledge. In IIEMD, knowledge is managed within the framework of a knowledge-based system that contains an ontological basis and an inference engine used by decision support services in the platform. Concerning AOP, knowledge is shared by agents, and each agent contains its own decision module that handles this knowledge. These two platforms are conceptual and have not been implemented in practice. Their outlines are given, although the details of their operation are omitted. Therefore, it should be noted that no operational s-maintenance architecture exists.

2.4. Maintenance, e-maintenance, s-maintenance

2.4.1. *General*

Before delving into the definitions of maintenance, e-maintenance and s-maintenance, we would like to clarify an important point. We reckon that the concept of e-maintenance is an abstract concept that should have a more general conceptual definition than the definition of a platform representing a model that implements this abstract concept. Furthermore, the platform's definition should also be independent from the specific technology used in a platform, since there might be different platforms that implement the e-maintenance platform model by means of different technologies.

The standards NF X 60–010 and 60 011 define maintenance as a set of actions that allow an asset to retain or recover its functions in a particular state or to be capable of providing a specific service. Thus, the AFNOR standard defines maintenance as "a set of all technical, administrative and management actions during the lifecycle of an asset aimed to retain or recover it into a state in which it can execute a required function".

2.4.2. *E-maintenance*

The term e-maintenance emerged at the beginning of the 2000s; it is described by a multitude of definitions that depend on the authors' point of view, expertise and on the targeted goal. In [MUL 08], Muller *et al.* identify various points of view such as maintenance strategies, maintenance plans, maintenance type and maintenance support.

Some consider e-maintenance as a maintenance strategy in which the tasks are managed electronically by means of real-time data obtained by means of digital and Internet technologies [TSA 02]. Others consider that e-maintenance is a maintenance plan that exploits CBM approaches [TSA 95], proactive maintenance, collaborative maintenance, remote maintenance (telemaintenance) and support services, real-time access to information, and integration of the production with maintenance [UCA 05]. Another point of view presented by Koc and Lee [KOC 01] identifies an e-maintenance system as a predictive maintenance system that predicts only the monitoring and anticipating functions such as the prognostics. However, Zhang *et al.* [ZHA 03] consider e-maintenance as a combination of web services technology and agents technology providing a means of executing intelligent and cooperative functions for an industrial automation system. Crespo Marquez and Gupta [MAR 06] define e-maintenance as an environment of distributed artificial intelligence that comprises the capabilities of information processing, decision support, communication tools, and collaboration between the maintenance process and expert systems.

From a corporate point of view, and in particular from an intervention-oriented point of view, e-maintenance is defined by Karim [KAR 08] as the part of a maintenance support system that enables the synchronization between the maintenance process and the operation and modification processes in order to reach corporate objectives required by the stakeholders, thanks to optimized information management over time [WIL 08], while providing information services. From a broader point of view, Moore and Starr [MOO 06] define e-maintenance as an information network of asset management, which integrates and synchronizes various maintenance and reliability applications in a single system, and provides information about the assets where and when it is necessary.

Consequently, we can note that each definition offers a partial view of maintenance (for example, predictive maintenance) and does not make any distinction regarding the concept of platform. A lot of confusion arises when a concept is linked to a set of rather specific technologies such as web services or intelligent agents.

2.4.3. *Definitions of the e-maintenance concept*

Faced with such a variety of definitions and points of view, a general definition is strongly recommended. A definition that includes the global process of maintenance would be a wise choice. For this purpose, in [MUL 08], Muller *et al.* take into account the different points of view and define e-maintenance as a component of the e-manufacturing concept. The latter is described as a maintenance support that comprises the resources, services and necessary management allowing a proactive execution of the decision process. This support includes not only e-technologies (ICT, web, wireless networks, Infotronic technologies), but also e-maintenance activities (operations or processes) such as e-monitoring, e-diagnostics, e-prognostics, etc.

For a more conceptual definition, we prefer the presentation of e-maintenance by Lee *et al.*, a major cornerstone in modern industries that takes into account the success of integrating e-manufacturing and e-business [KOC 05].

As long as e-maintenance draws inspiration from the e-business, it can be considered as one of its derived concepts. Indeed, we agree with the fact that the definition of e-maintenance should draw from the definition of electronic trade while respecting the definition of maintenance. For this purpose, we refer to the definitions both of maintenance and e-business.

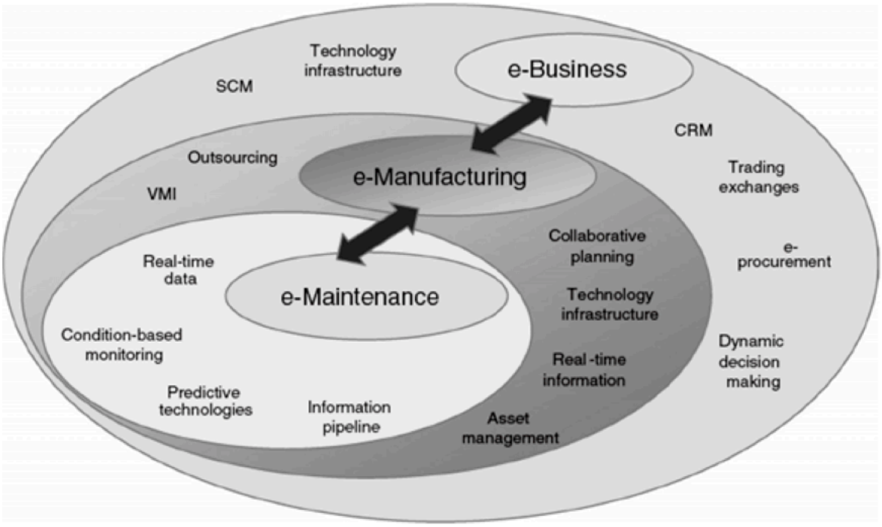

Figure 2.4. *Inclusion of e-maintenance within e-manufacturing and e-business*

Several definitions of e-business are illustrated in the literature; we will adopt the one presented by Jones *et al.*, who define e-business as the realization of activities that lead to an exchange of value, in which the parts interact electronically using network or telecommunication technologies [JON 00]. On the basis of this definition and that of maintenance, we define e-maintenance as follows:

Definition of the e-maintenance concept:

"E-maintenance is the realization of maintenance, in which all the actions or technical, administrative and management activities interact and cooperate via electronic means, using network or telecommunication technologies."

This definition takes into account the global process of maintenance by including the different points of view of maintenance and the different domains of expertise (i.e. technical, administrative and management). We underline the electronic interaction and the cooperation between the actions and the activities performed by different actors (human or software) involved in this process.

Definition of the e-maintenance platform:

We define the e-maintenance platform starting from the concept of maintenance. Since the latter focuses on the cooperative aspect, we thus have to take in consideration the definition of a cooperation platform.

Cooperation platforms are defined as a software work environment consisting of different software components, thanks to which these platforms act together to achieve global properties. Saint-Voirin affirms that a cooperative platform can be seen as a set of groupware with specific functions, all gathered into an integrated platform [SAI 06].

As a result, we define an e-maintenance platform as:

"*An e-maintenance platform is a cooperation platform that offers a set of intelligent maintenance support software components (integrated and / or remote applications) which will allow the maintenance actors to communicate and work together to perform a complete maintenance process.*"

Within this definition, we have highlighted the aspects of integration and distribution that characterize the majority of existing platforms and are imposed by the physical word and in industry. We have focused on the software components that present the different applications of diagnostics, prognostics, monitoring, etc., on the communication and interoperability between these elements.

2.4.4. *S-maintenance*

2.4.4.1. *General*

In order to improve the performance of maintenance processes provided by e-maintenance in terms of communication, exchange of knowledge and data among the systems, and knowledge exploitation, we propose the concept of s-maintenance. This concept defines a semantically compatible information environment. In this context, it provides a solution for the implementation of semantic interoperability at the level of a maintenance platform. Therefore, the main goal of this concept is to meet the needs of evolution and the demands of maintenance actors, which are the actual users of these systems. The main necessity can be summarized as "Having the right information in the right format for the right people in order to do the right things at the right time" [LEE 08]. This new generation of maintenance system will be based on knowledge engineering systems.

Definition of the s-maintenance concept:

S-maintenance is the realization of maintenance based on an expert knowledge of the domain, in which the systems manage this knowledge and share the semantics in a network, bringing out new generations of services and offering services on demand by means of adaptive and autonomous functions.

When we talk about knowledge management, this includes the formalization, acquisition, reasoning, maintenance, exploitation, reuse of knowledge and re-supply [MEN 00]. By on-demand service, we mean the result generated by interactions between the components with a system and a user, or by activities that are internal to the system, in order to respond to an unforeseen demand expressed by a user, which cannot be solved by the services that already exist in this system. The service provides a support to the user in order to execute the actions that need to be carried out.

2.4.5. *S-maintenance platform*

Collaboration is one of the fundamental features of s-maintenance since all the systems in a network act together towards the same goal by using and sharing common resources such as the expert knowledge of the domain, in this case. As a result, to define an s-maintenance platform, we need to consider the definition of a collaborative platform.

In fact, collaborative platforms are unified electronic platforms that facilitate synchronous and asynchronous communication by means of a variety of devices. The collaborative platforms offer a set of software components and services allowing the users to find each other, together with the information that they need, and to be capable of communicating and working together to reach common business goals. Hence our definition of an s-maintenance system actualizing the concept of s-maintenance:

Definition of an s-maintenance platform:

"An s-maintenance platform is a collaborative and distributed system based on knowledge engineering that provides dynamic and on-demand services according to the necessities of its users by means of functions of self-learning and self-management of the maintenance process."

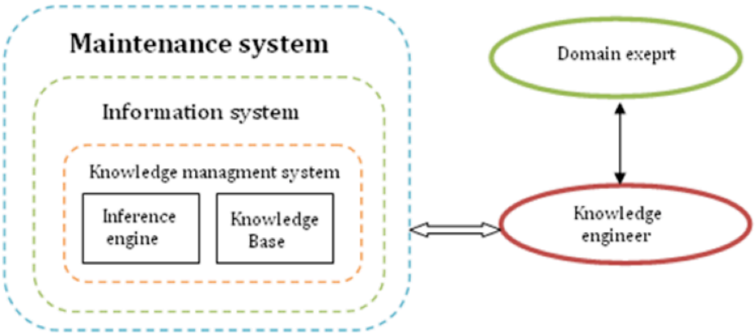

Figure 2.5. *S-maintenance platform*

Therefore, this system, based on knowledge engineering, exploits the semantics of the expert knowledge of the maintenance domain, and as a result, it has the possibility of evolving its degree of intelligence. To achieve this, we will use a knowledge-based system as the platform's kernel, which allows the inference of new knowledge and its exploitation starting from the maintenance domain ontology.

It should be noted as well that by dynamic services, we mean those upgradeable services that are capable of adapting their behavior to the different contexts of usage.

As a result, this concept does not stop at the provision of services that are integrated in the platform, as in the case of e-maintenance, but it goes further by offering services that adapt dynamically to the demands of the users and by ensuring self-X services without human intervention in the first phase, although they require an expert validation.

Relation between e-maintenance and s-maintenance platforms: The s-maintenance concept is based on the definition of e-maintenance, which is more general and depends, in turn, on the definition of maintenance. However, we impose some constraints that allow us to direct the realization of this concept towards the knowledge. Figure 2.4 illustrates this concept.

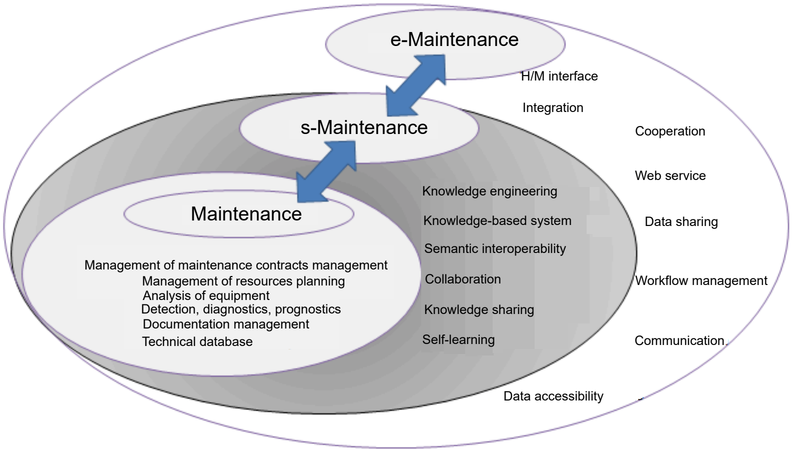

Figure 2.6. *Functionality inclusion in maintenance, e-maintenance and s-maintenance platforms*

Figure 2.6 shows the inclusive relation between maintenance, e-maintenance and s-maintenance platforms, and it characterizes each system starting from the definition of the related concept. It can be noted that the s-maintenance platform includes specific functions that may not be present in an e-maintenance platform. Moreover, the services provided by a maintenance or e-maintenance system are always included in an s-maintenance platform, as shown in Figure 2.6. These maintenance information systems offer functionality with an added value for the maintenance operators (end users). We address the problem of knowledge reuse and new indicators consultation within the context of a system of traditional maintenance, e-maintenance and s-maintenance.

2.5. Conclusion

In this chapter, we broached the characterization of new intelligent systems for maintenance. After quick research on the evolution of maintenance support systems, we ranked the different architectures of the information systems according to two criteria: the evolution of the exploited information and the relation among the systems that are integrated in these architectures. We defined the architecture of the s-maintenance domain, which is an extrapolation of existing e-maintenance architectures. We characterized these architectures and gave an overview of the state-of-the-art works regarding the existing e-maintenance architectures with respect to the specific features of s-maintenance, namely the type of maintenance considered, semantic interoperability, collaboration among the modules, type of offered services (dynamic or static) and knowledge engineering.

Generally, despite the difference in terms of services that are provided by e-maintenance systems, the weaknesses that we found are related to the intelligent reuse and exploitation of expert knowledge from this domain, to the standardization of this knowledge, and to the low degree of synchronization, which in most cases is limited to communication and seldom includes cooperation.

Furthermore, this overview on the latest e-maintenance architectures leads to the observation that the majority of the works in this domain do not make a distinction between the concept, the platform and the usage of e-maintenance technologies. Therefore, we proposed two definitions, one regarding the concept of e-maintenance, characterized by the cooperative and electronic interaction among the different actions of the global maintenance process, and the other concerning the platform model, characterized by the integration of intelligent computerized modules that perform the activities of the maintenance process.

We defined the concept of s-maintenance as the realization of maintenance based on the sharing of expert knowledge from this domain, which provides adaptive and autonomous services. This concept is implemented through an s-maintenance platform, which formalizes this knowledge and shares it among the various applications that are integrated in the system, which ensures technical and semantic interoperability. Being based on a knowledge management system with an inference engine that supports different kinds of reasoning, the platform has to provide on-demand services dynamically (for the indicators defined by the user) and ensure different kinds of self-X functionality. Among the latter, we can find the self-management of the platform's processes and self-learning related to the interactions of the users with the platform in order to ensure the dynamic feature of its knowledge database. After having answered the question about the characterization of new intelligent systems for maintenance, we developed, in our work, a first e-maintenance platform, called GamaFrame (Global Asset MAintenance

FRAMEwork), which then evolved into the knowledge-oriented SMAC-Platform (an s-maintenance platform), developed within the cross-border project SMAC supported by the program Interreg IV France-Suisse between the University of Franche-Comté and the Ecole Polytechnique Fédérale de Lausanne, and two SMEs: one, TORNOS, located in Jura, Switzerland, and the other, EM@SYSTEC, in Besançon.

3

Intelligent Traceability Application

3.1. Introduction

One of the challenges of the present study is making a product or equipment intelligent by combining it with a memory that traces its health state during its lifecycle by means of a product lifecycle management (PLM) system.

Thanks to NICTs, it is quite easy to implement intelligent products (smart components) that include a technical memory relative to their history, which can be easily consulted by various operators who are in charge of using, maintaining, repairing and making this product evolve. It should be noted that the usage of this information and/or knowledge arouses new challenges regarding decision support applications. These applications in the context of PLM lead to an improvement of the efficiency of the asset's maintenance operations, to an upgrade of its functions during a new design phase, and to the reuse of the item with a more precise knowledge of its behavior during its utilization phase. The prognostics of its state and/or the possible prediction of a malfunction may be integrated with a related proactive maintenance and an update or a downgrade, in other words, by performing predictive maintenance.

The purpose of our study is to monitor a subsystem and the health state of some of its components as well as their maintenance. In order to ensure the information's traceability, the most important part of information, which will be capitalized during the whole lifecycle of the component, will be assessed by means of indicators of proper functioning, a statistical calculation or a prognostic application. When we talk about prognostics, we refer to the

From Prognostics and Health Systems Management to Predictive Maintenance 2: Knowledge, Traceability and Decision, First Edition.
Brigitte Chebel-Morello, Jean-Marc Nicod and Christophe Varnier.

modeling of the failures of the monitored component and to the algorithm that evaluates the remaining useful life (RUL). These indicators will be the basis of decision support services, in particular for detecting undesirable events, capitalizing knowledge, returning information, for the prognostics of the RUL, and for recycling support systems. In this chapter, we will develop some decision support services.

3.2. Description of the equipment to be maintained

Our application domain is a ski lift, which is composed of two stations, one uphill and the other downhill, a transport cable for the transport of the cabins, and a tensioning system. In two out of three cases, the gearbox system is located at the driving station. The length of the ski lift's cable tends to vary with time, depending on the load and temperature. In order to maintain the cable at a more or less stable tension at the driving pulley, it is necessary to be able to stretch and retract the cable. In our case, the whole engine system, including the driving pulley, is mounted on a carriage that can move along the air line's direction, i.e. forward or backward. The tension is maintained by means of one or two hydraulic jacks.

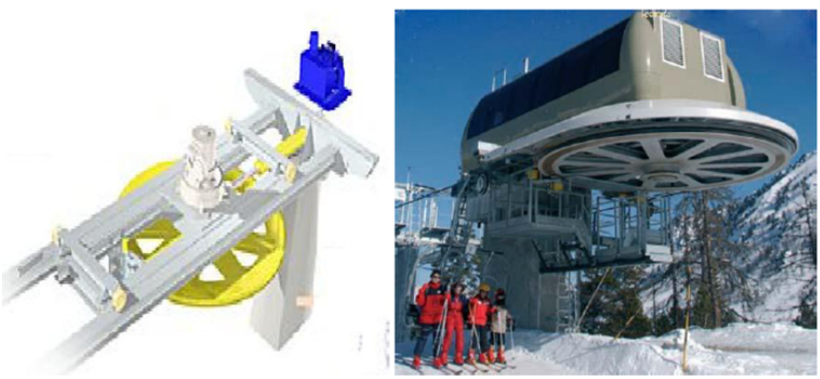

Figure 3.1. *Transport cable of a ski lift*

Our goal is to follow the health state of the hydraulic jacks during their whole lifecycle and to be able to access, at any moment, all the reliable information gathered about the component, its health state, and the maintenance performed on the component.

Another aim is to estimate the remaining useful life before the component's failure (RUL). In this application, we show the capability of our system to follow and capitalize knowledge about the lifecycle of the hydraulic jacks and a carrier. After describing the system, we will study the entire lifecycle of the hydraulic jacks. By means of data simulation regarding the jacks' operation, we will be able to estimate the health state of the component and its RUL. This estimation will be the basis of a service capable of assessing the possibility of recycling the component.

3.3. Infrastructure of intelligent equipment

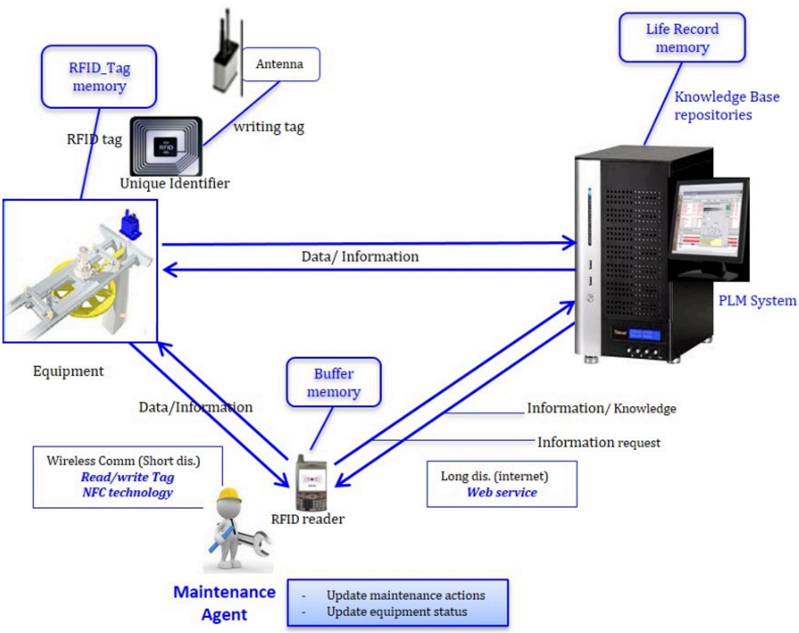

Figure 3.2. *Intelligent equipment*

Data, information and knowledge concerning the component are gathered in a distributed memory. As in a human body, three types of memory are integrated in the equipment with different read and write mechanisms:

– an instantaneous memory, an RFID tag (RFID: radio-frequency infrared detection), that stores the most recent information about the current health state of the equipment, its treatment, and the next maintenance intervention. This memory can be read locally through a mobile RFID reader (Samsung Galaxy Nexus III, which uses NFC (near-field communication)) available to the users.

– a buffer memory, MOBILE memory, included in the mobile reader, allowing the temporary storage of information when the connection with the maintenance platform is unavailable. It enables the synchronization between the two RFID memories and the technical memory.

– a long-term memory (lifecycle memory or technical memory) that lists all the problems and treatments undergone by the equipment and allows the tracing of the record of the component/system. This memory can be accessed only via the platform, which requires a means of remote communication with the mobile RFID reader.

3.4. The s-maintenance platform

The platform includes various functionalities that ensure the monitoring of a piece of equipment during its whole lifecycle, notably the equipment management, interventions management, monitoring management, RFID tag management, resources management, and memory card management.

In order to deliver these functionalities, the GamaFrame (Global Asset Maintenance Framework) platform uses a database that records the models, equipment and tags, and another technical database for monitoring management and storage of sensors' measurements. Each critical item of equipment and/or subset is combined with an RFID tag, which identifies the equipment in a unique way and provides a minimal memory. An RFID reader allows the consultation of information about this equipment, being connected to the remote e-maintenance platform by means of web services. Thanks to an RFID reader (fixed or mobile), the information contained within the tag can be read and eventually integrated with more complete information about this equipment, which can be accessed from the platform. Furthermore, this reader can send maintenance information so that a user may fill in a form available in the reader (mobile phone).

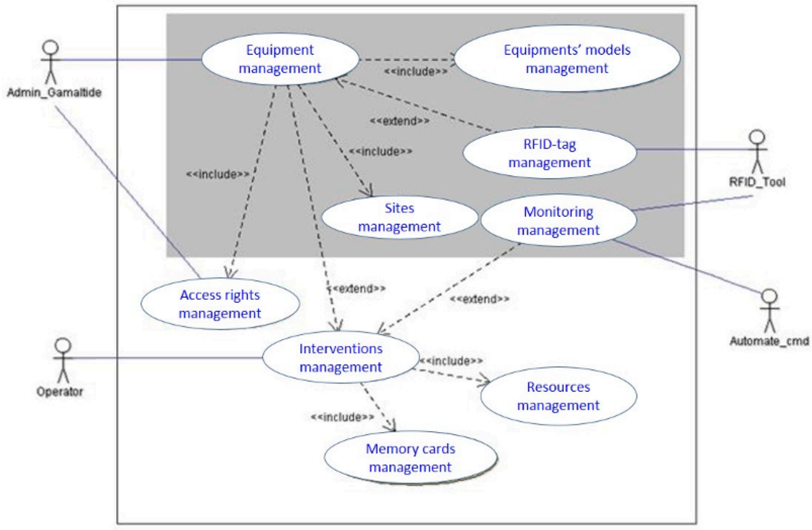

Figure 3.3. *Example of GamaFrame usage*

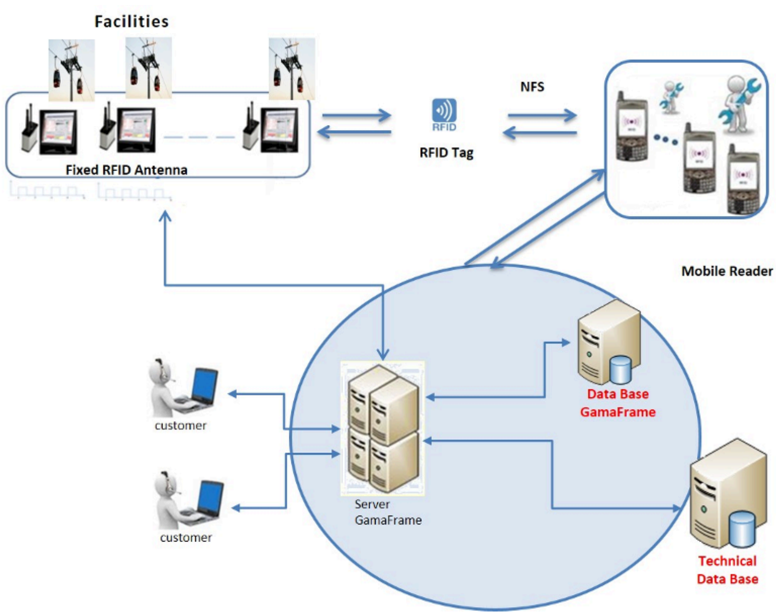

Figure 3.4. *Communication with GamaFrame platform*

The platform has a close relation with two distinct databases: the first one, included in the GamaFrame platform, is used for the storage of maintenance data and knowledge capitalization regarding a given piece of equipment, while the second one, a technical database, is dedicated to the storage of the sensors' measurements over a limited period of time. These measurements are recovered by fixed RFID tag readers during the vehicle's transition in the station, and they are sent via web services to the platform according to the transmitting frequency of the reader.

3.5. Web services

3.5.1. *Communication between the platform and the mobile reader*

The mobile reader, equipped with applications developed under the Android operating system, allows, on the one hand, the reading and writing of the RFID tag by means of NFC technology, and, on the other hand, the communication with the web services of GamaFrame platform.

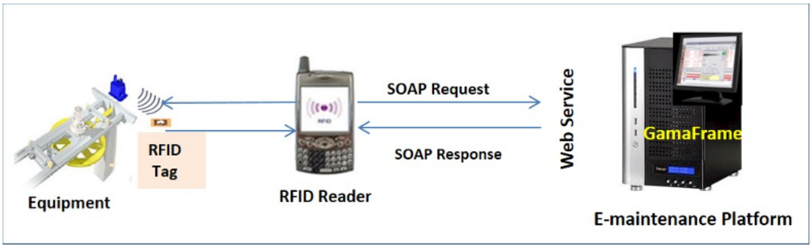

Figure 3.5. *Communication between platform and mobile reader*

The mobile reader includes a specifically developed application called GamaMobile, which implements the functions illustrated in the following sequence diagram; the functions are the platform connection control, the control of a user's access rights for accessing GamaMobile, the read and/or write within the tag, and finally, the usage of the web service for communicating between GamaMobile and GamaFrame.

For each component, an RFID tag is associated with an identifier and a memory. The identifiers are stored and processed in the e-maintenance platform. The RFID tag is read by means of NFS technology. Thus, a user can read the content of its memory and update it once the maintenance operations concerning this component have been performed. When the RFID reader is synchronized with the e-maintenance platform, the LifeRecord is updated via a web service.

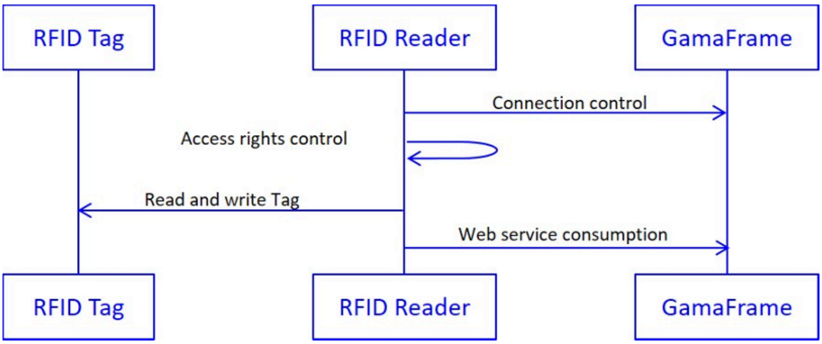

Figure 3.6. *Diagram of a general sequence of the mobile reader*

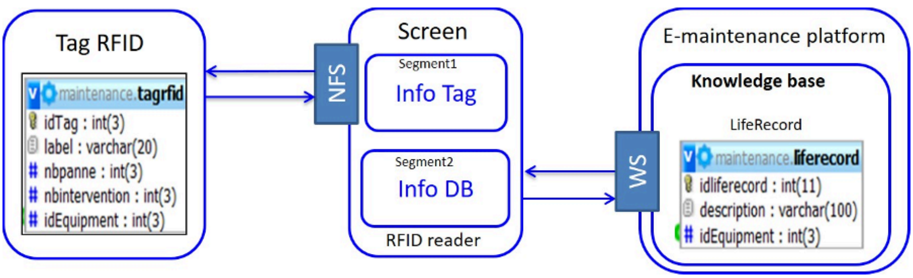

Figure 3.7. *Communication between RFID reader and platform*

3.5.2. *Web service: fixed RFID antenna-platform*

The read and write operations on RFID tags are performed via a fixed antenna. This antenna has the role of concentrating the data retrieved by the sensors. The interface between this fixed RFID antenna and the platform is implemented by means of the web services developed by us. Figure 3.8 illustrates this communication.

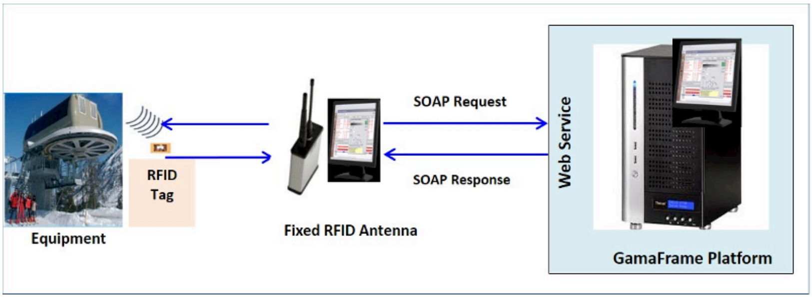

Figure 3.8. *Communication between the platform and the RFID antenna*

A web service is implemented within the GamaFrame server, accessible via the fixed RFID reader by means of a URL with configurable parameters, which is required for transferring data between the fixed simulator of RFID tags and the platform. Sensor data sent by the fixed simulator to the platform are stored in a technical database at the frequency of the vehicles passing at the station.

3.6. Service for monitoring diagnostic and prognostic

We monitored the cabins' temperature and weight, which vary on ski lifts and affect the load on the cable, and the number of trips carried out by the cabins, which allows the calculation of the exact operating time of the hydraulic jacks. Sensor data is gathered in real time at each cycle of ski cabins by using a data acquisition system. A technical database stores the data measured by the sensors at the facility. The sensor data represents the measurements obtained during an equipment's exploitation phase.

The various indicators relative to these cabins can be listed (the cabin's weight, the cumulative weight of the cabins on the traction cable, the load of this cable over a week, over a season, etc.) and followed over time to obtain the station's evolution, for instance by identifying the periods of intense, medium circulation, or off-peak periods).

By setting minimum and maximum thresholds that limit, for example, the weight of the cabins, it is possible to generate alarms that could warn when the situation is abnormal, and there is a need to launch fault diagnostics [CHE 13] or fault prognostics applications. We developed a prognostic method based on the failure experience in different systems of transport via cable, which we formalized in the form of a health indicator. This indicator provides an evolution trend of the degradation, treated with reasoning based on each case. When new sensor data relative to a cable transport system had arrived, we identified a similar health indicator and the present health state of the monitored jack by means of a similarity measure over sliding windows. This current health state thus allowed us to estimate the RUL of these systems [KHE 16].

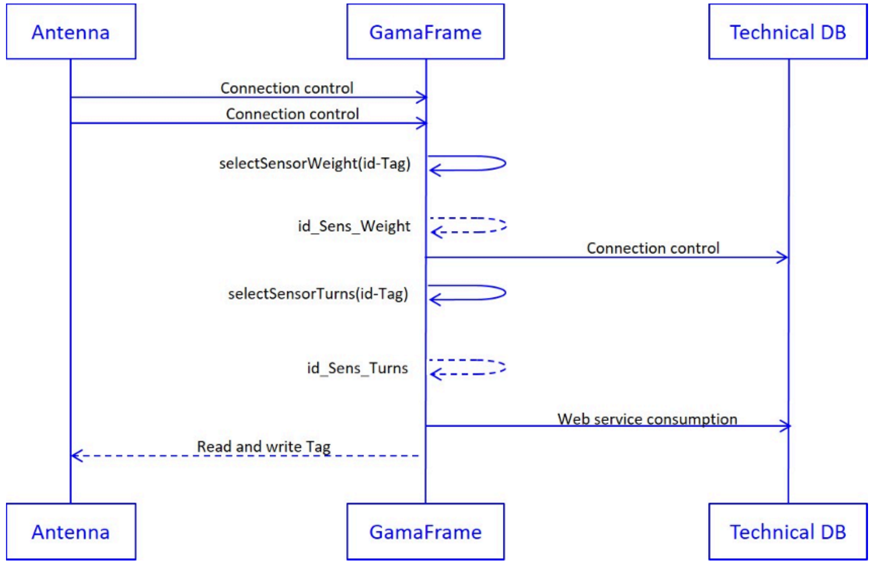

Figure 3.9. *Diagram of the sequences of technical measurements' insertion*

3.7. Knowledge capitalization service

We seek to capitalize the knowledge about this intelligent equipment over a given period of time within the components' lifecycle. The online monitoring implemented for the equipment is not sufficient alone to provide a general view of the proper functioning of a component. In fact, we should take into account the maintenance performed on the equipment and its actual operating time, without considering the idle operation due to line stops, failures, interventions, etc.

Figure 3.10. *Sensor data monitoring*

Therefore, we will simulate the behavior of this equipment by simulating the maintenance data, in order to then exploit the gathered data to calculate or estimate indicators which are the basis of our decision-making. For example, in the case of a possible recycling, an RUL estimation for this component, or a decision regarding the maintenance strategy to be developed. We will base ourselves on this mode (reference Figure 1.2) and on the platform ontology (reference in Figure 3.11) to ensure the knowledge capitalization in the platform and its effect on the LifeRecord and RFID tag memories.

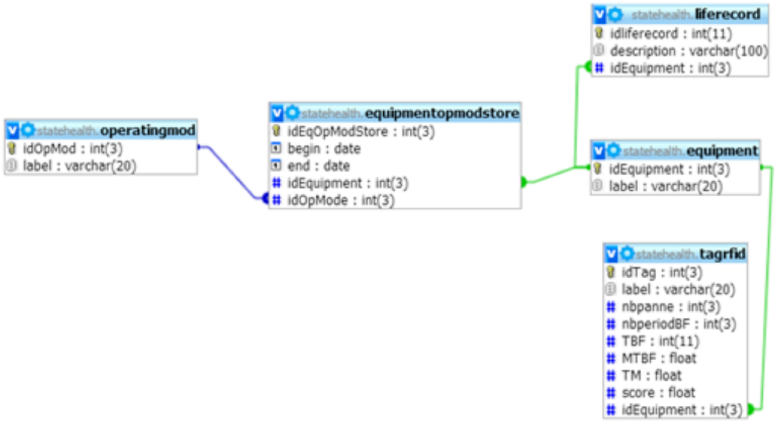

Figure 3.11. *LifeRecord memory model*

3.7.1. *Data model*

The data model that will be simulated will be based on the model described in Figure 3.11, with the following content of TagRFID:

– nb failure: number of failures;

– nbperiodBF: number of periods of proper functioning;

– TBF: time of proper functioning, which represents the number of days during which the equipment has been working normally (knowing that an equipment can function in a degraded state, although this will not be considered by this application);

– nbdaytrouble: number of days during which the equipment is out of order;

– MTBF: average time of proper functioning.

The long-term memory that capitalizes all the information about the maintenance and the health state of the component is located in the LifeRecord, which is a summary of the equipment's behavior. It is composed of:

– the starting date (first run);

– the current functioning mode;

– the date of the last maintenance;

– the type of the last maintenance;

– the failures and the relative period of time;

– the periods of proper functioning;

– the operational modes;

– the exploitation modes.

In this simulation of knowledge capitalization in the LifeRecord, special attention will be paid to the content of the various memories.

3.7.2. *Simulation of the life record*

The simulation of life record data is performed by a MySql application, MyAdmin. First of all, it is necessary to define the items to be monitored. Then, each of them has to be associated with an RFID tag. The RFID tag is a table containing a set of indicators that characterize the health state of the equipment, as illustrated in Figure 3.12.

idEquipme	label
1	hydraulic jack
2	carriage
3	pulley
4	cable

idTag	label	Nbfault	NbperiodBF	TBF	MTBF	nbdaytroubl	nbintervent	idEquipment
1	Tag_jack	0	0	0	0	0	0	0
2	Tag_carriage	0	0	0	0	0	0	0
3	Tag_pulley	0	0	0	0	0	0	0
4	Tag_cable	0	0	0	0	0	0	0

Figure 3.12. *Content of the RFID tag*

These indicators are initialized to zero and are updated during the equipment's monitoring. They define the equipment's failure rate (1/MTBF), starting from which it is possible to decide whether the equipment should be kept or scrapped. We will focus on the record of operating and failure intervals of time.

The exploitation's start date is chosen, as well as the hydraulic jack's identifier, by associating an identifier in operational mode (normal mode); the application is then executed.

Colonne	Type	Fonction	Null	Valeur
idEqOpModStore	int(3)			
begin	date			2013-03-01
end	date			0000-00-00
idEquipment	int(3)			1
idOpMode	int(3)			1
Exécuter				

Figure 3.13. *First simulation scenario*

Following this operation, a new line within the LifeRecord describing the equipment's current state is created. The equipment starts functioning in the normal mode on 01/03/2013.

idliferecord	description	idEquipment
1	root@localhost Id with 1 normal started from 2013-03-01	1

Figure 3.14. *Summary of data within the LifeRecord*

Within the RFID tag, the increase in the number of proper functioning intervals can be observed.

idTag	label	nbpanne	nbperiodBF	TBF	MTBF	nbdaytrouble	nbintervention	idEquipment
1	tag_verin	0	1	0	0	0	0	1

Figure 3.15. *Update of data within the RFID tag*

Knowing that the equipment underwent a failure on 03/10/2013, the normal period is ended to start the failure period.

The stopping of the equipment occurred following a failure. The list of failures is illustrated in Figure 3.17.

←T→				idEqOpModStore	begin	end	idEquipment	idOpMode
Modifier	Éditer en place	Copier	Effacer	1	2013-03-01	0000-00-00	1	1

Figure 3.16. *Simulation window*

idTrouble	label
1	pressure drop
2	blocking
4	leak
5	overheating

Figure 3.17. *Failure list*

A new equipment trouble store is inserted by initializing the date of the failure period. A new line is added to the LifeRecord that shows the end of the normal functioning and its duration of nine days in this case. The simulation continues so forth.

idTag	label	Nbfault	NbperiodBF	TBF	MTBF	nbdaytrouble	nbintervention	idEquipment
1	Tag_hydraulicjack	0	0	9	9	0	0	1
2	Tag_belt	0	0	0	0	0	0	2
3	Tag_cablecar	0	0	0	0	0	0	3

Figure 3.18. *LifeRecord of hydraulic jacks*

At the end of these simulations, we obtain a set of indicators related to the monitored components during their whole lifecycle. Figure 3.19. illustrates the results obtained after a simulation for six hydraulic jacks.

3.8. Decision support service for the recycling of hydraulic jacks

We have thus capitalized the knowledge about the entire lifecycle of these hydraulic jacks. By means of the indicators' calculation performed on this reliable information gathered during the whole lifecycle of the equipment, it is possible to make a decision that reflects the actual reality. We base ourselves on thresholds in order to make a distinction between the components in good working conditions and those to be scrapped. Knowing that the thresholds are, respectively:

$N_{threshold} = 3$ and $S = 50$ days and$(S = 5$ days$)$, we obtain: $45 <$ score < 55.

idTag	label	Nbfault	NbperiodBF	TBF	MTBF	TM	Score	recycling
1	Tag_hydraulicjack1	3	6	102	34	0,8	38,25	NOT OK
2	Tag_hydraulicjack2	2	3	113	56,5	0,6	84,75	NOT OK
3	Tag_hydraulicjack3	2	5	103	51,5	1	46,35	OK
4	Tag_hydraulicjack4	2	3	113	56,5	1	50,85	OK
5	Tag_hydraulicjack5	1	4	113	40	0,9	40	NOT OK
6	Tag_hydraulicjack6	1	5	102	58	0,6	87	NOT OK

Figure 3.19. *RFID tags relative to the hydraulic jacks*

It is known that the jacks' operation has a cycle of 10s, and their lifecycle is five years. The TM coefficient relative to the performed maintenance with respect to the planned systematic maintenance has a non-negligible impact on the component's recycling.

– Here, we note that the jacks 2 and 6 have a disastrous score due to the TM coefficient, and therefore they will not be recycled;

– the hydraulic jack 1 has undergone three failures. Therefore, it will be scrapped. In its LifeRecord, it can be seen that the third failure started on 15/04/2013;

– the hydraulic jacks 3 and 4 satisfy the condition of a score between 45 and 55, so they will be recycled;

– although the hydraulic jack 5 has an acceptable coefficient TM and it has undergone only one fault, it will be scrapped because its proper functioning period does not allow it to obtain a high enough score, and therefore it will not be recycled.

3.9. Conclusion

In this chapter, the approach proposed in the first two chapters for making a component and/or system intelligent is implemented on a ski lift. In other words, this system is capable of monitoring its health state during the whole lifecycle, and it can easily access its information at any moment. This information is reliable, since it is saved gradually during its processing, and it has to be available in order to decide whether the component can be recycled once more by means of an RFID reader. We proposed and implemented a closed-loop PLM of the models that are related to the RFID technology by using two memories, the first integrated locally in the system and the second implemented remotely in an s-maintenance platform.

We set up some decision support services that base themselves on the information observed, gathered and processed during the whole lifecycle of the monitored equipment. The fundamental service consists of a knowledge capitalization service, which can return knowledge relative to the component's health state in the form of synthetic indicators of the proper functioning periods, the number of faults, their seriousness, or simply of the events that intersperse the life of this equipment. A range of indicators, from the simplest to the more sophisticated, are available thanks to the modeling of health indicators via trends, which allow the determination of the remaining useful life (RUL) of the equipment. This RUL can be used to implement predictive maintenance strategies, as discussed in the second part of this book. Other indicators were exploited to define a service for equipments' recycling based on the information obtained from its monitoring.

We developed our approach for a ski lift in the context of an FUI project involving various companies and partially financed by European funds (FEDER). An architecture of intelligent components on a ski station was implemented. This architecture allows a monitoring of data regarding the station's functioning, consultation and updating of the RFID tag memory, the knowledge capitalization in the LifeRecord memory, and the access to any stored information via web services combined with the architecture. As a result, any information regarding the equipment is available, which enables a more accurate and reliable calculation of certain indicators and a more informed decision-making concerning the possibility of recycling the component.

We simulated the behavior of a critical component, a hydraulic jack installed on a carriage that provides the right tension to the cable that transports the ski cabins. This simulation consisted of examining the different condition scenarios to obtain the information defined by the ontology of the maintenance domain and to calculate the indicators during the whole lifecycle of the component. This enabled the implementation of a recycling support system, which depends upon the reliable calculation of the indicators. The calculated score is based on the expertise domain, and it takes into account the interventions and the actual functioning of the components. The e-maintenance platform allows the monitoring of the exploitation and the calculation of indicators in real time. The indicators' calculation is performed from the information specified in the knowledge model in the IMAMO ontology. This concept of intelligent equipment is indeed operational on a ski station. In this study, we developed the recycling service.

PART 2

Post-prognostic Decision

4

Position of Decision within the PHM Context

4.1. Introduction

As mentioned previously, the PHM process is a whole. In fact, it is useless to produce relevant indicators and to predict the useful life of an equipment as precisely as possible if no decision is made afterwards. Likewise, there is no point in making decisions if the information enabling these decisions is not relevant, reliable or accurate. Therefore, the added value of the PHM includes, by its very nature, a decision phase after the collection and interpretation of prognostic data [IYE 06]. In this context, a decision can be made in any situation in order to maintain the observed system in the best operating conditions.

The notion of decision within the PHM domain deserves to be clarified. In this chapter, we present a typology of decisions with a state-of-the-art overview on this subject. Then, we return to this topology while illustrating the presented decision types in relation with temporal constraints, which are mainly due to the interval of time within which the decision is applied or is supposed to remain valid. For example, the duration taken into account may be a week, in order to consider the equipment during its usage over this period, whereas the expected validity corresponds to the following day, knowing that input data might evolve over time. It is thus possible to take into account the availability of the equipment whose usage is planned for beyond one day. On the other hand, the considered duration may be a millisecond if, given a detected and

From Prognostics and Health Systems Management to Predictive Maintenance 2: Knowledge, Traceability and Decision, First Edition.
Brigitte Chebel-Morello, Jean-Marc Nicod and Christophe Varnier.

analyzed event, a decision has to be taken within a very short delay in order to preserve the operational conditions.

4.2. Definition of post-prognostic decision

In the literature, two terms designating the decisions in the PHM context are mainly encountered. Iyer *et al.* [IYE 06] introduced the term "post-prognostic decision", a decision that receives as an input the data calculated by the prognostic and analysis phases. A decision then consists of defining the maintenance operations, order of tasks and allocation of resources, and in managing the logistics chain related to maintenance from the perspective of optimizing the costs associated with the system's lifecycle, delay penalties, number of successful tasks, extension of production or safety. On the other hand, Balaban *et al.* [BAL 12] later proposed the term "Prognostic Decision Making (PDM)" to designate the way in which, autonomously or semi-autonomously, a system defines the actions to be performed by the system, or the configurations to be modified, in order to take into account the prognostic information.

We talk about "post-prognostic decision" to designate a decision that takes into account the data obtained from the prognostic phase, representing the remaining usage duration before maintenance for all monitored equipment. As defined in the literature, these decisions are oriented towards the optimization of the system in order to keep it in an operational state, in relation to its missions and its health state.

4.3. Which objectives?

Any kind of system involves maintenance phases along its lifecycle. Maintenance operations target different parts of those devices that jeopardize the system's mission if they break down. In many applications, corrective maintenance is not acceptable in view of the criticality of a mission or equipment with respect to the system. Notably, this is the case of applications that involve people, such as lifts or airplanes, although obviously it is easier to stop a lift in case of a breakdown than perform an emergency landing without damage. The risk is minimized by deciding preventive maintenances, thanks to the knowledge of degradation processes. Thus, important test campaigns provide knowledge about the duration of the equipment's utilization in nominal conditions. By adding a certain safety coefficient and by doubling or tripling the number of critical items, the probability of failure is reduced considerably, as is shown by the very low number of aircraft accidents. However, this reasonable approach is not completely satisfactory, because there is no certainty that the equipment always operates in nominal conditions. Furthermore, it is possible that some parameters, little known or unknown in advance, intervene in the aging of an equipment with the consequence of an accelerated aging of the system or item. Besides, systematic and preventive maintenance interventions do not cover all contingencies, since the usage conditions are not nominal over the entire period of utilization. The PHM bases itself upon this very idea to propose another way of maintaining systems by observing them, by trying to characterize their health state and by suggesting a value of remaining duration before maintenance execution.

Maintenance thus becomes predictive, since it consists of performing appropriate operations neither too soon nor too late with respect to the past and future usage conditions and to the current health state. The decisions on this matter consist of proposing maintenance operations in relation to the schedule of maintenance teams, even if it entails an arrest of the system until maintenance is performed, proposing utilization capacities for the systems or equipment such that the end of the ongoing mission is ensured, or proposing a modification of the mission in compliance with the availability of the system so that the latter can be maintained before a breakdown occurs.

Clearly, the purpose of a decision is to preserve the system against the occurrence of a breakdown that could not be foreseen without prognostic data. Therefore, the post-prognostic decision aims to increase the (i) availability, allowing the systems to always be exploitable, (ii) reliability and (iii) safety, by taking the necessary steps to perform the missions safely while reducing the costs, in particular by preventing direct and indirect costs ascribable to a breakdown occurrence.

4.4. Types of decisions

In the literature, numerous studies focus on PHM for applications or devices from a variety of domains for which either maintenance is a key challenge or the ongoing mission's completion is crucial. The decision's validity duration is also considered as a factor in different ways by the works illustrated in the following section. We will return to this point to provide another level of assessment of these approaches; here, we focus on the various domains and applications.

The different domains that we present in this overview of approaches with the inclusion of the decision phase in the PHM process are the aerospace domain [BAL 12, CAM 07, PRE 08], the energy domain with some applications relative to wind turbines [BES 10, HAD 11, KOV 11, VIE 12, LEI 15] or batteries [SAH 11, BEN 01a, RAO 03], the studies on electronic systems [SAN 05, WAN 00, BAR 03] or machining systems [CAM 10]. We divided these various considered contributions in three main categories. Each one addresses a certain type of decision, whose implementation involves the control system, optimization of maintenance or mission management.

In the remainder of this chapter, we cite a certain number of works relative to decision-making in PHM in different types of applications with different kind of actions to be undertaken in accordance either with the period of time before the decision takes effect, or with the type of action to be performed at the maintenance level, or with the definition or redefinition of future or ongoing missions by the monitored system.

4.4.1. *Automatic control improved by prognostics*

In the context of controlled applications for which prognostics implies a modification of the command very quickly, in order to ensure the system's integrity, several works propose to define some automatic actions.

Pereira *et al.* [PER 10] proposed a predictive model for managing actuators that distribute control tasks over several redundant units. This allocation of tasks depends on the information provided by the prognostics about the degradation of control units. Another approach for task distribution based on the output data of a prognostic process was described by Bole *et al.* [BOL 11] for the control of an autonomous vehicle with a monitoring of the engine's degradation. Along the same lines, we can also mention the article by Bogdanov *et al.* [BOG 06] on servomotors or that by Brown *et al.* [BRO 09, BRO 11] addressing fault-tolerant electromechanical controllers.

An automatic control capable of taking into account the prognostics to improve this control at the high decision-making frequency has a limited effect due to the required speed of decision-making and performing necessary actions. This kind of decision will not be developed further in the remainder of this book. However, the maintenance operations that need to be proposed in accordance with the lifetime have been studied beforehand.

4.4.2. *Optimization of maintenance*

The optimization of maintenance by means of its planning is a domain addressed by a large body of work regarding post-prognostic decision. Observation and analysis of data provided by this observation enable the estimation of the health state value of some components liable to break down with a trend expressed by the remaining useful life (RUL) with a certain level of uncertainty. This value depends on the values observed not only with respect to past utilization but also with respect to future usage. It enables the proposition of a global health state of the entire system under observation [CAM 07]. Similarly, an intelligent prognostic tool for maintenance using a data-based approach was proposed by Asmai *et al.* [ASM 10] with the goal of preventing a breakdown risk early enough so that a planning of maintenance operations may be possible before the fault occurs. Other existing contributions propose a set of maintenance rules for very different applications such as electronics, aerospace or energy production.

4.4.2.1. *Electronic systems*

Several contributions in the domain of maintenance planning were proposed in the 2000s. For example, Sandborn *et al.* [SAN 05] determined the most appropriate moment for the maintenance of an electronic system. However, few studies about this aspect are based on the PHM domain, since the lifetime of electronic components is expected to be much longer than the lifetime of the system that uses them [SAN 05]. Moreover, the electronic components' health state and lifetime are studied in view of their usage in harsh conditions, for which gathered data is hardly exploitable, often imperfect and incomplete [SAN 05]. Some works address this issue by taking into account monitoring limitations [WAN 00, BAR 03], whereas other results for this kind of application base their studies on the hypothesis of a perfect knowledge of the equipment's health state and on the absence of uncertainty in the system's monitoring [VAL 89, CHO 91].

4.4.2.2. *Aerospace domain*

For aerospace applications, Balaban *et al.* [BAL 12] proposed an algorithm based on probabilistic methods and prognostic information in order to produce maintenance rules. Camci *et al.* [CAM 07] developed a tool for integrating maintenance data into the PHM process in order to use diagnostic and prognostic methods in a real-life environment on military airplanes.

4.4.2.3. *Wind farms*

Given the importance of maintenance and the difficulty of intervention in wind farms, wind turbines have been widely studied from the point of view of the PHM, i.e. at the level of their observation and analysis of their health state with the purpose of optimizing their maintenance [BES 10, HAD 11, KOV 11, VIE 12, LEI 15] Wind farms involve specific features which introduce particular constraints such as the usage of heavy maintenance tools, cumbersome spare parts that are expensive and lengthy to produce and skilled manpower [KOV 11]. It is also necessary to take into account the constraints related to meteorological conditions [BES 10]. Moreover, if we consider that the monitored wind turbines are installed offshore at sea, the maintenance problem becomes even more complex and costly.

Lei *et al.* [LEI 15] showed that the decisions related to the implementation of a predictive maintenance operation are not the same from the economical point of view if we consider a wind farm or a single wind turbine, in particular due to the fact that the system's environment, which is different in the two cases, has to be taken into account, even if they have the same remaining useful life (RUL). In the case when a wind farm is considered not as a whole but as a set of wind turbines, Vieira *et al.* [VIE 12] propose to change the value of the health state at which a wind turbine should not be used anymore, with the purpose of planning a maintenance intervention on the whole wind farm in order to maximize the lifecycle of the components. In this case, the authors demonstrate that the utilization of wind turbines is improved individually. Other optimization approaches based on conditional maintenance of components of the wind turbines with different damage degrees were developed by Besnard *et al.* [BES 10]. They compared three types of state monitoring of the wind turbines' blades, via a visual inspection, a monitoring by means of ultrasounds and thermography, and a continuous monitoring through fiber optics. Besnard *et al.* determined the optimal maintenance strategy according to wear conditions using a Monte Carlo method.

Haddad *et al.* [HAD 11] sought to optimize the maintenance of a wind farm as well, by defining subsets of offshore wind turbines to be maintained and taking into account the components, monitoring (degradation), future utilization and cost constraints. An approach to this maintenance planning problem in the same context was tackled by Kovacs *et al.* [KOV 11] from the viewpoint of an exact optimization by means of a problem's model in the form of a mixed integer linear programming. Herr *et al.* [HER 14a, HER 14b, NIC 13] proposed an approach that modifies the equipment's exploitation conditions with the purpose of lengthening the global utilization period of a distributed platform while including similar constraints as in the wind farms. In such conditions, maintenance is foreseen at the end of the planning horizon.

4.4.3. *Adjustment of missions with respect to the equipment's health state*

As mentioned in the introduction, another kind of decision is possible by means of an estimation of the remaining utilization period of a component. This does not involve an optimization of the maintenance, but rather an optimization of the missions that have to be achieved collectively by several components, or eventually by a single one. The decisions to be made with regard to this can be of different kinds, depending on whether they are made by each component individually in an independent way, or collectively, in consultation. The consequence of such decisions has an effect on the reconfiguration of the system, on the reordering or redefinition of the missions that the system has to fulfill [BAL 12]. Although this path laid out by Balaban *et al.* is only at its beginning, other works have already been proposed in the field of production planning [ASM 10, HAD 11], in the domain of the management of autonomous vehicles [PRE 09a, TAN 11, BAL 11], batteries [SAH 11, BEN 01a, RAO 03] and sensor networks [ELG 15, YON 13].

Here again, Iyer *et al.* [IYE 06] pioneered the proposition of a general platform for user's decision support in the domain of fleets of systems. It is composed of a first simulation module for testing scenarios with the evaluation of decisions for each of them with respect to a prefixed objective, and a second module that searches for optimal solutions. A collaboration with the user can take place in the case when no solution was found, in order to search for other possible scenarios that can lead to optimal strategies.

With the aim of adjusting a mission to the values provided by the prognostics, Balaban *et al.* [BAL 12] formalized an approach that consists of finding an appropriate compromise with respect to the initial mission's plan. This method is situated between the extension of the system's utilization period before maintenance and the maximization of the mission's efficiency, i.e. the maximization of production rate. Similarly, Skima *et al.* [SKI 16] studied a reconfiguration of a system based on the health state of its components in order to ensure a conveying mission. This idea is encountered in the approaches described in the following section.

4.4.3.1. *Production planning*

The knowledge of the RUL can be used in production planning [ASM 10] by providing useful information about the health state of production equipment. Therefore, decisions can be made regarding tasks to be launched or not with full knowledge of the facts, in order to avoid production losses with all the consequences that a breakdown may entail. The decisions to be made can be different, such as continuing the production, arresting a machine to avoid its degradation beforehand, foreseeing a preventive maintenance or modifying the production parameters in order to adjust them to a machine's state and thus reduce its workload [HAD 11]. In the case of a modification to be foreseen, the production plan is disturbed and either it is retained with marginal modifications or the whole production planning has to be reviewed in order to be adjusted to the new situation and to optimize one of the meaningful characteristics of the production device. The prognostic results thus have a direct influence on the operating conditions of the machines involved in production tasks. This analysis remains valid if the tasks to be performed are part of a more general mission [LEB 01, KAR 13]. If this is the case, the modification of machine parameters has a direct impact on the success of the mission's objectives, whether they will be reassessed or not depending on the conditions.

4.4.3.2. *Management of autonomous vehicles*

The emergence of autonomous systems suggests numerous new applications in which the mission's success is a crucial issue. It appears that it is essential for an autonomous system to be able to make decisions at a speed compatible with the variation of the mission's conditions, which can be considered as a sequence of tasks to be carried out. Therefore, the mission will be considered completed once the whole sequence of tasks has been processed [PRE 09a, PRE 09b]. The factors that may challenge the success of the mission are possible failures of the items composing the system or a change of environmental conditions, such as the meteorological conditions. We can mention, as an example of an autonomous application, a fleet of autonomous unmanned vehicles (AUVs), which are increasingly used for exploration missions on land, at the sea surface, for underwater and air missions (drones) or space missions (mobile rovers) [TAN 11].

The missions carried out today by autonomous vehicles concern surveillance, exploration, search and rescue missions, as well as interventions in contaminated or limited-access areas. Prescott *et al.* [PRE 09a] proposed a strategy for analyzing the reliability of such systems and making a prognostics of their health state in real-time, with everything integrated in a decision module such as the one for military drones described by the same authors in [PRE 08]. Tang *et al.* [TAN 11] developed a prototype of autonomous vehicle in order to assess and validate methods that include diagnostics and prognostics for the management of unforeseen events. Various techniques were developed and automated in order to function in real-time for this management of unforeseen events [TAN 08, TAN 10, EDW 10, ORC 10, DEC 11] and [ZHA 11]. The prototype illustrated by Tang *et al.* [TAN 11] was subjected to several types of failures, including leaks and punctures of vehicle's tires, low levels of charge and degradation in the battery, retrieval of incorrect data about the state of the vehicle or short circuits in the engine. RUL estimations were used in two different ways, either by taking them into account as constraints or directly integrating them in the cost function used to define the vehicle's trajectories. The optimization of the mission planning was tested experimentally by cross-referencing the parameters while taking into account the health state of the vehicles and the period of utilization of the batteries [TAN 11]. This study revealed that by optimizing the batteries' lifetime, the vehicles traveled a greater distance in a longer time, whereas by trying to minimize the duration of the missions, the distance traveled was lower with a higher energy consumption.

Balaban *et al.* [BAL 11] performed the same analysis with autonomous mobile robots. The authors used a platform to put to the test their decision algorithms for different cases of failure (mechanical, electronic and battery charging process failures). Rather than searching for the RUL of a component, these algorithms find the actions that optimize the lifetime of a robot globally with respect to the success of the ongoing and future missions.

4.4.3.3. *Battery management*

As mentioned previously, the battery's lifetime is crucial for the performance of autonomous vehicles. Several contributions were presented with the aim of suggesting the remaining useful life of the batteries [SAH 08, GOE 08, SAH 09]. At the same time, models of discharge of the batteries on drones showed that the discharge rate of a battery depends not only on its initial level of charge [SAH 11], but also on its health state and its usage profile. This study was extended by a modeling of the battery's behavior that includes a toleration of a high amount of uncertainty regarding the demand [SAH 12] by means of optimizing the available energy.

When the battery is composed of several blocks, its lifetime is shorter than in the case of a mono-block battery with an equivalent charge. As a result, new needs with regard to the batteries require a planning of the utilization order of these blocks [BEN 01a, BEN 01b] if it is necessary both to meet the demand and to lengthen the battery's lifetime as much as possible. The problem that arises consists of knowing which block should be used and at which moment. The best strategies are capable of ensuring an equivalent lifetime of multi-block batteries with respect to monolithic batteries with the same capacity. Similar results were obtained by Rao *et al.* [RAO 03] for portable electronic systems.

In a similar context, with the purpose of optimizing the usage of autonomous energetic sources, such as fuel cells, Herr *et al.* [HER 15, HER 17, CHR 15] propose a new approach of convex optimization. They include a model of aging in which the accessible power depends on the health state.

4.4.3.4. *Management of sensor networks*

In environments that are difficult to access, hostile or very extended, the utilization of wireless networks of sensors equipped with several stations for data gathering and a large number of sensors (several hundreds) seems to be necessary in order to collect useful information [ELG 14, ELG 15, SIN 13]. Certain production equipment of which it is important to know a certain amount of physical quantities have to be equipped with wireless sensors due to their required location [ELG 14]. Thus, a problem arises regarding the autonomous lifetime of the sensors, which most often use small non-rechargeable batteries [CAR 00]. A challenge consists of maintaining a connected network of sensors with a reconfiguration, if required, of the paths traveled by the information of a station's sensors, in order to limit the energy consumed for transmitting the gathered information [ELG 15].

Within the scope of monitoring composite structures in carbon fiber, Yontay *et al*. [YON 13] proposed an optimization of a wireless network of sensors with the goal of maximizing its lifetime by adjusting the frequency of inspections with respect to the amount of degradation of the observed structure. For this purpose, a dynamic planning of the sensors' observation was proposed by the authors.

4.5. The subject of a decision

An overview of the literature shows that there exists a number of works whose aim is to exploit the information obtained from the observation of physical quantities to improve the usage of the observed equipment or systems. Taking into account the assessments and analyses of gathered information, an issue consists of knowing which decision should be made and what can be subject to an action in order to maintain the system in operational conditions as long as possible, or to conclude the whole ongoing mission or a part of it.

The first factor that comes to mind consists of deciding to stop the equipment before it reaches its expiration date, which would inevitably entail a corrective maintenance. The related decision is then to foresee, as quickly as possible, a replacement or a maintenance intervention for the equipment reaching its end of life and, if possible, exploit the provided value of RUL to anticipate this operation of replacement or maintenance and to take into account all the consequences entailed by an equipment's arrest. If the equipment is not the only item in a system but it belongs to an equipment fleet, planning the maintenance/replacement phases will be crucial in order to limit the provoked interference. By taking into account the remaining useful life of the different items that constitute the system, this planning should seek for the best sequence of maintenance interventions in each scenario in order to limit the impact of these operations. However, the interference caused by the phases of anticipated maintenance should not be considered as a waste of time, because the monitored systems wear inevitably and maintenance phases are unavoidable during the equipment's lifetime. In this sense, planning maintenance or replacement of equipment before the occurrence of a breakdown contributes to protecting the system from degradation accelerated by the appearance of failures. Besides, we should not forget the cost related to the corrective maintenance interventions, which are always more expensive than an anticipated maintenance due to the fact that the latter is restricted to one piece of equipment and is performed in controlled conditions. A typical counter example is the occurrence of a breakdown on a train that has to be stopped in the middle of the countryside.

Another possible action consists of intervening on the lifetime of the component, and thus on the lifetime of the system, by modifying the operational conditions of its utilization. The component's mission is thus modified in order to postpone the maintenance as far as possible by operating in a degraded mode. In such case, either the mission is ensured collectively by many components or the mission is modified by lowering its objectives; however, the mission is terminated, even if this involves a longer time or an incomplete goal. In this case, the maintenance intervention that will restore the system to its nominal operational conditions is carried out either at the appropriate moment or at the end of the mission, involving in the latter case a maintenance of the whole system.

In the following sections of this chapter, we illustrate the various types of decisions to be made depending on the available time to make this decision and on the amount that this decision or these decisions involve. Then, we present different optimization techniques which can be used to seek the right decisions.

4.6. Typology of decisions in PHM (temporal, granularity and objective types)

4.6.1. *Typology of decisions within PHM*

The various contributions involving decision-making in the PHM process can be classified according to different axes. In Figure 4.1, we propose a representation of the various types of decision along a time axis and an axis representing the dimension of the considered system. Different types of decision can be highlighted at the intersection of the values of these two axes, varying from control (in the sense of a command in the automation domain) to logistics actions that are more spread out over time.

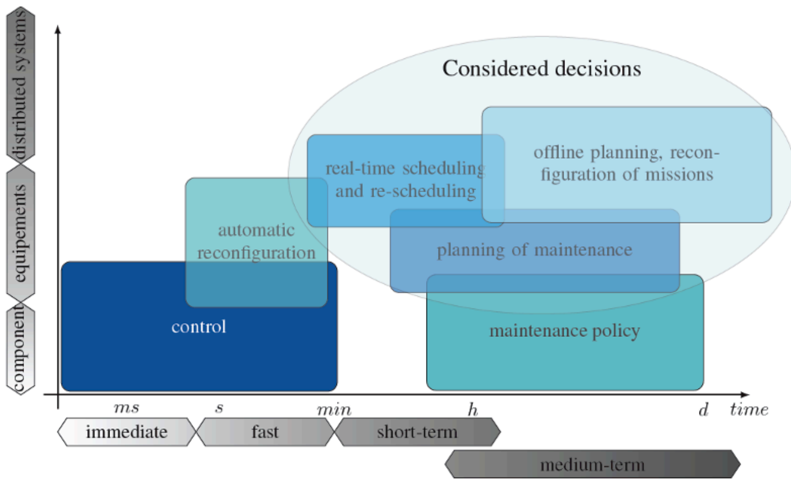

Figure 4.1. *Typology of post-prognostic decision. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

The classification along the proposed time scale follows the temporal segmentation of decisions introduced by Bonissone *et al*. [BON 07] and based on decision horizons. Three classes are identified by these authors:

i) unique decisions, made once;

ii) multiple and repeated decisions;

iii) large-scale decisions affecting the lifecycle of the considered system.

At a tactical level, we thus initially encounter an immediate level (between a nanosecond and a millisecond), which includes the automatic control decisions such as the ones in the electronic, electromechanical or automatic domains. Auto-diagnostics and real-time control are part of this decision level.

Then, there is a second, fast level for frequencies of the order of a second, which includes semi-autonomous decisions that are applied, for example, in the domain of automation for tasks of control using prognostics, supervision or detection of anomalies. At a short-term level, ranging from a minute to several hours, we find the decisions with a greater impact such as online scheduling and rescheduling. Diagnostics and prognostics also enter into this category.

On the other hand, the tactical level brings together the medium-term decisions which refer to longer decision periods (days or weeks), for example, for planning, offline planning or mission reconfiguration. The works presented in this book are related to the two latter types of decision process, i.e. the short- and medium-term categories.

4.7. Decision methods

The decisions to be made concern equipment that is likely to break down if no decision is made. The decisions are the result of an algorithm that receives as an input the system's state and all the data relative to the past and future usage of this system. In this way, these decisions aim to define how the equipment or the entire system should be used. A decision may consist of not using a certain piece of equipment before maintenance, of choosing a degraded operating mode for a piece of equipment to increase its lifetime and thus enable the conclusion of a mission, of changing the goal to be reached by the system, etc.

In general, the decision processes are the result of the solution of an optimization problem with the aim of reducing the maintenance-related cost, maximizing the utilization time of a system before maintenance or maximizing a mission's goal. Depending on the problem, it is possible that its optimal solution is simple and a greedy algorithm may be sufficient. In more general cases, involving a certain amount of heterogeneity, the decision problems that concern us here are most often NP-complete; in other words, there is no polynomial algorithm capable of yielding an optimal solution. In the best case, the problem can be modeled in the form of a linear program, although with integer variables. If this program has a limited number of variables, the most efficient optimizers, such as Gurobi [GUR 14] or Cplex [CPL 17], are capable of revealing an optimal solution. Unfortunately, the problems related to real-life situations involve a large number of variables, and it is necessary to go through the conception of sub-optimal algorithms based on greedy heuristics or meta-heuristics. These sub-optimal algorithms have a polynomial complexity and provide a solution within a reasonable time, compatible with the time constraints within which the decisions have to be made. It is not always possible to propose a limit or an approximation of the algorithm in the worst case and thus to know the distance between the proposed solution and the optimal one. Studying the problem in a configuration in which an optimal solution exists helps to compare the optimal solutions with sub-optimal solutions and to analyze the behavior in the case of an heuristic or meta-heuristic approach.

New approaches are being studied, in order to solve this kind of operational research problems by means of mathematical problems, linear or not. The solutions are not always optimal, but some recent results guarantee the convergence of the research solution with solutions that are not too far from the optimal ones. The properties to be shown in order to solve the problem via this approach are mainly convex properties of the constraints and of the goal function. Most of the times this requires the mathematical programs to be rewritten by setting the required hypotheses.

4.8. Summary

As we have mentioned here, the decision phase is an inevitable part of the PHM process in the same way as the decision and analysis phases. The decisions can be of different kinds according to whether the time available to make it is long or short, whether the system includes more or less critical elements, whether it is a distributed system with homogeneous or heterogeneous equipment. Most works in the literature are based on the health state of the equipment for the optimization of maintenance. Some works focus on taking into account the data provided by prognostics in the decision-making phase before maintenance. When the studied system has to fulfill a mission during which an arrest or a maintenance operation is not possible, the existing research rarely considers the case of distributed systems, in which the mission is the result of collaboration between several machines. In that case, it is a matter of optimizing the usage not of a specific machine, but of a group, which changes the paradigm and lays out the path to new approaches. If we consider again the application cases described previously, this type of decision concerns the management of batteries or sensor networks.

The common denominator of the work mentioned herein is the possibility offered by the knowledge of the remaining useful life, which enables, for example, the modification of the operational conditions of the equipment involved in the production or in the fulfillment of a mission. In this way, it is possible to optimize the usage of a production system. This reveals an important number of complex optimization problems; we provide some examples of how to tackle them in the following chapter.

5

Towards a Policy of Predictive Maintenance

Over the last few decades, maintenance policies implemented in industry have evolved significantly. Indeed, while initially the maintenance activities were limited to a reparation of equipment after a breakdown, today, technological transformations enable the implementation of predictive activities. The task of choosing the right maintenance policy for each equipment, component or subset becomes somewhat more complex. It appears then that this strategic choice has to be optimized in order to minimize the maintenance cost of the entire industrial system in operational conditions.

In the industrial world, the two main maintenance policies that are actually implemented are the corrective policy (also called *failure-driven maintenance* or *run-to-failure maintenance*) and the systematic preventive policy (also called *time-based maintenance*). They correspond to strategies that can be easily implemented:

– corrective maintenance responds to the principle of waiting until the system does not perform its function anymore. It is a purely reactive approach, in which unforeseen events (functional failure, production rejection, or breakdown of equipment) appear, and equipment's restoration operations are triggered after the occurrence of the event. Very often, they cause production to be paused, which may be very costly. This type of policy can be suitable only in the case of secondary equipment, whose failure does not jeopardize the production system in its entirety;

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– systematic preventive maintenance, on the other hand, as revealed by its name, aims to prevent the malfunctioning of equipment by planning some operations (replacement of a component or subsystem, lubrication, etc.) at regular intervals of time, which preserves the equipment in nominal operating conditions. In this case, in order to minimize the total intervention cost, a difficulty consists of choosing the appropriate frequency of the operations representing a compromise between too frequent stopping of the equipment, which correspond to production losses, and too late interventions, which lead to a high risk of failure. The choice of the periodicity depends on the statistical knowledge of the average MTBF (mean time between failures) for an equipment used in nominal operating conditions.

In most situations, decisions related to maintenance strategies are based on the experience of managers, respecting the recommendations provided by the equipment's manufacturers, and the analysis of the record of failures. However, they do not avoid unexpected situations since, even in the case of preventive maintenance, there always exists a risk of failure for a component or a related subsystem.

The growth of automation and the integration of mechatronics[1] in industrial equipment both now enable the maintainers to gather a great amount of useful information for the identification of an equipment's current health state. In fact, by multiplying the number of sensors in modern equipment, the maintainer can access very rich information, which is capable of revealing premature or delayed wear of the components or subsystems by means of suitable processing. In this way, the maintainer can plan the maintenance interventions to be as close as possible to the end-of-life limit. This approach or maintenance policy is known by the name of condition-based maintenance (CBM) [JAR 06], [SHI 15].

In the case of a condition-based maintenance, operations are triggered only when certain measurable parameters reach a threshold value. The implementation of maintenance operation depends on a certain kind of predetermined event (information provided by a sensor, measurement of a

1 Definition from the Oxford English Dictionary: Technology combining electronics and mechanical engineering.

parameter, analysis of information, etc.) which reveal the equipment's degradation state.

More recently, methods capable of estimating the remaining useful life of a component or subsystem have appeared. They are based on available health-state data in order to predict the future evolution of the system's health parameters. These approaches are called prognostics, and they form a set of processes known as prognostics and health management (PHM) [THU 01b], [KAL 06]. By means of prognostics, it is possible to plan the maintenance interventions in accordance with the evolution of the equipment's parameters; this is the principle of predictive maintenance.

Note that there is no universally accepted definition of the concepts of conditional and predictive maintenance. Here, we highlight the differences that can be discerned in many scientific articles on these topics. Some authors reckon that the two definitions are exactly the same [SHI 15], [LEE 06]. Others add some nuances [IUN 12]. The Afnor[2] standard NF 13306 X60-319 proposes the following definitions:

– Conditional maintenance: preventive maintenance based on the monitoring[3] of an asset's functioning and/or of meaningful parameters of its functioning with the integration of ensuing actions.

– Predictive maintenance: conditional maintenance executed in accordance with predictions extrapolated from analysis and assessment of meaningful parameters regarding an asset's degradation.

From the Afnor standard's definition, it can be seen that a difference is retained. From our point of view, the main gap lies in the notion of extrapolating meaningful degradation parameters. When conditional maintenance is limited to a short-term future vision, the prognostics allows it to take into account forthcoming equipment's usage conditions, and eventually, it may even lead to a modification of operational conditions, in terms of decision, in order to modify the remaining duration of utilization before maintenance.

2 French standardization association.

3 The monitoring of the functioning and of the parameters can be performed according to a schedule, to the demand, or continuously.

The maintenance manager thus has at his/her disposition a panel of available maintenance policies for guiding the global maintenance strategy. Of course, it is not a matter of choosing a unique policy for all the equipment to be maintained, but rather to determine which is the appropriate policy for each piece of equipment or even for a single component or subsystem. Beyond that, it is also convenient to choose a suitable periodicity either of component replacements or of inspections. This kind of decision problem can take different shapes depending on the objective that needs to be optimized, the hypotheses and data considered, or on production constraints that have to be complied with. Recent works have tackled this optimization problem; in the following section, we develop some of these approaches.

First, we will define the considered hypotheses and data; afterward, we will highlight the possible decisions that constitute a lever for choosing the best combination of strategies. The optimization objectives are then detailed, before concluding with the implemented methods.

5.1. Decision problem

The general form of a decision problem can be described in the following way: let's consider a set of machines that produce items or services, and a maintenance service composed of a group of operators that ensure the maintenance of the machinery. The problem that arises thus consists of knowing when each component or subsystem of the machines should be maintained in order to allow the production system to perform its mission in nominal conditions. A constraint of this problem is the capacity of the maintenance service in terms of resources (human and material). The planning of maintenance operations depends on the implemented policies. Therefore, it is convenient to define a global policy that maximizes the equipment's production availability and minimizes the underlying maintenance costs.

5.2. Hypotheses and data

A system producing items or services is composed of a set of subsystems or components. The problem that we tackle here consists of choosing the best maintenance strategy for each component or subsystem.

Several works focus on the optimization of maintenance strategy for a single piece of equipment. The proposed approaches do not take into account the interaction that may exist in production systems characterized by an increasing complexity. Some researchers have addressed this kind of problem by considering predictive maintenance as one of the possible action levers. We can cite in particular the works by Z. Yang *et al*. [YAN 08], P. Tamilselvan *et al*. [TAM 12], A. Kovacs *et al*. [KOV 11], or by F. Camci [CAM 09].

The majority of the works proposed focus on a quantitative assessment of different maintenance scenarios on the basis of resulting costs of maintenance and production operations. These costs involve the present and future degradation level of the equipment, maintenance actions, profits of the manufactured goods or provided services, etc. They constitute fundamental information for any maintenance decision.

The data considered in these decision problems are detailed in the following sections.

5.2.1. *Equipment*

The considered system producing items or services is composed of a set of equipment, which together ensure a global production mission. Each piece of equipment is composed of subsystems or components subject to wear related to their utilization. The equipment then undergo some maintenance operations, which ensure their restoration to a nominal functioning state. The maintenance operations consist of replacements of components or subsystems, lubricative operations, regenerative operations, etc.

According to the application, the equipment to be maintained may be organized in different topologies:

– parallel equipment;

– series equipment;

– parallel-series equipment.

5.2.1.1. *Parallel equipment*

In this case, the production machines are all independent. Each of them provides a service that does not affect and is not affected by the other machines.

This kind of organization can be found for example in a wind farm [KOV 11], in which each wind turbine functions independently from its neighbors, or a fleet of vehicles [CAN 14], where each vehicle has an independent route.

In the context of parallel machines, the performance of the production system corresponds to the sum of the individual outputs of each machine composing the system.

5.2.1.2. *Series equipment*

The series type of organization can be found mostly in systems producing items. In order to be produced, an item may undergo several manufacturing steps that are performed one after another, always in the same order. The system is then composed of several machines, each one performing a manufacturing step. This type of organization can be found in assembly lines for vehicles, semiconductor manufacturing [YAN 08], automated machining centers [DIE 06], etc.

A decrease in performance of a piece of equipment can have an impact on the other equipment in the production line. Therefore, the global availability of the system is not always guaranteed, even if some equipment are capable of fulfilling their mission.

5.2.1.3. *Parallel-series equipment*

Finally, the organization in the parallel-series equipment generalize the two types above. In this case, the system is composed of many production phases, in which each manufacturing phase can be performed by several machines. In this way, some equipment are independent (in parallel), but they supply a global production line. Therefore, the performance of a production step may affect the following phases.

In the last two types of organization, the maintenance of certain equipment may lead to a necessary arrest of other equipment of the system and cause indirect production losses.

5.2.2. *Maintenance operations*

The decision problem consists of defining a planning of maintenance operations. These operations vary depending on the strategy. The most common operations are the replacements of faulty parts (before the breakdown in the case of preventive maintenance and after the breakdown in corrective strategies). The main goal of the decision is to provide a plan of operations for each machine to be maintained by taking into account the constraints such as the availability of material and human resources or spare parts.

In decision problems, the maintenance operations are often classified according to four categories:

– Corrective operations: operations that are not planned; they appear in the planning as soon as an equipment breaks down and cannot fulfill its mission anymore. The equipment is stopped until its restoration at the end of the maintenance operation. The duration of the interventions is not always continuous, since a diagnostic phase is often required. A palliative operation may be performed beforehand. This leads to a restart of the equipment in conditions that can be degraded in terms of performance. If a palliative operation is performed, then a second reparation operation has to be planned in order to restore the nominal functioning of the equipment;

– Systematic preventive operations: operations that are entirely identified and programmed at regular intervals of time. For example, an air conditioner filter has to be replaced every X hours of utilization. For these operations, the duration is known and fixed, since a known maintenance procedure is performed;

– Conditional maintenance operations: these operations are also entirely identified. Unlike preventive operations, they are triggered when the evolution of a meaningful parameter of health state of a component or subsystem reaches a previously set threshold. For example, the tires of a vehicle have to be replaced when the tread wear indicator is reached. The maintenance operation is planned only when the threshold is exceeded. Therefore, these operations can be easily planned, and they take into account the current health state of the equipment;

– Predictive maintenance operations: in this case, the operation is subject to the existence of a module capable of providing a future evolution prognostics of meaningful parameters of the health state of a component, or more generally, a system. The prognostic module provides information that specifies the remaining useful life (RUL) before maintenance. This information enables the planning of a known maintenance operation.

A hypothesis that is very often considered in this kind of decision problem is that the maintenance is said to be “perfect”. This means that the health state of the equipment is perfect immediately after the maintenance operations, and therefore, the machine is considered as new.

5.2.3. *Maintenance resources*

In order to be performed, maintenance operations need a mobilization of resources. These operations are carried out by operators, sometimes by means of specific tools, and require spare parts. Thus, several kinds of resources should be taken into account in optimization problems regarding maintenance strategies:

– Operators: human resources, which may be subject to availability constraints, in particular related to work shifts. Sometimes, a single operation may require several operators at the same time. The equipment to be maintained are not always situated in a single place, and the operators may have to move in order to intervene. The traveling time required may not always be negligible, and it may affect the performance of the maintenance service. Finally, very often the operators have characteristic competencies, and therefore they are capable or authorized to perform only certain interventions;

– Spare parts: for the restoration of a system’s state, the maintenance operations consist of replacing components or upkeeping (greasing, draining, etc.). Such a task can be carried out only in accordance with the availability of spare parts or of the consumable material which it employs. Some parts or consumable items are available from a stock, but the most expensive ones require supply delays that have to be foreseen within maintenance planning. The operations are triggered only if the related spare parts and consumable items are available;

– Specific tools: the operators use tools to perform maintenance operations. Besides classic tools, which can be considered to be available without limitations, it can happen that some operations can be carried out only by means of heavy equipment, which are shared between the operators or even rented from external companies. For example, the maintenance of a wind turbine may require a specific crane. This entails that the operations have to be planned in accordance with the availability of the specific tool, so that several operations on different equipment can be planned at the same time in order to distribute the related costs.

All the elements described above are constraints that have to be taken into account within the decision problem.

5.2.4. *Costs of maintenance and production*

In any decision problem seeking a solution, the goal is to find a response in which the economical aspects are optimized. Maintenance does not contravene this rule. In fact, the maintenance service has been considered for a long time in business as a cost center. Only recently has it been perceived as a tool at the service of industrial performance. To achieve this objective, it is quite useful to identify the different costs incurred by maintenance activities:

– costs of the reparation operations: these are direct costs that include the cost of replacement parts or consumable materials required to restore the functioning of an equipment. They also include the cost of labor and eventually the cost related to the utilization of specific tools;

– costs of breakdowns: these costs are the ones that should be avoided. A breakdown occurs unexpectedly and causes high costs related to the production's arrest (see below), the restoration of the functioning state (with a replacement of components which is generally more expensive than in the case of preventive maintenance);

– costs of production losses: the arrest of a machine may lead to production losses. The cost of these losses depends on the duration of the arrest. The loss of income is not the only component of losses; the costs may be also related to a lack of quality, commercial penalties, or company's brand image, which is far less quantifiable;

– costs of operators' travels: when the equipment are not located in the same place, operators need to travel. The costs related to these movements are direct and indirect. When an operator does not move, the commute time is a non-productive period, which entails extra costs;

– costs of storage of replacement parts: in order to ensure rapid availability of spare parts, the latter are often stocked so that the maintenance operations using them can be planned without constraints. The cost of this storage is often considerable, and thus it should be taken into account.

Furthermore, it is important to consider the investment required for the implementation of a predictive or conditional maintenance policy. In fact, such strategies need the equipment to be equipped with sensors in order to measure the quantities representing the system's health state. The cost of the monitoring systems should thus be included in the decisions.

There is no unique cost model. The costs depend considerably on several environmental parameters of the production system such as the type of production (small, medium or large series), architecture of the production system, localization of machines, expertise of maintenance operators, type of production equipment, etc.

5.3. Implementation: an approach of maintenance planning supported by prognostic information

Here, we intend to present a decision approach which aims to plan maintenance operations for a predictive maintenance policy. The presentation that follows is adapted from the works by F. Camci [CAM 15].

In this approach, a set of geographically distributed machines is considered, such as a set of offshore wind farms or a set of railroad switches. A maintenance operator or a maintenance team has to ensure the upkeep of this set. The equipment are subject to degradation caused by their operation, and they have to be maintained when their state requires it. The problem therefore consists of defining the appropriate planning of maintenance operations for the set of machines.

The equipment to be maintained are assumed to be monitored by a system that delivers relevant information about their current health state and failure risks. The latter may be expressed in the form of a breakdown probability. As long as the system is not maintained, the breakdown risk persists, and it is necessary to plan a maintenance operation, which consists of replacing the degraded component. The equipment's health state is assumed to be completely renewed after each intervention of a maintenance operator or team.

In the considered model, the data taken into account to make planning decisions are the breakdown probabilities of the machines (or components) that have to be maintained. They are issued from predictions, for the time preceding the first maintenance operation on a machine, and from a reliability analysis, for the time after a maintenance operation.

The tackled problem aims to find an optimal planning strategy of the maintenance operations. The notion of optimality is related in this case to the total cost of production and maintenance of the set of equipment.

The problem that is tackled can be expressed as follows:

– resources: the system is composed of a set of machines $\pi_i, 0 \leq i \leq n$, geographically remote one from another at a distance d_{π_i,π_0}. π_0 represents the maintenance center, which is the departure and final destination of the maintenance operator. A single operator is available for all the operations, with the constraint of work shifts. Any exceeding of the foreseen schedule leads to an extra financial cost;

– prognostic and reliability model: for each machine, the remaining life before maintenance is expressed in terms of a predicted probability of breakdown. Thus, at an instant t, the breakdown probability is denoted by $P_{P,t}$, for any t preceding the maintenance. After a maintenance operation, the breakdown probability at an instant t is denoted by $P_{R,t-LM}$, with LM the time passed since the last maintenance. The degradation within a unit of time (e.g. a day) is considered to be negligible;

– maintenance operation: the machines undergo only one maintenance operation within the decision horizon. The maintenance operations are known for all the machines, and their duration is denoted by t_i^r.

5.3.1. *Cost modeling*

On the basis of these hypotheses, the decision problem consists of finding an allocation that determines the periods in which the maintenance operations for each machine should be performed, and planning in order to set the order of the machines' visits. The decision's goal is to minimize the total cost of the calculated solution. This cost combines the failure costs (C^F), maintenance costs (C^M), the costs of travel between the machines and to/from the maintenance center (C^T), and the costs of extra work hours (C^W). Thus, the objective function to be minimized is:

$$Min(C^F + C^M + C^T + C^W) \quad [5.1]$$

The different costs are detailed in the following sections.

5.3.1.1. *Cost of failures*

The failures cause direct costs due to the equipment's repair (F_i) and indirect costs ascribable to the unavailability of equipment, which induces production losses or the inability to fulfill a required mission. The latter costs depend on the duration of the unavailability periods (denoted by δ_i for each time unit). The failure-related cost for each time t is calculated as:

$$C^F_{i,t} = P_{i,t} \times (F_i + \delta_i \times DT_i) \qquad [5.2]$$

where $P_{i,t}$ is the probability of failure of machine i at an instant t, and DT_i is the time of unavailability of machine i.

Therefore, the cost over the planning horizon can be calculated as:

$$C^F = \sum_{i=1}^{n} \left(\sum_{t=1}^{T} C^F_{i,t} \right) \qquad [5.3]$$

Note that the failure probability is a piece of information obtained either from a prediction by a prognostic system or from a reliability analysis, depending on the considered instant t. Before a maintenance operation, $P_{i,t} = P_{P,t}$, whereas after the maintenance operation $P_{i,t} = P_{R,t-LM_i}$ (where LM_i is the time passed since the last maintenance operation). F. Camci [CAM 15] proposes that this duality is taken into account by using a binary variable in his model. Let $x_{i,t}$ be a variable with a value equal to 1 if the machine i has already been maintained at an instant t and is equal to 0 otherwise. This enables the definition of the failure probability by means of equation 5.4:

$$P_{i,t} = P_{P,t} \times \left(1 - \min\left(\sum_{k=1}^{T} x_{i,k}, 1 \right) \right) + P_{R,t} \times \min\left(\sum_{k=1}^{T} x_{i,k}, 1 \right) \quad [5.4]$$

5.3.1.2. *Cost of maintenance*

The cost of maintenance (C^M) is the sum of the costs of all the planned maintenance operations for all the machines. Thus, if $x_{i,t} = 1$ then the maintenance cost $C^M_{i,t} = \gamma_i$. Of course, this cost should be considered only if the maintenance can take place; in other words, only if a failure occurs.

Therefore, this cost depends on the failure probability and can be expressed by equation [5.5].

$$C^M = \sum_{t=1}^{T} \left(\sum_{i=1}^{n} (1 - P_{i,t}) \times (x_{i,t} \times \gamma_i) \right) \qquad [5.5]$$

5.3.1.3. *Cost of travels*

The cost of travels depends on the order of visits of the equipment within the same period of time t. We denote by π_i^t the i^{th} visited equipment at a time t. If the visiting order is fixed, then the cost of travels is the sum of costs of travel between the equipment. It is expressed by the equation 5.6:

$$C^T = c_d \times \sum_{t=1}^{T} \left(\sum_{i=1}^{n_t} d_{\pi_{i-1}^t, \pi_i^t} + d_{\pi_{n_t}^t, \pi_0^t} \right) \qquad [5.6]$$

where c_d is the travel cost per unit of distance and n_t is the number of equipment visited at instant t.

5.3.1.4. *Cost of extra work hours*

The normal work duration (D_w) and the upper limit of this duration (D_w^{up}) are fixed. If the normal duration is exceeded during a period of time, then the extra hours will have to be paid for. The cost of these hours is expressed by equation 5.7.

$$C^W = \gamma_i \times C_\gamma \times \max \left(\left(\sum_{i=1}^{M_r} \left(TT(d_{\pi_{i-1}^t, \pi_i^t}) + t_i^r \right) + TT(d_{\pi_n, \pi_0}) - D_w \right), 0 \right) \qquad [5.7]$$

where $TT(x)$ is the time of traveling x, and t_i^r is the maintenance duration on the equipment i.

5.3.2. *Constraints to be satisfied*

The only constraint that should be taken into account in this problem is that of the limited work hours of the maintenance operator. This duration is limited by D_w^{up}. The set of constraints to be satisfied is therefore given by the relation 5.8:

$$\forall t, \sum_{i=1}^{M_r} \left(TT(d_{\pi_{i-1}^t, \pi_i^t}) + t_i^r \right) + TT(d_{\pi_n, \pi_0}) \leq D_w^{up} \qquad [5.8]$$

5.3.3. *Objective function*

In this problem, the goal is to minimize the total cost of the entire maintenance of all the equipment. Therefore, the objective function consists of minimizing $C^F + C^M + C^T + C^W$.

The decision problem is thus modeled by a mathematical program, with the set of variables ($x_{i,t}, i = 1 \dots n, t = 1 \dots T$) as decision variables, which specifies which equipment should be maintained for each period t, including the order of visits within each period, which affects the costs of travel and hours exceeding the normal work hours.

5.3.4. *Problem's solution*

In order to solve certain mathematical programming problems, such as integer linear programs, methods exist, traditionally based on branch and bound procedures. Solvers for the implementation of this kind of approach are available on the market. In particular, we can mention Cplex [CPL 17], Gurobi [GUR 14] or Lindo [LIN 17]. However, although they are capable of providing an optimal solution for this type of decision problem, these solvers are very often limited by the size of the considered problems. In fact, the implemented solving approaches have an exponential mathematical complexity and do not guarantee a reasonable time required to find the solution.

Alternative solutions consist of seeking not for an optimal solution, but for an approximate one, if possible, close to the optimal solution. Many techniques may be contemplated; for example, we can cite all the metaheuristic approaches: stochastic descent, genetic algorithm, ant colony algorithm, etc.

By implementing an approach based on a genetic algorithm, F. Camci represents the solutions of a decision problem via a sequence of binary values. The chosen coding should enable the modeling of both the allocation of maintenance operations in periods and the order of equipment visits within the same period.

This method was proposed for the maintenance of railway infrastructure equipment. In fact, the maintenance of railway points in a given sector is a problem that requires the movement of maintenance operators. The implementation of the developed approach has shown that it is possible to optimize the total cost of maintenance in operational conditions for this kind of equipment.

5.4. Summary

The results presented in this chapter illustrate a post-prognostic decision approach. An important point is that the introduction of the prognostic concept leads to a change in the way in which maintenance planning is comprehended. In fact, by means of preventive maintenance policies, in particular with the systematic one, planning can be done in a recurring way. Predictive maintenance proposes a new paradigm in which it is necessary to question the planning of interventions regularly, in accordance with the evolution of the health state of the equipment. This entails that the management of maintenance resources becomes more complex, since predictive maintenance may create periods of under- and overload in the maintenance service.

The approaches proposed in this chapter constitute the first step in response to this issue. The currently considered hypotheses are still very restrictive. In order to make these methods feasible in industry, it is necessary to make them evolve by integrating all the constraints. For example, the management of spare parts' stocks should include the dynamic aspect of the predictions. Beyond the planning that incorporates predictive aspects, the acceptability of the solutions by maintenance actors should also be assessed. Indeed, the implementation of this new maintenance paradigm requires a greater degree of flexibility.

6

Maintenance in Operational Conditions

6.1. Statement of the problem

The problem presented here is an illustration of post-prognostic decision. The goal of the application considered is to yield a certain amount of production, an amount that can be assimilated to a flow of materials, of energy, etc. This production is ensured by a platform consisting of a set $\mathscr{M}$ of m machines M_j, such that $M_j \in \mathscr{M}$ with $1 \leqslant j \leqslant m$. Each operating machine performs the same kind of task in parallel with other operating machines, knowing that the machines do not all operate at the same time. The produced quantity is the sum of quantities produced by each one of the machines, which potentially all have different throughputs. The performance of each machine can be controlled, within the limits of its capabilities, with respect to a certain number of discrete running profiles; in other words, only a finite number of configurations are possible. Finally, all the machines are subjected to wear and, as a result, have a limited lifetime. A PHM process implemented in the platform makes it possible to know this lifetime, called remaining useful life (*RUL*). We suppose that the *RUL* is related to the running profile, as we will illustrate below in a more formal way. This work was the subject of several publications, in particular [HER 14a, NIC 13].

6.1.1. *Objective*

The goal of the application is to meet a certain production demand $\sigma(t)$ for as long as possible before a maintenance of the fleet of machines becomes necessary. This length of time is called the production horizon $\mathcal{H}$. The

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optimization problem can be tackled by considering a discrete subdivision of the production horizon in K intervals of time with a size ΔT such that $\mathcal{H} = K\Delta T$. The decision regarding the machines' exploitation is then made according to this periodicity, which, for example, can be a periodicity of an hour, a half-day, or a day.

6.1.2. *Hypotheses*

For the sake of simplification, and without loss of generality, we consider that the demand is constant over time, i.e. $\sigma(t) = \sigma$. Therefore, the production of running machines $\rho_{tot}(t)$ at the instant t is greater than or equal to the demand ($\rho_{tot}(t) \geq \sigma(t)$, $\forall t \leq \mathcal{H}$). We accept that any overproduction is lost. Furthermore, a machine cannot be used if its *RUL* is strictly lower than the length of an interval ΔT, and it degrades only when it is used. Moreover, supply and storage problems related to production are not considered here.

6.1.3. *Modeling of running profiles*

Each machine M_j $(1 \leqslant j \leqslant m)$ has a finite number of different performance levels. We set n as the number of running profiles $N_{i,j}$ defined for each machine in the following way: $N_{i,j} = (\rho_{i,j}, RUL_{i,j})$, with $0 \leqslant i \leqslant n-1$ and $1 \leqslant j \leqslant m$. Let $N_{0,j}$ be the nominal profile of machine M_j; $N_{0,j}$ provides the maximum throughput and is associated with the minimum *RUL*. In comparison, a sub-nominal profile yields a lower throughput, but for a longer time (see Figure 6.1). According to this principle, we have the following relations: $\rho_{0,j} > \rho_{1,j} > \ldots > \rho_{n-1,j}$ and $RUL_{0,j}(k) < RUL_{1,j}(k) < \ldots < RUL_{n-1,j}(k)$ for any interval k $(1 \leqslant k \leqslant K)$.

Furthermore, we set $Q_{i,j} = \rho_{i,j} \times RUL_{i,j}$ to be the quantity that can be produced by the machine M_j with the running profile i during an interval of time $RUL_{i,j}$ with the related production throughput $\rho_{i,j}$. The values of throughput in the various profiles are such that we reasonably have $Q_{0,j} > Q_{1,j} > \ldots > Q_{i,j} > \ldots > Q_{n-1,j}$. In this way, we are tempted to operate the machines in their nominal state, the most efficient one, yet we will demonstrate in the following that this is not always a solution that leads to the best result, given the fact that all overproduction is lost.

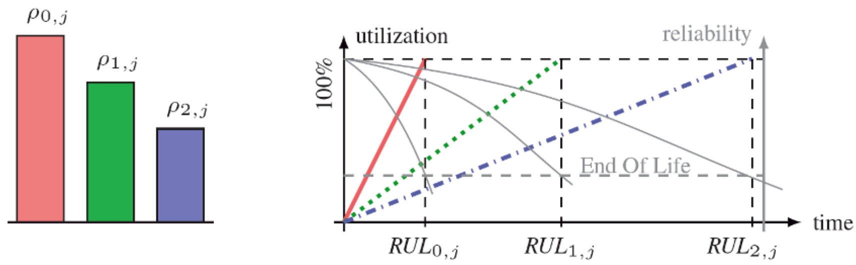

Figure 6.1. *Running profiles with discrete throughput variation for a machine M_j. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

Besides, in the proposed model, the order in which the running profiles are selected during the utilization of a machine does not have any impact on the evolution of its health state, and thus on the evolution of the *RULs* related to each profile. Without taking into account the performance levels reached, examples of scenarios proposed in Figure 6.2 show that it is possible to exceed the *RUL* of the nominal profile, $RUL_{0,j}$, by using a machine with three different subsequent running profiles, $N_{0,j}$, $N_{1,j}$ and $N_{2,j}$. The second scenario illustrated in this figure shows that an appropriate selection of profiles $N_{i,j}$ over time can extend the period of utilization of a machine, not only beyond the *RUL* of a nominal profile $RUL_{0,j}$, but also beyond the *RUL* of a sub-nominal profile ($RUL_{1,j}$ in the considered example).

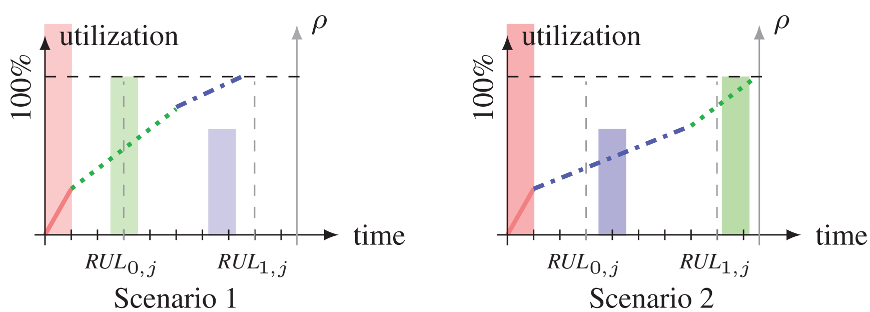

Figure 6.2. *Utilization of a machine M_j with several running profiles while considering a discrete variation of the provided throughput. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

This extension of the utilization length of time enabled by the usage of several running profiles can be exploited on several machines that operate in parallel and contribute together to the same demand, on the condition that this demand can be met even if the machines operate in sub-nominal modes. In this way, considering several running profiles introduces the possibility of varying the exploitation (or scheduling) of a set of machines if the maximization of the production horizon is an objective. In section 6.1.5, an example illustrates the motivating reason behind this work.

6.1.4. *Optimization problem* MAXK

The problems that arise in the context introduced above with a demand to be met are expressed by the following notation:

$$\text{MAXK}(\sigma_k \,|\, \sigma,\ \rho_{i,j} \,|\, \rho_j \,|\, \rho,\ RUL_{i,j} \,|\, RUL_j).$$

This general notation represents an optimization problem that consists of defining a planning of machines that maximizes the production horizon $\mathcal{H} = K\Delta T$. The level of required throughputs, or demand, is denoted by σ_k if this demand varies over time. The demand is denoted by σ if it remains constant within the whole production horizon. The last two parameters characterize the properties related to the set of machines $\mathscr{M}$. Each machine $M_j \in \mathscr{M}$ $(1 \leqslant j \leqslant m)$ has, in fact, n running profiles $N_{i,j}$ $(0 \leqslant i \leqslant n-1)$, which impose the values of $\rho_{i,j}$ and the relative utilization intervals $RUL_{i,j}$. In the case when a single running profile is considered for each machine $(n = 1)$, the set of machines may be either homogeneous or heterogeneous in terms of throughput. In the first case, we have $\rho_{i,j} = \rho$, and in the second one, $\rho_{i,j} = \rho_j$ $(0 \leqslant i \leqslant n-1$ and $1 \leqslant j \leqslant m)$. Since the machines may have different health states at the beginning of planning, *RUL* values may be different, whichever the variant of considered optimization problem. If only one running profile is considered, *RUL* values are always denoted by $RUL_j(k)$ with k the interval of time comprising the instants t between the dates $(k-1)\Delta T$ and $k\Delta T$, and with $1 \leqslant k \leqslant K$. This also enables a representation of different states taking place in the machines during the planning process, knowing that the schedule is not chosen systematically for each interval.

For the sake of simplification, in what follows, we denote by $RUL_{i,j}$ the *RUL* value corresponding to the profile $N_{i,j}$ of the machine M_j at the schedule's start ($k = 1$) and *RUL*$_j$ the *RUL* value corresponding to the profile $N_{0,j}$ of the machine M_j for the same interval when this machine has only one profile.

6.1.5. *Application example*

To illustrate the relevance of this approach, a naive application example is proposed in order to show that using a machine with its most efficient profile is not always the best solution when it is necessary to extend the production horizon while respecting a required level of service; this may happen even if the efficiency of the machines decreases with their running profiles, in which lifetime is longer but the throughput becomes lower, as was pointed out above.

Consider a set $\mathscr{M}$ of four machines ($\mathscr{M} = \{M_1, M_2, M_3, M_4\}$) with which a certain throughput has to be produced. At each instant t, this total throughput has to reach at least the level of a constant demand of $\sigma = 450$ throughput units. The objective is to maximize the time during which this level of service is being reached. At time $t = 0$, M_1 is supposed to be capable of providing two different throughputs, which correspond to two running profiles: $\rho_{0,1} = 450$ during one interval of time (*RUL*$_{0,1}(1) = 1$) or $\rho_{1,1} = 125$ during three intervals (*RUL*$_{1,1}(1) = 3$). At $t = 0$, the other machines M_j ($j = 2, 3, 4$) can produce either $\rho_{0,j} = 350$ during one interval of time (*RUL*$_{0,j}(1) = 1$) or $\rho_{1,j} = 75$ during three intervals (*RUL*$_{1,j}(1) = 3$) - see Table 6.1. The features of these running profiles decrease exponentially with decreasing throughput. For any instant $t > 0$, the features of each profile $N_{i,j}$ ($0 \leqslant i \leqslant n-1$ and $1 \leqslant j \leqslant m$) depend on the past usage of the machine M_j. In accordance with these hypotheses, the considered optimization problem is the following: $\textsc{max}\mathrm{K}(\sigma,\, \rho_{i,j},\, RUL_{i,j})$.

Three different scenarios of machines' utilization are proposed. In the first scenario (*S1*), the machines are used with their most efficient profile, $N_{0,j}$, and no overproduction is authorized. It can be seen in Figure 6.3(a) that in this case, the platform can operate for four intervals of time. However, the demand is met only during the first interval ΔT, during which the machine M_1 alone reaches the required throughput. For the three following intervals ($t > \Delta T$), the throughput delivered by the machines does not meet the demand σ. In fact, $\rho_{0,2}, \rho_{0,3}, \rho_{0,4} < \sigma$. Therefore, in the scenario *S1* with $K = 1$, the production horizon is equal to one interval of time ($\mathcal{H} = \Delta T$).

		$t = 0$	$t = \Delta T$	$t = 2\Delta T$	$t = 3\Delta T$
Scenario *S1* ($\mathcal{H} = \Delta T$)	M_1	(450,1)	(450,0)	(450,0)	(450,0)
		(125,3)	(125,0)	(125,0)	(125,0)
	M_2	(350,1)	(350,1)	(350,0)	(350,0)
		(75,3)	(75,3)	(75,0)	(75,0)
	M_3	(350,1)	(350,1)	(350,1)	(350,0)
		(75,3)	(75,3)	(75,3)	(75,0)
	M_4	(350,1)	(350,1)	(350,1)	(350,1)
		(75,3)	(75,3)	(75,3)	(75,3)
Scenario *S2* ($\mathcal{H} = 2\Delta T$)	M_1	(450,1)	(450,0)	(450,0)	(450,0)
		(125,3)	(125,0)	(125,0)	(125,0)
	M_2	(350,1)	(350,1)	(350,0)	(350,0)
		(75,3)	(75,3)	(75,0)	(75,0)
	M_3	(350,1)	(350,1)	(350,0)	(350,0)
		(75,3)	(75,3)	(75,0)	(75,0)
	M_4	(350,1)	(350,1)	(350,1)	(350,0)
		(75,3)	(75,3)	(75,3)	(75,0)
Scenario *S3* ($\mathcal{H} = 3\Delta T$)	M_1	(450,1)	(450,0)	(450,0)	(450,0)
		(125,3)	(125,2)	(125,1)	(125,0)
	M_2	(350,1)	(350,0)	(350,0)	(350,0)
		(75,3)	(75,0)	(75,0)	(75,0)
	M_3	(350,1)	(350,1)	(350,0)	(350,0)
		(75,3)	(75,3)	(75,0)	(75,0)
	M_4	(350,1)	(350,1)	(350,1)	(350,0)
		(75,3)	(75,3)	(75,3)	(75,0)

Table 6.1. *Evolution of features over time for the running profiles ($N_{i,j} = (\rho_{i,j}, RUL_{i,j})$) of each machine M_j for each of the three scenarios in Figure 6.3*

When overproduction is authorized (scenario *S2*), two machines can be used in parallel. This enables an increase in the horizon to two intervals (see Figure 6.3(b), with $\mathcal{H} = 2\Delta T$). The machine M_1 is still used during the first interval, for $0 \leqslant t \leqslant \Delta T$. The machines M_2 and M_3 are then used in parallel during the second interval, for $\Delta T \leqslant t \leqslant 2\Delta T$. For $t \geqslant 2\Delta T$, $RUL_{0,1} = RUL_{0,2} = RUL_{0,3} = 0$ and $\rho_{0,4} < \sigma$. If the production stops at the end of the two intervals, the platform has a residual potential. Since the machine M_4 has not been used, it does not require any maintenance. If the machines can be used only with their nominal running profile $N_{0,j}$, the planning proposed in Figure 6.3(b) is the optimal one. In fact, no other combination of machines' contributions meets the demand beyond two intervals.

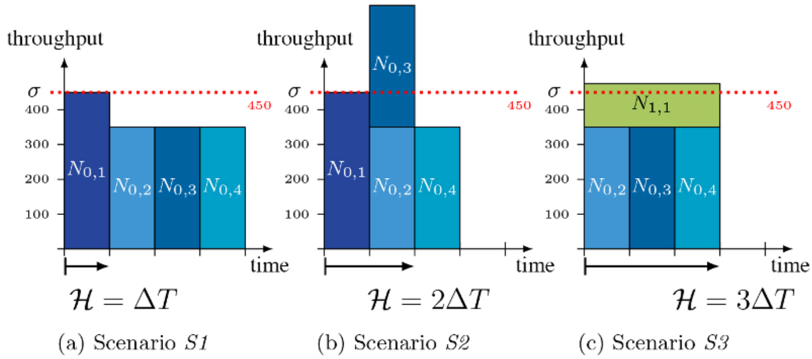

Figure 6.3. *Example of machines' utilization with a discrete number of running profiles. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

In order to further extend the production horizon, it is thus necessary to use the machines in a different way. The third scenario (*S3*) illustrated in Figure 6.3(c) consists of using the machine M_1 with a lower throughput, which enables its utilization for a longer time than with its nominal profile, and consequently enables the demand to be met over three intervals of time. In fact, by using this machine with a throughput of $\rho_{1,1} = 125$, its contribution can be added to that of one of the other three machines ($\rho_{0,j}$, with $j = 2, 3, 4$) at each interval. After having been used during an interval, the machines M_2, M_3 and M_4 reach their end of life ($RUL_{0,2} = RUL_{0,3} = RUL_{0,4} = 0$ for $t \geqslant \Delta T$). The same happens for the machine M_1 at the end of the third interval ($RUL_{1,1} = RUL_{0,1} = 0$ for $t \geqslant 3\Delta T$). Since there is a limited number of combinations for the choice of machines and of their running profile for each interval, it can be easily seen that no other choice reaches the demand σ for a greater number of intervals. $K = 3$ for $\mathcal{H} = 3\Delta T$ is therefore an optimal solution to the optimization problem $\textsc{maxK}(\sigma, \rho_{i,j}, RUL_{i,j})$ considering the set $\mathcal{M}$ of machines described previously. The last scenario *S3* shows that decreasing the efficiency of a machine enables an extension of the platform's utilization duration while respecting the required service level.

6.2. Properties and study of complexity

For the problem considered here, it is possible to define an upper bound (UB) for the number of intervals K that can be completed. As a result, the optimal value of K is lower than this bound UB. As we will see later, since this problem is NP-complete in the strong sense in the general case, this bound will help measure the performance of sub-optimal approaches that are proposed for the problem when an optimal approach is impossible. Furthermore, we carried out a study of the problem's complexity in order to analyze the cases in which an optimal solution can be found via a polynomial algorithm and the cases in which only a sub-optimal approach is possible. However, in all the cases, we propose an optimal modeling of the solution by formulating a mathematical program, which we linearize in the form of an integer linear program (ILP). This linear program can then be solved when the size of the problem, i.e. the number of variables, is not too large, by resorting to a commercial solver such as Gurobi [GUR 14] or Cplex [CPL 17].

The most general problem that considers a constant demand over time, $\textsc{maxK}(\sigma,\, \rho_{i,j},\, RUL_{i,j})$, is first defined. Complexity results are then demonstrated for different configurations of the optimization problem with a constant demand. In certain conditions, it is shown that an optimal solution can be found in a polynomial time. The proof of NP-completeness of the most generic problem by taking into account heterogeneous machines with several running profiles is then provided.

6.2.1. *Upper bound for* $\textsc{maxK}(\sigma,\, \rho_{i,j},\, RUL_{i,j})$

An upper bound, denoted by $\mathrm{UB}(\sigma,\, \rho_{i,j}, RUL_{i,j})$, can be defined for a generic problem $\textsc{maxK}(\sigma,\, \rho_{i,j}, RUL_{i,j})$ that considers a demand σ constant over time and a set of machines that are heterogeneous in terms of throughput and *RUL*. If all the machines are used with the running profile related to their greatest efficiency, $\max_{0\leqslant i<n}(\rho_{i,j} \cdot RUL_{i,j})$, this UB, defined by equation [6.1], corresponds to the maximum theoretical number of intervals K during which the demand σ can be met:

$$\mathrm{UB}(\sigma,\, \rho_{i,j},\, RUL_{i,j}) = \left\lfloor \frac{\sum_{j=1}^{m} \max_{0\leqslant i<n}(\rho_{i,j} \cdot RUL_{i,j})}{\sigma \Delta T} \right\rfloor \qquad [6.1]$$

This bound can be reached, although in very restrictive conditions. The only such case is when no overproduction occurs during the whole production horizon and when all the machines have reached their end of utilization before the maintenance at the end of the planning, i.e. when the platform's machines have provided all their best capabilities, in other words, with their nominal profile and without losses. In practice, this situation very seldom occurs. The construction of $\mathrm{UB}(\sigma,\ \rho_{i,j}, RUL_{i,j})$ can be seen from the geometrical point of view as a filling of a rectangular surface, whose height corresponds to the value of demand σ. Since this height is fixed, the potential of all the machines is used to fill the surface in such a way that most parts of the rectangles with width equal to $K\Delta T$ are filled.

6.2.2. *Complexity of the problem* MAXK$(\sigma,\ \rho, RUL_j)$

First of all, let's consider the problem MAXK$(\sigma,\ \rho, RUL_j)$, in which all the machines are homogeneous, i.e. all of them can provide the same throughput ρ. However, different *RULs*, denoted by RUL_j, may be associated with them. The total required throughput, σ, is constant over time. By hypothesis, this demand can be met by q machines such that $(q-1)\rho \leqslant \sigma \leqslant q \cdot \rho$, with $q \in \mathbb{N}^*$ the minimum number of machines necessary to reach σ for each interval of time ΔT such that $q \leqslant m$. The problem can be expressed in the following way: how do we use q machines from a set $\mathscr{M}$ of m machines, in order to maximize the production horizon? The number of completed intervals relative to the optimal solution of this optimization problem is denoted by $\mathscr{K}(\mathscr{M}, q)$.

Consider a relaxation of this problem, in which time is continuous. In this case, a machine can be replaced by another at any instant t, and the maximum production horizon is denoted by $\mathscr{K}_{cont}(\mathscr{M}, q) \cdot \Delta T$ (see equation [6.2]):

$$\mathscr{K}_{cont}(\mathscr{M}, q) = \frac{\sum_{1 \leq j \leq m} RUL_j}{q} \qquad [6.2]$$

$\mathscr{K}_{cont}(\mathscr{M}, q)$ is a UB for $\mathscr{K}(\mathscr{M}, q)$, which can be reached only in very restrictive conditions. As in the case of the UB defined previously, the construction of $\mathscr{K}_{cont}(\mathscr{M}, q)$ can be seen as a geometrical problem, whose solution does not always respect the features of the machines' running profiles.

6.2.2.1. *Optimal greedy algorithm for* MAXK$(\sigma,\ \rho, RUL_j)$

The problem MAXK$(\sigma,\ \rho, RUL_j)$ is very similar to a classical parallel machines' scheduling problem $P_q|prmp|C_{max}$ studied by Pinedo in [PIN 95], in which m tasks have to be scheduled on q machines in parallel, with an objective of minimizing the total tasks' execution time (makespan).

First of all, two identical hypotheses are encountered in each of these scheduling problems, notably the discretization of time in intervals and the authorization of a discrete preemption. In the problem $P_q|prmp|C_{max}$, the latter hypothesis means that the tasks can be interrupted before the end of their execution and restarted later, without any consequence on their execution time. In the problem $\textsc{maxK}(\sigma, \rho, RUL_j)$, preemption would eventually take place between two consecutive intervals of time, and its authorization means that an arrest can be defined during a machine's utilization, without modifying its *RUL*.

Then, a parallel can be drawn between the different elements of each problem. The q machines that have to operate in parallel in order to meet the demand σ in the problem $\textsc{maxK}(\sigma, \rho, RUL_j)$ are equivalent to the q resources in parallel considered in $P_q|prmp|C_{max}$. Instead of m tasks to be executed in $P_q|prmp|C_{max}$, the problem $\textsc{maxK}(\sigma, \rho, RUL_j)$ considers m machines to be used. The execution time of m tasks can be assimilated to the *RULs* of the m machines. Performing a task in its entirety then corresponds to using the whole potential of a machine.

The LRPT (Longest Remaining Processing Time first) algorithm was proposed by Pinedo [PIN 95] to find an optimal scheduling for the problem $P_q|prmp|C_{max}$ with discretized time. For each interval of time, this algorithm consists of scheduling the tasks with the longest remaining execution time as a priority. This is possible thanks to the hypothesis of authorized preemption. The obtained schedule is active, without delays and time-outs. These features are compatible with the scheduling problem considered in this section, $\textsc{maxK}(\sigma, \rho, RUL_j)$. The latter can thus be solved in an optimal way by using the greedy algorithm *LRUL* (Longest Remaining Useful Life first), based on the principle of the LRPT algorithm. In the same way as LRPT, the *LRUL* algorithm consists of using the machines with the longest *RUL* as a priority. Arrests and restarts of machines are authorized at the beginning of each interval of time. At the beginning of each interval k ($1 \leqslant k \leqslant K$), the q machines with the longest *RUL* at the time $k\Delta T$ are then exploited for an interval of time.

6.2.2.2. *Complexity of the problem* MAXK(σ, ρ, RUL_j)

Several lemmas come in useful to define the complexity of the considered optimization problem MAXK(σ, ρ, RUL_j).

LEMMA 6.1.– If $q < m$ and $\max_{1 \leqslant j \leqslant m}(RUL_j) \geqslant \mathscr{K}_{cont}(\mathscr{M}, q)$, then $\mathscr{K}(\mathscr{M}, q) = \mathscr{K}(\mathscr{M}', q - 1)$, with $\mathscr{M}' = \mathscr{M} \setminus \{M_{j'}$ such that $RUL_{j'} = \max_{1 \leqslant j \leqslant m}(RUL_j)\}$.

According to lemma 6.1, solving a problem that satisfies these properties is equivalent to solving the same problem for a demand $\sigma' = \sigma - \rho$, without taking into account the machine with the longest *RUL* that exceeds the UB $\mathscr{K}_{cont}(\mathscr{M}, q)$.

PROOF.– If $\max_{1 \leqslant j \leqslant m}(RUL_j) \geqslant \mathscr{K}_{cont}(\mathscr{M}, q)$, the machine with the longest *RUL* is used during the whole planning horizon. Then, the maximum number of intervals in which the demand can be met, $\mathscr{K}(\mathscr{M}, q)$, is not limited by this machine. The value $\mathscr{K}(\mathscr{M}, q)$ can thus be determined by solving the problem without considering the machine with the longest *RUL*. The contribution ρ of this machine to the total service is however retained. The demand associated with the new optimization problem is then $\sigma' = \sigma - \rho$, and the number of machines required to meet this demand is $q' = q - 1$. □

LEMMA 6.2.– If $q \leqslant m$, $RUL_j(1) \geqslant 1\ \forall 1 \leqslant j \leqslant m$ and $\max_{1 \leqslant j \leqslant m}(RUL_j(1)) \leqslant \mathscr{K}_{cont}(\mathscr{M}, q)$, then an optimal schedule for the problem MAXK(σ, ρ, RUL_j) can be determined by using the greedy algorithm *LRUL* (Largest Remaining Useful Life first). In such a case, the production horizon of this planning is $\mathscr{K}(\mathscr{M}, q)\Delta T = \lfloor \mathscr{K}_{cont}(\mathscr{M}, q) \rfloor \Delta T$.

PROOF.– By construction, using the *LRUL* algorithm and due to the fact that $RUL_j(0) \geq 1$ for any j such that $1 \leq j \leq m$, there always exist q machines such that $RUL_j(k) \geq 1$ for all k, such that $0 \leq k \leq k_1 = \lfloor \sum_{1 \leq j \leq m} (RUL_j(0) - 1)/q \rfloor$. When $k = k_1 + 1$, then $RUL_j(k_1 + 1) \leq 1$ for all j such that $1 \leq j \leq m$ and $\sum_{1 \leq j \leq m} RUL_j(k_1) = m + r$ with $r = \sum_{1 \leq j \leq m}(RUL_j(0) - 1) \mod q$. At a time $k_1 \Delta T$, k_1 intervals are completed and the demand can be met for $\lfloor (m + r)/q \rfloor$ other intervals. It is then possible to find a schedule that uses the *LRUL* algorithm and completes $k_1 + \lfloor (m + r)/q \rfloor$ intervals with $k_1 + \lfloor (m + r)/q \rfloor = \sum_{1 \leq j \leq m}(RUL_j(0) - 1)/q - r/q + (m + r)/q - r'/q$ with $r' = (m + r) \mod q$. After simplification, the previous formula becomes $\sum_{1 \leq j \leq m} RUL_j(0)/q - r'/q = \lfloor \sum_{1 \leq j \leq m} RUL_j(0)/q \rfloor = \lfloor \mathscr{K}_{cont}(\mathscr{M}, q) \rfloor$. □

THEOREM 6.1.– An optimal solution can be found in a polynomial time for the problem MAXK$(\sigma,\ \rho, RUL_j)$, in $O(\mathscr{K}_{cont}(\mathscr{M}, q) \cdot m \cdot \log(m))$.

PROOF.– The complexity of the algorithm that provides an optimal scheduling for the problem MAXK(σ, ρ, RUL_j) was proved in the following research report [HER 14c] for any case. At first, simple cases were considered, when $q > m$, $q = 1$, and $q = m$. For these three cases, the solution can be found respectively with an algorithmic complexity of $O(1)$, $O(m)$ and $O(m)$. In the other cases, the problem is solved by using the *LRUL* algorithm, whose complexity is $O(\mathscr{K}_{cont}(\mathscr{M}, q) \times m \times log(m))$. □

6.2.3. *NP-completeness of the generic case*

In the most generic case, the problem MAXK$(\sigma,\ \rho_{i,j}, RUL_{i,j})$, which takes into account heterogeneous machines with several running profiles, appears to be NP-complete in the strong sense.

THEOREM 6.2.– The research of an optimal solution to the problem MAXK$(\sigma,\ \rho_{i,j}, RUL_{i,j})$ is an NP-complete problem in the strong sense.

PROOF.– The NP-completeness of the problem in the general case was proven in the following research report [HER 14c], by means of a simplification, in order to obtain a problem of 3-partition [GAR 79], which is known to be NP-complete in the strong sense. □

6.3. Optimal approach

An approach based on an exact solution method is proposed to tackle the general optimization problem MAXK$(\sigma,\ \rho_{i,j}, RUL_{i,j})$. In the previous section, it was shown that this problem is NP-complete in the strong sense. However, a characterization of the optimization problem can be proposed by means of an optimal formulation. Here, we propose expressing the problem in the form of an ILP.

6.3.1. *Linear programming*

A variant of the optimization problem MAXK$(\sigma,\ \rho_{i,j},\ RUL_{i,j})$ can be defined in the following way: considering the health state of the available machines, i.e. the values of $RUL_{i,j}$ ($0 \leqslant i \leqslant n-1$ and $1 \leqslant j \leqslant m$), is there a schedule that allows these machines to meet the demand σ_k during a given number of intervals K? For a given horizon $K\Delta T$, this solution research can be modeled in the form of a mathematical program.

Let $x_{i,j,k}$ ($0 \leqslant i \leqslant n-1$, $1 \leqslant j \leqslant m$ and $1 \leqslant k \leqslant K$) be a binary variable such that $x_{i,j,k} = 1$ if the machine M_j is used with its running profile $N_{i,j}$ during the interval k, and $x_{i,j,k} = 0$ otherwise. The definition of a variable for each interval of time ensures that the arrests/restarts of the machines as well as the modifications of the running profiles during the utilization are admitted only at the beginning of an interval.

The constraints of the mathematical program express both the requirements in terms of service and the limits of machines' usage. The first set of constraints, defined by equation [6.3], limits the utilization of a machine during an interval k. In fact, each machine can be used only once per interval, with a single running profile $N_{i,j}$:

$$\sum_{i=0}^{n-1} x_{i,j,k} \leqslant 1 \quad \forall 1 \leqslant j \leqslant m, \forall 1 \leqslant k \leqslant K \qquad [6.3]$$

The second set of constraints, defined by equation [6.4], ensures that the machines are not used for a longer time than their *RUL*. We consider that, if a machine M_j is used with a running profile $N_{i,j}$ during an interval k, $\Delta T / RUL_{i,j}$ units of time have to be subtracted from the initial value of *RUL* associated with the profile $N_{i,j}$. The sum of all the portions subtracted in succession from the initial lifetime during the utilization of a machine must not exceed 100%:

$$\sum_{i=0}^{n-1} \frac{\sum_{k=1}^{K} x_{i,j,k} \cdot \Delta T}{RUL_{i,j}} \leqslant 1 \quad \forall 1 \leqslant j \leqslant m \qquad [6.4]$$

The last set of constraints (equation [6.5]) ensures that the demand σ is met during the whole production horizon, i.e. for all intervals k such that $1 \leqslant k \leqslant K$:

$$\sum_{j=1}^{m} \sum_{i=0}^{n-1} (x_{i,j,k} \cdot \rho_{i,j}) \geqslant \sigma \quad \forall 1 \leqslant k \leqslant K \qquad [6.5]$$

The mathematical program defined by the equations [6.3], [6.4] and [6.5] allows for a verification of the existence of a solution for the decision problem without any objective function. However, the addition of an objective function enables, according to certain criteria, the selection of the best configuration of machines among all the solutions of the mathematical program. Coherently with the hypotheses detailed in the statement of the problem in section 6.1, the objective function proposed in equation [6.6] aims to minimize total overproduction over the entire production horizon. The minimization of potential that remains at the end of the schedule could also be considered. This objective function would potentially lead to some overproduction, but it would maximize the number of machines that reach the end of life at the production horizon's end. This would enable a maximal grouping of maintenance operations and thus a minimization of the related costs:

$$\min \quad \sum_{k=1}^{K}\left(\sum_{j=1}^{m}\sum_{i=0}^{n-1} x_{i,j,k}\cdot \rho_{i,j,k} - \sigma\right) \qquad [6.6]$$

Since all the constraints are linear, the mathematical program can be solved by means of linear programming. The corresponding ILP is defined by the system of equations [6.7]. The only variables are the binary variables $x_{i,j,k}$. The quantities $\rho_{i,j,k}$, $RUL_{i,j}$ and σ are input data of the problem.

$$\begin{cases}
\min & \displaystyle\sum_{k=1}^{K}\left(\sum_{j=1}^{m}\sum_{i=0}^{n-1} x_{i,j,k}\cdot \rho_{i,j,k} - \sigma\right) & [6.7a]\\
 & \displaystyle\sum_{i=0}^{n-1} x_{i,j,k} \leqslant 1 \qquad \forall 1 \leqslant j \leqslant m,\ \forall 1 \leqslant k \leqslant K & [6.7b]\\
\text{such that} & \displaystyle\sum_{i=0}^{n-1} \frac{\sum_{k=1}^{K} x_{i,j,k}\cdot \Delta T}{RUL_{i,j}} \leqslant 1 \qquad \forall 1 \leqslant j \leqslant m & [6.7c]\\
 & \displaystyle\sum_{j=1}^{m}\sum_{i=0}^{n-1}(x_{i,j,k}\cdot \rho_{i,j}) \geqslant \sigma \qquad \forall 1 \leqslant k \leqslant K & [6.7d]\\
\text{with} & x_{i,j,k} \in \{0,1\}\ \forall 1 \leqslant i \leqslant n-1,\ \forall 1 \leqslant j \leqslant m,\ \forall 1 \leqslant k \leqslant K & [6.7e]
\end{cases}$$

6.3.2. *Optimal solution*

The linear program presented above allows us to find the best solution to the considered decision problem for a fixed number of intervals K. This approach is not adequate for solving the optimization problem $\text{MAXK}(\sigma,\ \rho_{i,j}, RUL_{i,j})$, which consists of determining the maximum number of intervals K for which a solution exists. For example, a binary search may be used to find the greatest value of K in a logarithmic number of steps over the space $[1, \text{UB}(\sigma,\ \rho_{i,j}, RUL_{i,j})]$, with UB the UB for K (see section 6.2.1). It is possible to further reduce this interval by considering a lower bound equal to any solution provided by a heuristic approach which will necessarily be lower than the optimal value.

6.4. Sub-optimal solution

The optimal approach using the linear program illustrated in the previous section can be used only for small instances of the problem, i.e. with few machines, few different running profiles for each machine and a short horizon. For example, five machines, with two possible profiles each, and a horizon of $20\Delta T$ lead to a problem involving more than 200 variables. For realistic problem sizes, it is necessary to tackle the solution with a sub-optimal approach based on heuristics that are capable of proposing valid solutions in a polynomial time.

The heuristics that we propose solve the generic problem with a constant demand $\text{MAXK}(\sigma,\ \rho_{i,j},\ RUL_{i,j})$. Each of them allocates enough machines to meet the demand for each interval k, while doing this for the greatest possible value of k. The heuristics that we defined propose solutions that are very close to the optimal values in the case of the best ones, as we will show later.

However, in any case, there remain some machines that can be used again; in other words, the potential is not exhausted completely. The horizon cannot be extended, since, in this case, there are not enough machines to complete another interval of time. Therefore, we propose reconsidering the proposed schedule by means of a reparation phase, whose goal is to swap the utilization order of the machines in order to increase the number of machines with a non-null potential. In this way, together, these machines will be able to complete another interval. This is a post-processing applied to heuristics, and we will show later that the lowest value of the obtained solutions is even closer to the UB, the latter being greater than the optimal solution.

In the following sections, we present some of the heuristics analyzed in this study. These heuristics are illustrated via figures by using the configurations of machines described in Figure 6.4.

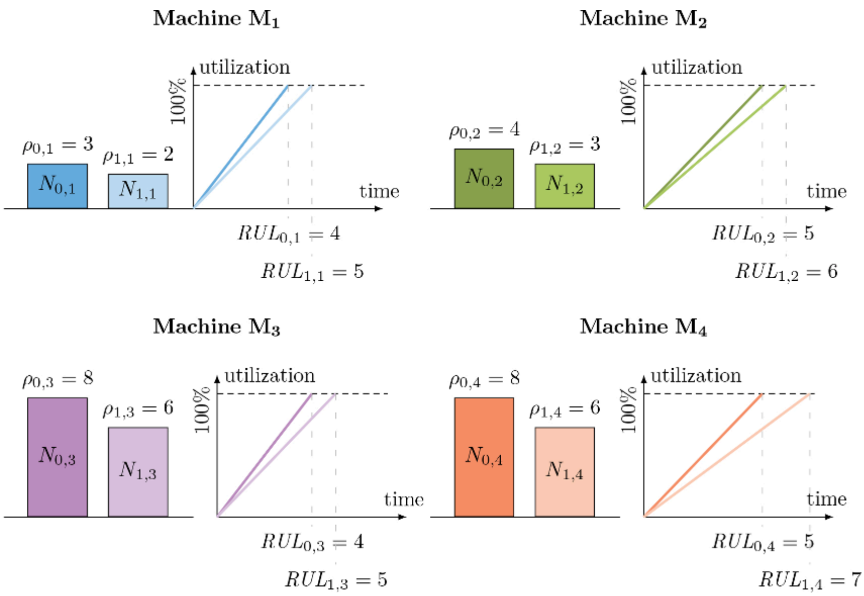

Figure 6.4. *Platform of machines considered in order to illustrate the solutions obtained via different heuristics. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

6.4.1. *Heuristics*

6.4.1.1. *H–LRF: heuristic that favors the longest RULs*

The heuristic H–LRF (Largest *RUL* First Heuristic) operates on groups of intervals and favors the machines' usage with their running profile $N_{n-1,j}$, which provides the lowest throughput and has the longest *RUL*. The idea consists of maximizing the utilization time of each machine in order to maximize the utilization of the whole set. A subset of machines with the greatest values of $RUL_{n-1,j}$ is selected in such a way that the total throughput, ρ_{tot}, reaches at least the level of the demand σ. If the throughputs of profiles $N_{n-1,j}$ of the available machines are such that it is impossible to reach σ ($\rho_{tot} < \sigma$), the total throughput is then increased by using, if possible, the machine M_j with the greatest $RUL_{n-1,j}$ with its profile $N_{i-1,j}$ instead of $N_{i,j}$. This process is reiterated until at least the total throughput provided reaches the demand ($\rho_{tot} \geqslant \sigma$). The solution is applied to the maximum number of intervals, corresponding to the minimum *RUL* of the selected machines. The process of selecting the machines and the related running profiles is illustrated in Figure 6.5. It terminates as soon as the remaining potential can no longer meet the demand.

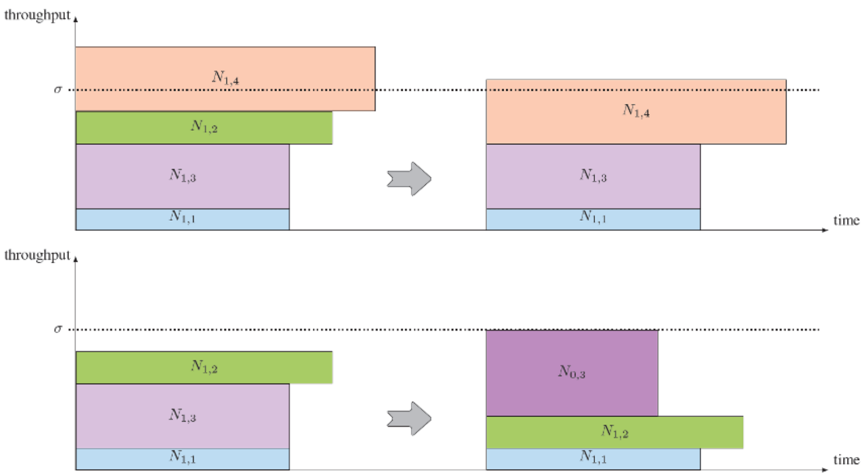

Figure 6.5. *Illustration of the operating principle of the H–LRF heuristic. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

The Figure 6.6 illustrates a solution obtained by means of H–LRF heuristic by considering the set of machines described in Figure 6.4.

6.4.1.2. *H–HTF: heuristic that favors the greatest throughput*

The heuristic H–HTF (Highest Throughput First Heuristic) is based on the same operating principle as the H–LRF. The difference lies in the fact that, this time, the running profiles that provide the greatest throughputs, $N_{0,j} = (\rho_{0,j}, RUL_{0,j})$, are favored. Let's recall that $\rho_{0,j} = \rho\max_j = \max_{0 \leqslant i < n} \rho_{i,j}$ and $RUL_{0,j} = RUL\min_j = \min_{0 \leqslant i < n} RUL_{i,j}$ for every machine M_j. Two variants of H–HTF can be considered. The first, H–HTFlt (Highest Throughput First, low throughput), selects in first place the machines with the smallest nominal throughput $\rho_{0,j}$, while the second, H–HTFht (Highest Throughput First, high throughput), selects the machines with the greatest nominal throughput. In both variants, the smallest subset of machines that allows the demand σ to be met is selected. If the provided throughput is greater than the demand ($\rho_{tot} > \sigma$), the contribution of the machine M_l with the smallest *RUL* associated with the selected profile (denoted by $N_{i,l}$) is decreased, but only if the total throughput remains greater than or equal to the demand. If possible, the machine M_l is then used with the profile $N_{i+1,l}$ instead of profile $N_{i,l}$ that was selected previously. This enables an extension of the lifetime of machine M_l, and therefore of the solution's horizon. In the same way as in H–LRF heuristic, the number of intervals during which the solution can be applied is limited by the selected machine with the smallest *RUL*. This process is repeated as long as the remaining machines are capable of meeting the demand σ. The different steps are described in Figure 6.7 for the two variants of the heuristic, H–HTFlt and H–HTFht.

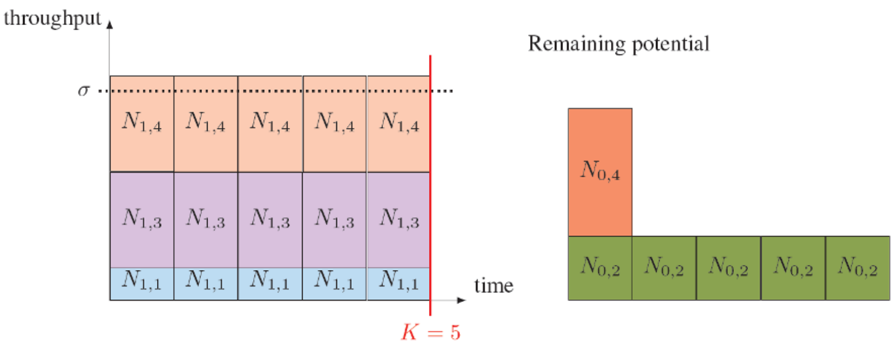

Figure 6.6. *Schedule obtained from the H–LRF heuristic. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

The solutions obtained from each of the two variants of the H–HTF heuristic are detailed in Figure 6.8. For the considered set of machines (see Figure 6.4), the horizon reached is the same ($\mathcal{H} = 5\Delta T$), although the machines' utilization is different.

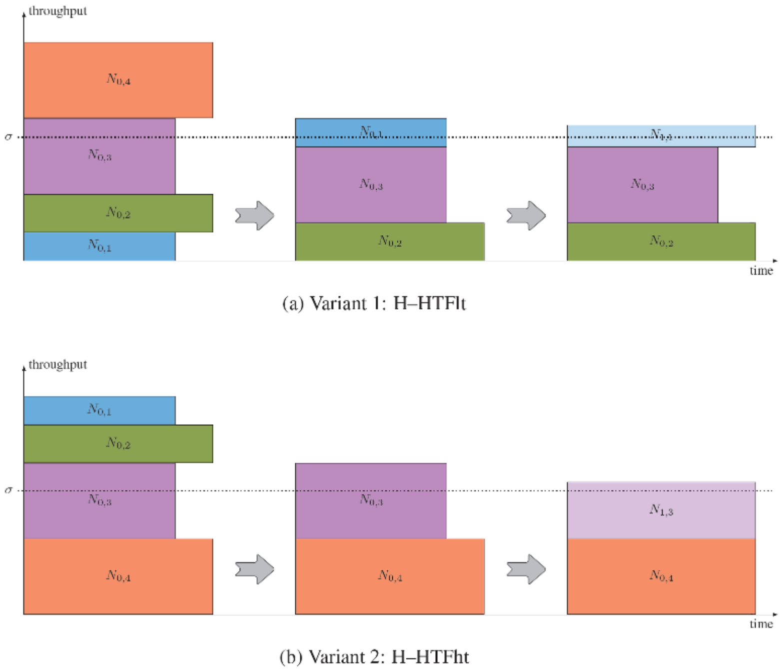

Figure 6.7. *Illustration of the operating principle of the two variants of the H–HTF heuristic. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

6.4.1.3. *H–DP: heuristic based on dynamic programming*

The heuristic H–DP (Dynamic Programming Heuristic) is more elaborate than the previous ones. For each interval of time k, by taking into account the machines that are available at the beginning of the interval, the goal is to find the best scheduling of the machines that makes it possible to reach at least the level of the demand σ, while minimizing the overproduction. It is then necessary to determine the best subset of machines to be used and to select, for each among them, the most appropriate running profile. The algorithm capable of making this choice is based on the solving principle of a knapsack problem. The main difference with this classical problem of combinatorial optimization lies in the fact that the sum of the values ($\rho_{i,j}$) of the selected objects (M_j) has to be greater than or equal to the knapsack's capacity (σ). Furthermore, each object M_j can be associated with different values $\rho_{i,j}$ ($0 \leqslant i < n$), and only one of them can be selected for the solution. The considered goal is the minimization of the sum of values related to the machines, in the case when this sum exceeds the total maximum weight of the knapsack σ.

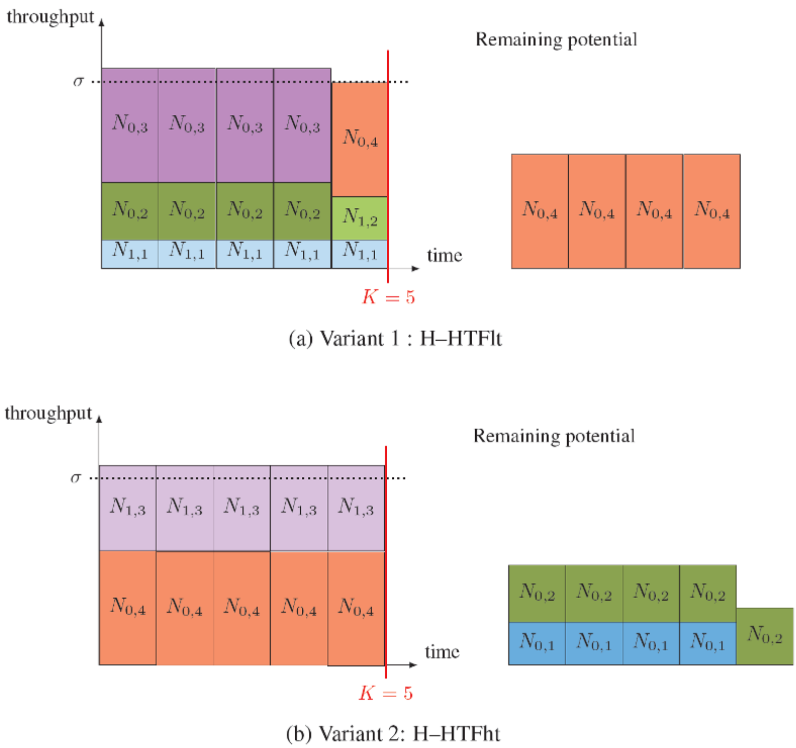

Figure 6.8. *Schedules obtained from the two variants of the H–HTF heuristic. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

The algorithm developed for H–DP uses the approach of dynamic programming in two dimensions. The research of a solution can be illustrated as a filling of a $2D$ matrix (see Figure 6.9). Each available machine is considered one after another, in increasing order of nominal throughput $\rho_{0,j}$ of the available machines. This sorting limits the number of intermediate solutions stored and minimizes both the required memory and the execution time. The machines with equal nominal throughput are sorted according to the decreasing order of their $RUL_{n-1,j}$. The running profile of each machine is then considered in succession, from the most sub-nominal profile $(N_{n-1,j})$ to the nominal one $(N_{0,j})$. Respecting this order for each research of solution enables a homogeneous wear of the set of machines. In fact, a certain turnover is followed, which preserves the maximum number of different available machines until the end of the planning. This enables an extension of the production horizon.

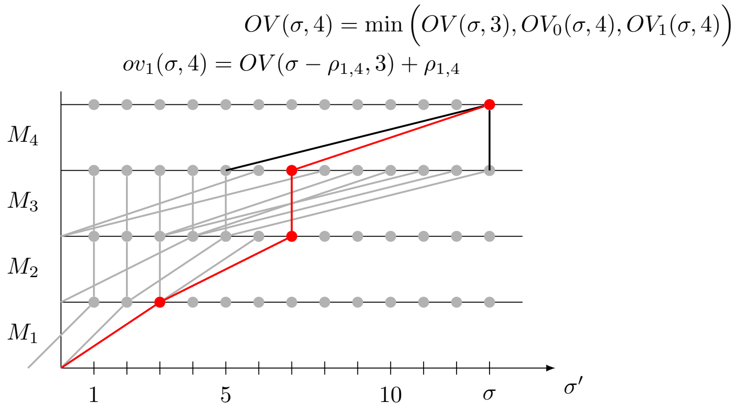

Figure 6.9. *Illustration of the operating principle of the dynamic programming in two dimensions. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

For each machine M_j, the total throughput targeted σ' is increased from 1 to σ. For each successive value of σ', each running profile of M_j is considered to determine whether the machine has to be selected or not. Testing all the possibilities yields the definition of the best configuration with respect to the objective. A recursive mathematical formulation of optimal solution's construction is given in equations [6.8], [6.9] and [6.10].

Let $ov_i(\sigma', j)$ be the total throughput obtained with the first j machines, by using together the j^{th} machine in its i^{th} running profile and the optimal configuration obtained with the first $j-1$ machines for the demand $\sigma' - \rho_{i,j}$ (see equation [6.8]). Let $OV_i(\sigma', j)$ be the variable that contains the value of $ov_i(\sigma', j)$ if it reaches at least the demand's level σ. Otherwise, $OV_i(\sigma', j) = +\infty$ (see equation [6.9]). Thus, it is possible to consider only those solutions that reach at least σ' at each step and therefore reach σ for the global solution. Finally, let $OV(\sigma', j)$ be equal to the optimal total throughput, i.e. a throughput greater than or equal to the demand σ', obtained with the first j machines (see equation [6.10]). The optimal total throughput for the current interval is located at the position $OV(\sigma, m)$ of the $2D$ matrix OV used by the algorithm. Each choice performed for each couple (σ', j) is stored during the process of the solution's research. Thanks to this, it is possible to reconstruct the solution for the demand $\sigma' = \sigma$. In the case of equivalent solutions, the algorithm chooses the solution that involves the least number of different machines:

$$ov_i(\sigma', j) = OV(\sigma' - \rho_{i,j}, j-1) + \rho_{i,j} \text{ with } 1 \leqslant i \leqslant n-1 \qquad [6.8]$$

$$OV_i(\sigma', j) = \begin{cases} ov_i(\sigma', j) & \text{if } ov_i(\sigma', j) \geqslant \sigma' \\ +\infty & \text{otherwise} \end{cases} \qquad [6.9]$$

$$OV(\sigma', j) = \min\left(OV(\sigma', j-1), \min_{0 \leqslant i \leqslant n-1} OV_i(\sigma', j)\right) \qquad [6.10]$$

An example of the solution is given in Figure 6.10. It can be seen that the selection process performed by the H–DP heuristic minimizes the overproduction for the longest time possible. The solution applied to each interval of time is optimal given the health state of the whole set of machines at the beginning of the interval. However, the global schedule is not necessarily optimal.

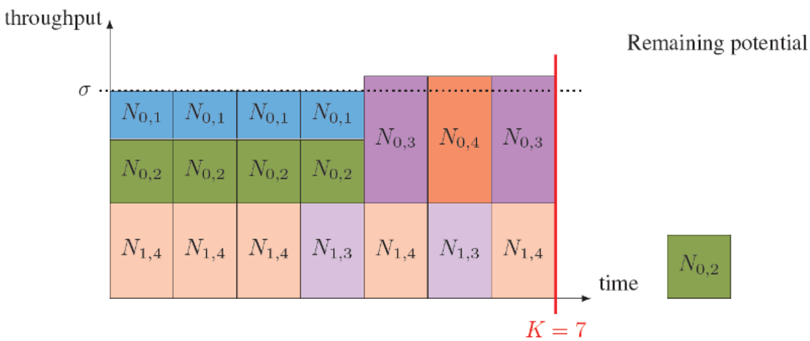

Figure 6.10. *Scheduling obtained with the H–DP heuristic. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

6.4.2. *Improvement of the heuristics*

The results developed below show that the heuristics proposed above do not provide optimal solutions, while all the machines have a non-null potential; in other words, all the machines are not completely used until their end of life. All these machines cannot complete an extra interval collectively. If by chance one of these machines has a potential that exceeds several intervals, this machine could take the place of another machine that has no potential at the end, for the duration of an interval of time. In this way, there would be one more machine among those with remaining potential at the end of the schedule, and another interval could then be completed. If this is not sufficient, then it would be necessary to restart and recover the process for another interval, until this is not possible anymore. This reparation principle is justified by means of a very simple example in the following section.

6.4.2.1. *Illustration of the reparation principle*

The reparation principle can be explained with an example involving three machines that can be used with only one running profile. The schedule obtained with the heuristic based on dynamic programming H–DP is illustrated in Figure 11.1(a). It can be seen that the machine M_3 is never used during this planning. Therefore, some potential remains, although no interval can be added in this situation. In fact, the machine M_3 is not powerful enough to meet the demand σ alone. It would be necessary to use this machine in parallel with itself, which is impossible.

Despite everything, there is another possibility of using the machine M_3. Since it has not been used during the first scheduled interval ($0 \leqslant t \leqslant \Delta T$), it can be swapped with the machine M_2 for one interval. This entails an overproduction during this first interval, but it yields two different machines available at the end of the schedule. Thus, the demand can be met for an extra interval by using the machines M_2 and M_3 in parallel (see Figure 11.1(b)). The same swap can be done for the second interval in the schedule. In this way, it is possible to recover the machine M_2 for one interval and again to increase the number of completed intervals by 1 (see Figure 11.1(c)). In this example, applying the reparation principle enables thus a complete utilization of the potential provided by the set of machines and an extension of the production horizon from $\mathcal{H} = 4\Delta T$ to $\mathcal{H} = 6\Delta T$.

6.4.2.2. *Reparation strategy*

The strategy that we propose is greedy and it operates in the following way, whichever the heuristic used to prepare an initial solution with at least one completed interval ($K \geq 1$). As it has been said in the introduction of this section, the idea consists in swapping the machines whose *RUL* is non-null at the end of the schedule with some machines used in the planning until their potential becomes null after an interval k such that $k \leq K$.

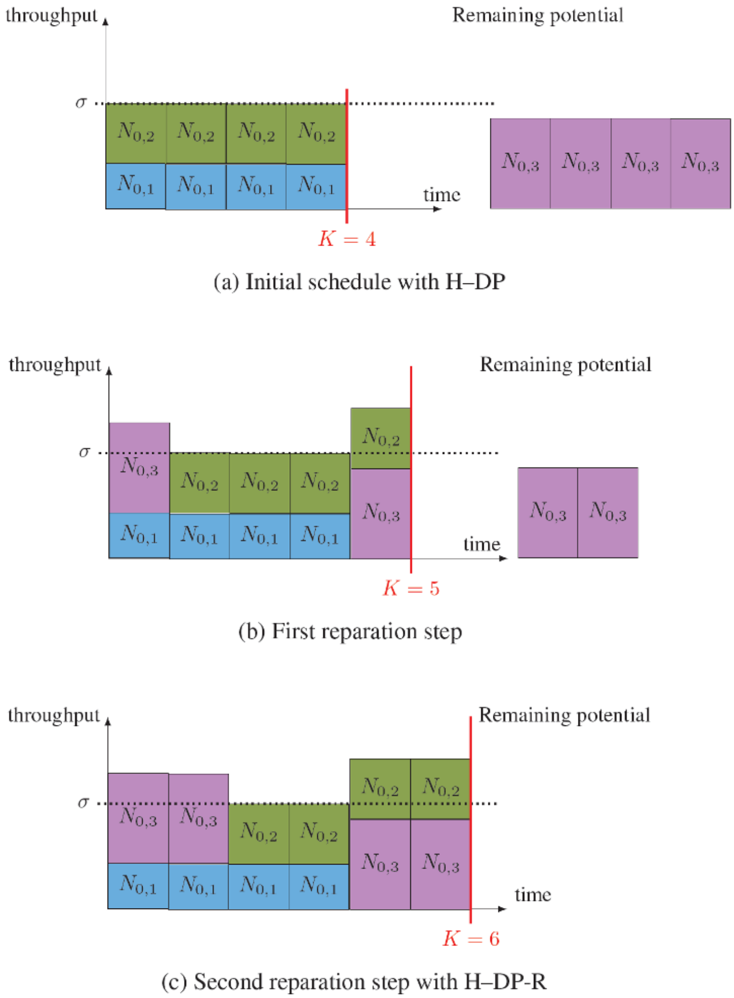

Figure 6.11. *Reparation strategy. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

Let $\mathscr{M}_{RUL\neq 0}$ and $\mathscr{M}_{RUL=0}$ be two subsets of machines whose values of *RUL* are respectively greater than zero and equal to zero for $k > K$. The reparation consists in constructing the subset of machines $\mathscr{M}_{RUL\neq 0}$ sorted in decreasing order of *RUL* (for $k > K$) with the smallest size and to search the first interval k_{swap} such that each machine of $\mathscr{M}_{RUL\neq 0}$ does not appear in the interval k_{swap} anymore, and such that there exists a subset of machines $\mathscr{M}_{k_{swap}} \subset \mathscr{M}_{RUL=0}$ which are used during this very interval k_{swap}. In addition, the following relation has to be true in order for the swaps to be valid, in virtue of the fact that the demand should always be satisfied:

$$\sum_{M_j \in \mathscr{M}_{k_{swap}}} \rho_{*,j} \leq \sum_{M_j \in \mathscr{M}_{RUL \neq 0}} \rho_{max,j}$$

Then, the two subsets $\mathscr{M}_{k_{swap}}$ and $\mathscr{M}_{RUL \neq 0}$ are swapped. This process is iterated until an extra interval can be added to the initial schedule. The greedy reparation algorithm stops when no other swap is possible.

By associating the heuristics described previously with the reparation process, we propose three new heuristics: H–LRF-R, H–HOF-R and H–DP-R, where "R" stands for "reparation".

6.5. Simulation results

Simulations are required to evaluate and compare the efficacy of the proposed sub-optimal approaches. For this purpose, we built a simulator capable of generating problems and platforms relative to the problem $\text{MAXK}(\sigma,\ \rho_{i,j},\ RUL_{i,j})$.

For each optimization problem, several configurations were generated, which serve as a basis for the application of strategies implemented by the different heuristics. Each configuration corresponds to a platform of machines in accordance with the model described at the beginning of this chapter. The parameters are the following:

– m defines the number of the platform's machines. We chose m such that $m \in \{10, 25, 50\}$;

– n defines the number of different running profiles per machine. We chose n such that $n \in \{1, 2, 5, 10\}$;

– $\sigma_k = \sigma$ is the constant demand over the whole production horizon. Only one demand is associated with a particular problem; however, several demands corresponding to different configurations were tested;

– α defines the workload applied to the platform such that $\sigma = \alpha \times \rho max$ with $\rho max = \sum_{j=1}^{m} \rho_{0,j}$ the maximum throughput that can be provided by the platform with the machines that it contains in its initial configuration. We consider values of α such that $30\% \leq \alpha \leq 90\%$.

For each configuration, 20 different problems were generated randomly, and the results that are illustrated represent the average of the results obtained from the set of 20 problems depending on the platform's workload α.

6.5.1. *Comparison with the upper bound* UB

The results obtained from the three other heuristics, H–LRF, H–HTF and H–DP, are compared in Figure 6.12, in which the UB UB, defined by the formula [6.1], is represented as well. This bound decreases when the workload α increases. A high workload corresponds to a high demand σ. Thus, the higher the load, the greater the number of machines required to meet the demand and the lower the number of intervals that can be completed.

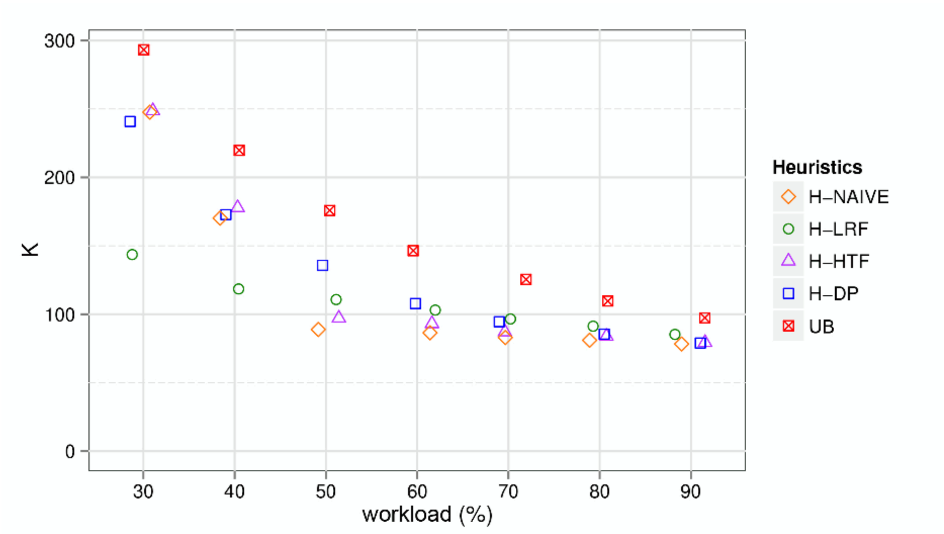

Figure 6.12. *Average number of completed intervals as a function of the workload $\chi - m = 25$ machines, $n = 5$ running profiles. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

The variation of the number of machines m, as well as that of the number of running profiles n do not have a significant impact on the results obtained with the heuristic H–HTF. In fact, this heuristic favors the nominal running profiles. For each machineM_j, the nominal profile $N_{0,j}$ is always associated with the same throughput $\rho_{0,j}$ and with the same value of *RUL*, *RUL*$_{0,j}$, whichever the number of considered running profiles. However, using the machines with different running profiles during their lifetime can be of interest.

The heuristic H–LRF remains the least efficient with respect to the other heuristics for low loads, but its efficiency is close to that of H–HTF starting from $\alpha = 50\%$ (see Figure 6.12). For high workloads, the throughputs provided by sub-nominal profiles are potentially not sufficient enough to meet the demand. H–LRF aims then to select certain machines with their nominal profile, especially as the workload increases. The difference between the strategies of H–LRF and H–HTF lies mainly in the selection of the machines to be used for each scheduled interval: H–HTF favors the machines that provide the greatest nominal throughput, whereas H–LRF selects the machines with the lowest throughput in order to minimize overproduction. With the latter strategy, it is possible to preserve more potential for the end of the planning and therefore to complete more intervals. For α greater than or equal to 70%, H–LRF thus outperforms H–HTF. H–LRF is also capable of reaching greater production horizons than H–DP for these high workloads. However, H–DP can obtain the best results for medium loads ranging from 50% to 60%.

Although the H–DP heuristic, based on dynamic programming, does not provide the best results for all the workloads, its performance is never far from the heuristics that outdo it. Furthermore, H–DP has the advantage of being efficient and reliable in all the considered cases, whichever the workload, the number of machines or the number of running profiles.

In the previous figures, it can be seen that the results obtained with all the heuristics tend to get closer one to another as the workload increases. In fact, whichever the implemented strategy, the number of possibilities of selecting the machines and the related running profiles decreases when the demand σ is close to the maximum throughput that can be provided by the platform.

6.5.2. *Improvement by means of reparation*

The reparation is capable of improving the results obtained with the heuristics H–HTF and H–DP in a significant way. The number of completed periods with H–HTF-C (respectively, with H–DP-R) reaches, on average, 94% (respectively, 93%) of the UB $\text{UB}(\sigma,\, \rho_{i,j},\, RUL_{i,j})$ for all the workloads (see Figure 6.13). When swaps of machines are possible, the reparation thus improves the results, yielding values that are very close to the optimal ones, and achieves this for whichever efficiency of the initial heuristic (without reparation).

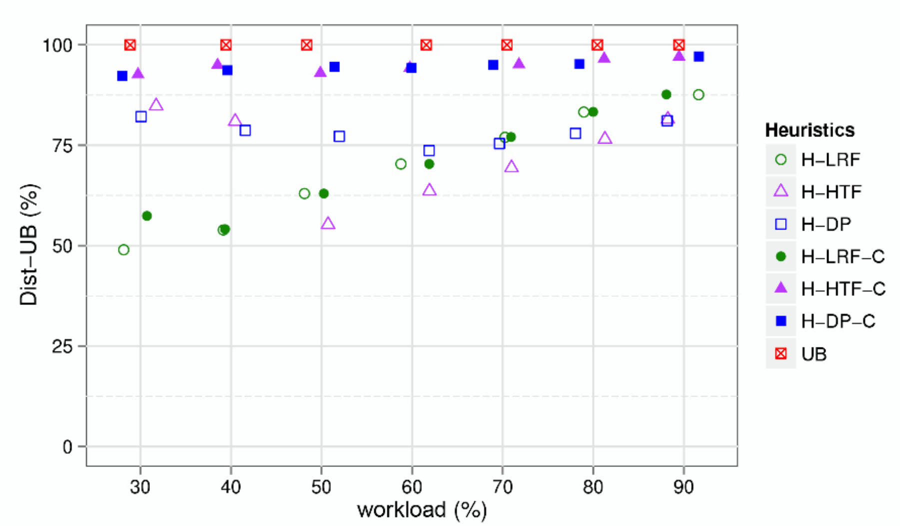

Figure 6.13. *Improvement by means of reparation - $m = 25$ machines, $n = 5$ running profiles. For a color version of this figure, see www.iste.co.uk/chebel-morello/maintenance.zip*

6.6. Summary

Several solution methods were presented in this chapter for the problem of maximizing the lifetime of a set of machines when each of them can provide a discrete number of throughput levels. It was demonstrated that the optimization problem is NP-complete in the strong sense in the general case. An optimal formulation using an ILP is capable of finding the optimal solutions in a reasonable time for small-sized problems. For problems with a greater size, and thus more realistic, several heuristics provide schedules that define which machines have to be used at each instant and with which running profile. A post-processing of the obtained results significantly improves the solutions' performance, getting closer to the optimal solution. This theoretical study on this problem shows the relevance of this approach and the confidence in the obtained results.

This chapter illustrates what a post-prognostic decision approach can be. This kind of decision is capable of maintaining a certain service level given a heterogeneous platform and the knowledge of the health state of each of its components. We made the hypothesis that the predictions of the lifetime of this equipment (*RUL*) are not questioned during the implementation of the planning. However, it is quite possible to imagine an application of the proposed heuristic methods in an iterative way when significant variations of the health state of the components and of the platform appear. A new planning then proposes as long a production horizon as possible in accordance with the most up-to-date health state of the equipment. This process falls within a predictive maintenance context.

Index

C, D, E, F, H

I, K, L, M, N

O, P, R, S

From Prognostics and Health Systems Management to Predictive Maintenance 2: Knowledge, Traceability and Decision, First Edition.
Brigitte Chebel-Morello, Jean-Marc Nicod and Christophe Varnier.

Conclusion

Summary

Making increasingly complex equipment reliable and maintaining it in operational conditions whilst ensuring its durability requires an increased monitoring of critical elements and of associated maintenance strategies, notably of the predictive maintenance, which is capable of anticipating any failure. A piece of equipment's health state monitoring draws on the acquisition of relative information, be it technical data or expert knowledge, during processing and capitalization in order to ensure the traceability of the operating state and to provide the knowledge required by decision algorithms to propose an informed decision. In our studies, this equipment's monitoring is performed by means of a remote distributed platform that integrates a set of decision support systems for maintenance. Such a platform offers services in connection with all the strategies of maintenance, in particular with the predictive maintenance strategy, which is capable of preventing any evolution of the health state towards failure by means of actions appropriate for the situation.

The goal targeted in this book is to make equipment intelligent and reliable by bestowing it with the ability to make decisions about the actions to be undertaken regarding its health state and its aptitude to fulfill its missions.

The first chapter developed an approach that makes a product intelligent, knowing that, in this case, the product is a complex piece of equipment. In order to make a product or piece of equipment intelligent in McFarlane's sense – to ensure the traceability of experienced events, to reason about this

From Prognostics and Health Systems Management to Predictive Maintenance 2: Knowledge, Traceability and Decision, First Edition.
Brigitte Chebel-Morello, Jean-Marc Nicod and Christophe Varnier.

information, and to decide the actions to be undertaken – this equipment is integrated into a closed-loop data sharing infrastructure "CL2M" capable of managing the knowledge that concerns it and stored in a corporate memory beforehand. This memory is distributed into two memories, one embedded in the product in an RFID tag and another located remotely which lists all the events undergone by the product.

The implemented CL2M architecture is capable of connecting the product to a platform: an e-maintenance platform at first, it later becomes an s-maintenance platform (s for semantics), which ensures real-time monitoring of the product's health state while offering maintenance management strategies.

A knowledge capitalization approach based on this knowledge-oriented platform, consisting of s-maintenance, was proposed and used. It is based on the construction of an ontology called IMAMO-RFID, which is adapted to so-called "intelligent" equipment. This ontology stems from different ontologies that combine the concepts of maintenance, lifecycle and distributed corporate memories. The integration of this ontology into a knowledge-based system, which includes an inference engine that supports different kinds of reasoning, constitutes the heart of the s-maintenance platform and allows the equipment (1) to be intelligent, (2) to exploit at any moment the knowledge capitalized during the product's lifecycle and (3) to propose decision support systems according to the available information. This equipment can offer several services ranging from predictive maintenance with RUL calculation and decision-making to many other maintenance strategies such as systematic, corrective or conditional maintenance.

The feasibility of this approach was tested by implementing it on a ski lift. Some critical elements of this ski lift were equipped with sensors in order to be able to monitor their health state during the whole lifecycle, easily access information concerning them at any moment, and provide this information to the actors (both software components of the platform and human operators) in order to inform them about the equipment's condition.

Within the context of Industry 4.0, predictive maintenance is designed for completing the policies of systematic preventive maintenance. For this purpose, acquiring expert knowledge derived from both a capitalization procedure and a monitoring method, is essential. As it was shown in

[GOU 16], processing gathered data makes it possible to extract useful information such as the health state and the remaining useful life of the critical equipment in a system. By associating this information with the knowledge of past and future usage, it is possible to implement a decision strategy suitable to the context.

Numerous works in this domain have focused on the prognostic phase. However, this information is not an end in itself but must be integrated by a decision phase, which is a realization of the operational implementation of the whole PHM process.

In this context, this book highlights different kinds of decisions in connection with industrial issues. These decisions concern (1) adjustment of a system's command, (2) implementation of a predictive maintenance strategy, (3) modification of equipments' operational conditions and (4) re-definition of missions. All these decisions have a common goal of optimizing the system's service quality, reliability, availability and safety with a reduction of costs as a result.

Outlook and prospects

The intelligence degree of a piece of smart equipment, which is none other than a piece of equipment connected to an s-maintenance platform, depends on the functions offered by the s-maintenance platform and the decision support services. S-maintenance is a promising new concept, which we defined as the realization of maintenance based on the sharing of expert knowledge of the domain and the provision of adaptive and autonomous services. This concept is implemented by means of an s-maintenance platform: a collaborative platform that formalizes this knowledge and sharing between different applications integrated in the system, which ensures a technical and semantic interoperability. The first version of this new generation of platforms, providing on-demand services for indicators defined by a user, has been implemented. One of the prospects consists in offering dynamic services more advanced than those of this first version. In our work, we proved the feasibility of developing a self-learning and self-management maintenance system by means of a dynamic experience feedback method. Such a method exploits the behavior of the process during the actual execution of the maintenance platform. Feedback regarding activities will help to make the existing knowledge explicit on the platform, thus formalizing and sharing collective knowledge.

In fact, trace engineering provides a new form of experience reuse and appears to be the most suited means for providing this feedback through the dynamic aspect of knowledge included in the s-maintenance platform. For this purpose, we developed a trace-based system for tracing and analyzing activities carried out via a maintenance platform. This trace-based system exploits the events of a log file that lists all the interactions between the users and the processes of the s-maintenance platform.

One of the paths to be explored is the development of mechanisms of collaboration between the different applications within the s-maintenance platform. The latter would thus ensure the capitalization of knowledge regarding several connected pieces of equipment and would allow them to collaborate with each other.

The concept of intelligent objects enables a decentralized management of decisions regarding the equipment. This decentralized management allows each piece of equipment to capitalize its expert knowledge extracted from the sensor data, which ensures the monitoring of the health state of its constituent elements and allows it to make decisions regarding itself. For a collaboration between autonomous equipment, the collaborative mechanisms of an s-maintenance platform may be exploited in order to extend the autonomous and individual decision-making to a collective one, for example in the management of air traffic, where each airplane is capable of re-defining its trajectory depending on that of the other airplanes passing nearby.

Most research highlights the fact that the utilization duration of a system before maintenance is reduced to the lifetime of its critical components. Therefore, the date of the next maintenance is defined by the shortest lifetime among those of the critical components. This simplification may conceal the critical aspects of some secondary components for which a systematic preventive strategy is sufficient from the economic point of view. Thus, there may be a conflict between maintenance strategies and it appears it is necessary to ponder how maintenance is taken into account from the global point of view of a whole system.

Furthermore, organizing maintenance services does not yet take into account the amount of changes entailed by the implementation of predictive maintenance in its operations. It is important to be able to demonstrate the possible benefits of PHM as well. Obviously, the prognostic is not profitable in all the cases and those systems should be identified in which the gain would be the most tangible, at least in terms of people's safety and the availability of systems. Several businesses focused on land and air transport are actively interested in this PHM issue, from the observation to the decision.

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