INTERNATIONAL SERIES IN OPERATIONS RESEARCH AND MANAGEMENT SCIENCE

Operations Research • Management Science

Manufacturing and Service Enterprise with Risks

A Stochastic Management Approach

Masayuki Matsui

Springer

Manufacturing and Service Enterprise with Risks

Recent titles in the INTERNATIONAL SERIES IN OPERATIONS RESEARCH & MANAGEMENT SCIENCE

Frederick S. Hillier, Series Editor, *Stanford University*

Axsäter/ *INVENTORY CONTROL, 2nd Ed.*
Hall/ *PATIENT FLOW: Reducing Delay in Healthcare Delivery*
Józefowska & Węglarz/ *PERSPECTIVES IN MODERN PROJECT SCHEDULING*
Tian & Zhang/ *VACATION QUEUEING MODELS: Theory and Applications*
Yan, Yin & Zhang/ *STOCHASTIC PROCESSES, OPTIMIZATION, AND CONTROL THEORY APPLICATIONS IN FINANCIAL ENGINEERING, QUEUEING NETWORKS, AND MANUFACTURING SYSTEMS*
Saaty & Vargas/ *DECISION MAKING WITH THE ANALYTIC NETWORK PROCESS: Economic, Political, Social & Technological Applications w. Benefits, Opportunities, Costs & Risks*
Yu/ *TECHNOLOGY PORTFOLIO PLANNING AND MANAGEMENT: Practical Concepts and Tools*
Kandiller/ *PRINCIPLES OF MATHEMATICS IN OPERATIONS RESEARCH*
Lee & Lee/ *BUILDING SUPPLY CHAIN EXCELLENCE IN EMERGING ECONOMIES*
Weintraub/ *MANAGEMENT OF NATURAL RESOURCES: A Handbook of Operations Research Models, Algorithms, and Implementations*
Hooker/ *INTEGRATED METHODS FOR OPTIMIZATION*
Dawande et al/ *THROUGHPUT OPTIMIZATION IN ROBOTIC CELLS*
Friesz/ *NETWORK SCIENCE, NONLINEAR SCIENCE AND INFRASTRUCTURE SYSTEMS*
Cai, Sha & Wong/ *TIME-VARYING NETWORK OPTIMIZATION*
Mamon & Elliott/ *HIDDEN MARKOV MODELS IN FINANCE*
del Castillo/ *PROCESS OPTIMIZATION: A Statistical Approach*
Józefowska/*JUST-IN-TIME SCHEDULING: Models & Algorithms for Computer & Manufacturing Systems*
Yu, Wang & Lai/ *FOREIGN-EXCHANGE-RATE FORECASTING WITH ARTIFICIAL NEURAL NETWORKS*
Beyer et al/ *MARKOVIAN DEMAND INVENTORY MODELS*
Shi & Olafsson/ *NESTED PARTITIONS OPTIMIZATION: Methodology and Applications*
Samaniego/ *SYSTEM SIGNATURES AND THEIR APPLICATIONS IN ENGINEERING RELIABILITY*
Kleijnen/ *DESIGN AND ANALYSIS OF SIMULATION EXPERIMENTS*
Førsund/ *HYDROPOWER ECONOMICS*
Kogan & Tapiero/ *SUPPLY CHAIN GAMES: Operations Management and Risk Valuation*
Vanderbei/ *LINEAR PROGRAMMING: Foundations & Extensions, 3rd Edition*
Chhajed & Lowe/ *BUILDING INTUITION: Insights from Basic Operations Mgmt. Models and Principles*
Luenberger & Ye/*LINEAR AND NONLINEAR PROGRAMMING*, 3rd *Edition*
Drew et al/*COMPUTATIONAL PROBABILITY: Algorithms and Applications in the Mathematical Sciences*
Chinneck/*FEASIBILITY AND INFEASIBILITY IN OPTIMIZATION: Algorithms and Computation Methods*
Tang, Teo & Wei/*SUPPLY CHAIN ANALYSIS: A Handbook on the Interaction of Information, System and Optimization*
Ozcan/*HEALTH CARE BENCHMARKING AND PERFORMANCE EVALUATION: An Assessment using Data Envelopment Analysis (DEA)*

A list of the early publications in the series is found at the end of the book

Manufacturing and Service Enterprise with Risks

A Stochastic Management Approach

Masayuki Matsui
Professor of UEC, Tokyo

Springer

Masayuki Matsui
The University of Electro-Communications
Tokyo, Japan
matsui@se.uec.ac.jp

ISSN: 0884-8289 7
ISBN: 978-0-387-84803-7 e-ISBN: 978-0-387-84804-4
DOI 10.1007/978-0-387-84804-4

Library of Congress Control Number: 2008932169

Printed on acid-free paper

springer.com

Preface

The subject for this book is my life work on the enterprise modeling and integration by a stochastic/queuing form, and the book plan was conceived before my stay in the USA in 1996–97 as a visiting scholar. The first title was “Stochastic Management and Design of Manufacturing Systems.” The first version was attempted in 2001; however, this version was inappropriate and was not revised till now.

It is 40 years since I attempted a stochastic approach to manufacturing and management due to the limitations of statistical approaches. The century in which industrial engineering and management rose to the forefront was one in which a static/statistical approach was applied to the development of classical models and general/average theory.

This book presents a stochastic management approach to the manufacturing and service enterprise with risks by a game/strategic view, and is based on many papers in production/queueing studies that have appeared in famous journals. The book’s objective is to discuss and show the goals and constraints on manufacturing and service enterprises, and to provide a strategic/collaborative solution for management with risks in heterogeneity.

This book mainly focuses on the three manufacturing classes: continuous, point-wise, and flexible stream types under risks. These manufacturing streams are first studied using the respective stochastic processes, and are characterized and developed as a queueing/strategic control problem of look-ahead/buffer, selection/switch-over, and arrangement/routings. Moreover, the behaviors of some design/control variables are shown and useful theories for design are established.

Under these types, the MGM (management game model), consisting of sales (service) and production centers, is developed for the problem of profit maximization subject to risky lead time (speed). The concept of gaming in sales and production is introduced; the two-stage design method is applied to the three enterprise types, and the management/design strategies (elliptical in shape) are presented at the base of the proposed pair-matrix table (map).

Generally, the theory of constraints (TOC) is a noncooperative improvement approach; however, the MGM is a cooperative design approach and superior to a collaborative approach with the TOC. Moreover, its strategic map coincidentally corresponds to the BSC (balanced scorecard). Finally, a gaming approach is applied to a chain of two MGMs in an SCM (supply chain management), and the win-win strategy is discussed and founded on the case of Toyota versus Dell. Further, the two parallel SCMs are treated in a similar manner as the series SCM.

Based on the abovementioned ideas and objectives, this volume contains the following 7 Parts with 25 subchapters.

Part I, Introduction. There are many risks involved in globalization and heterogeneity. This part is an introduction to the strategic enterprise system and management under risks. Moreover, it introduces and distinguishes the environmental and internal risks for readers. The main focus is manufacturing and service (sales) enterprises, and these chains are found in the so-called SCMs.

Part II, Stochastic Management Model. From a system view, enterprises are regarded as a 3M&I system that consists of huMan, Machine/material, Money, and Information. Furthermore, management is defined as the art of organizing a 3M&I system, and its structure is distinguished into the following two types: cycle and game models. The respective stochastic models are prepared, developed, and later applied.

Part III, Stream Risk Processes. This Part treats the stochastic/queueing control (strategy) of stream risk processes. There are two typical streams: continuous versus point-wise types. The respective configurations for streams are called assembly line and job shop. The configuration risks mainly occur at the time of demand/processing fluctuations, and these risks should be treated advantageously in the case of enterprises.

Part IV, Flexible Risk Processes. This Part treats the stochastic/queueing control (strategy) of parallel risk processes. In the configuration of flexible networks, there is a flexible machining/assembly system (FMS/FAS) of the central server type. In this system, the superiority of hybrid ordered-entry (HE) routing is pointed out in paralleling.

Part V, Ellipse Management with Risk. This Part considers a few applications of MGM theory to the basic manufacturing systems. The ellipse theory on the pair-matrix table is found to be applicable to the management/design strategies of major manufacturing systems. The strategy maps (elliptical in shape) are shown for the four configurations, and the respective forms of strategic management are distinguished.

Part VI, Demand and Supply Risk Chain. This Part treats a few supply chains consisting of unit-enterprise modules—namely MGMs—under chain risks. Both the series and the parallel types of MGM chains are found. The respective cooperation/collaboration strategies would provide a different maximization property at total profit in an SCM. In such a case, the existence of a maximum is found on a balance matrix as a win-win condition in balancing.

Part VII, Emerging Challenge. This Part provides the conclusions toward further management and strategy development under risks. A theory of pair-matrix strategy is presented and discussed in this part; a two-stage design is summarized and concluding remarks are provided.

Throughout this book, manufacturing and service management with risks are treated by adopting a stochastic/queueing view. It is important for readers to know how to formularize the management strategy according to risks and this book would be useful for this purpose.

This work is the fruit of much guidance and cooperation from many people to whom I am very grateful. First of all, I am grateful to many members of the Matsui Laboratory at The University of Electro-Communications, Tokyo. Above all, I sincerely thank Drs. Tetsuo Yamada and Jing Sun, my research colleagues, for their kind help.

Next, I acknowledge the contribution of the many researchers who reviewed the first version. Special appreciation is expressed to Dr. Shimon Y. Nof, Professor at Purdue University, Dr. J.George Shanthikumar, Professor at the University of California in Berkeley; H.C. Tijms, Professor at Vrije Universiteit, Amsterdam; Takehisa Fujisawa, Emeritus Professor at the University of Electro-Communications, Tokyo; and Toshinao Nakatsuka, Professor at Tokyo Metropolitan University.

I also wish to thank Dr. Jiro Fukuta, old Emeritus Professor at Gifu University, Japan, and Dr. Hajime Makabe, Emeritus Professor at the Tokyo Institute of Technology. Moreover, I am indebted to old Professors Shoichi Isotani and Tetsuro Shingu of Hiroshima University, Japan, and Emeritus Professor Youtaro Ogiwara, The University of Electro-Communications, Tokyo, for introducing me to a life of scholarship.

Finally, for their contributions to the English review, thanks are due to Dr. T. Fujisawa, Ms. Kyoko Hasegawa, Associate Professor at Ishinomaki Senshu University, Japan, Mr. Ron Belisle, Excellence-English Editing, Japan, and Mrs. Akiko Irick, USA. I also wish to thank my wife, Kazuko, who has been supporting my research endeavors for a long time.

Tokyo, Japan Masayuki Matsui

Contents

About the Author

Dr. Masayuki Matsui is a professor in the Department of Systems Engineering at The University of Electro-Communications, Japan. He received a BS and MS in Industrial Engineering from Hiroshima University, and a DEng in research on conveyor-serviced production systems from the Tokyo Institute of Technology, Japan. He was a visiting scholar at UC Berkeley and Purdue University in 1996–97. His recent research interests are industrial engineering, production and operations management, management theory, operations research, quality management, and artificial intelligence. He is the author of over 300 technical papers and 10 books. Currently, he is President of the Japan Industrial Management Association (JIMA) and is a board member of the International Foundation of Production Research (IFPR). He served as the editor/director of the JIMA journal (2000–05), was honored with the JIMA Prize and Award in 2005, and is currently a Senior Member of IIE. He is listed in *Nihon-Shinshiroku* (Who's Who in Japan), *Marquis Who's Who in Science and Engineering*, and *Marquis Who's Who in the World* (USA).

Part I
Introduction

Chapter 1
Management in the Age of Risk

1.1 Introduction

Modern enterprises increasingly rely on each other by managing risks [2] and depend on globalization. The modern management approach is moving toward a collaborative age of risk, such as ERP/SCM (Enterprise Resource Planning/Supply Chain Management), which is applied to handle heterogeneity.

A new management theory is desirable for restructuring an efficient demand and supply system in this new age, and it is here called the demand-to-supply system and management under market and operational risks. This approach does not involve the equilibrium theory, but the relative theory of demand and supply. A new theory is presented on the basis of stochastic/queueing reality and is directed to the integration of marketing, production, and OR model [3].

Generally, a relative relation of demand and supply is regarded as that of customer/job (demand) and service/processing (supply) on a queueing/traffic form. In this book, this relation is referred to as the gaming of demand (sales) and supply (production).

1.2 Target Enterprise

1.2.1 SCM and Enterprises

A typical SCM is seen in Fig. 1.1, and this book is devoted to a class of so-called production-type and sales-type SCMs. The target enterprises are especially referred to as the manufacturing and service systems and are assumed to consist of production and sales centers.

The quantitative SCM is a class of quantity discounts, bullwhip effects [4] and multi-echelon inventory [1], and recent studies have examined this class [6, 10, 12, etc.]. Also, this problem is regarded as a collaboration/integration problem [7, 9], and there is a tendency for it to be studied by multi-agents approach in artificial intelligence and so on.

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_1, © Springer Science+Business Media, LLC 2009

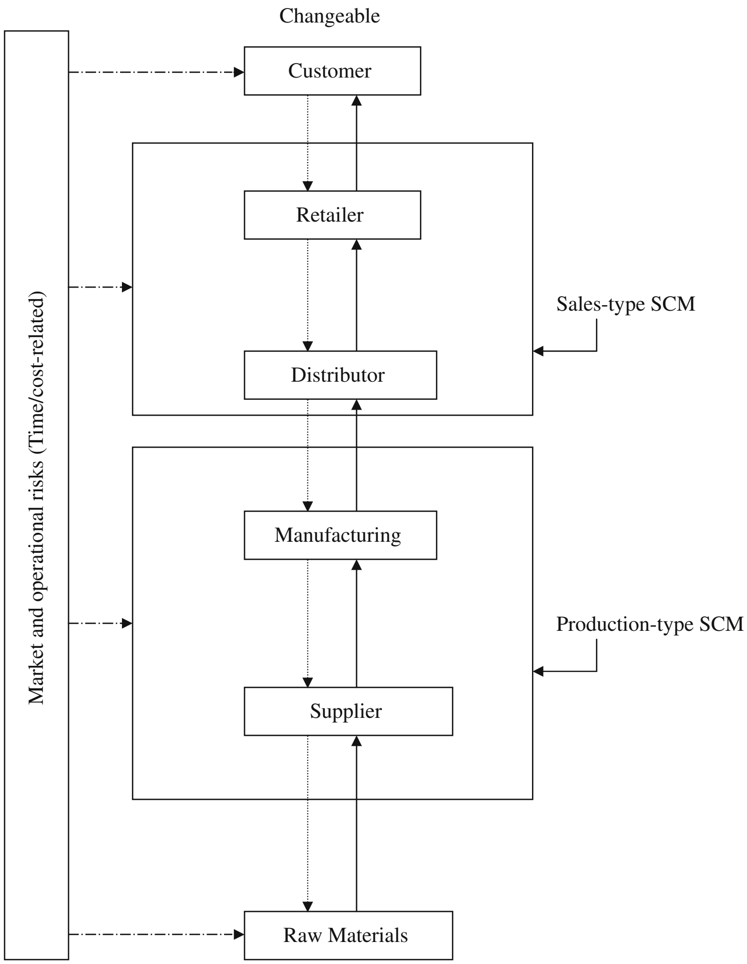
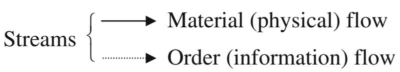


Fig. 1.1 Typical SCM under global risks



We are concerned with the theory of constraints (TOC) and total optimization [5] for a win-win strategy under risks, and we present the game/strategic approach for manufacturing/service enterprises and SCM under changeable risks. This book is a step toward this direction and develops a new theory of demand and supply strategy for enterprises.

1.2.2 Manufacturing and Service Processes

1.2.2.1 Manufacturing Processes

In the production-type SCM, there are certain types of manufacturing processes. One classification of the manufacturing process is on the basis of order specification, and it is classified into make-to-order and make-to-stock types in the distributed networks (Fig. 1.2a).

The jobs-shop production system is a class of a make-to-order type, and it includes machining and assembly processes. The mass production system is a class of a make-to-stock type, and consists of both the machining processes (a lot of flexibility) and assembly processes (conveyor system). The pull/push system coordinates or integrates both processes.

In subsequent sections section of this book, we focus on the manufacturing systems of a conveyor, job-shop, flexible, and lot/cell. These systems are characterized as the operation/control issues of look-ahead, selection, arrangement, and pull/push types, respectively.

1.2.2.2 Service Processes (Logistics)

In the sales-type SCM, there are also different types of service processes. Two typical processes are the tree and cyclic types on the basis of logistics (Fig. 1.2b). These problems have been found to be similar to the later class of routing/release models in the flexible manufacturing systems (FMS)/job-shop.

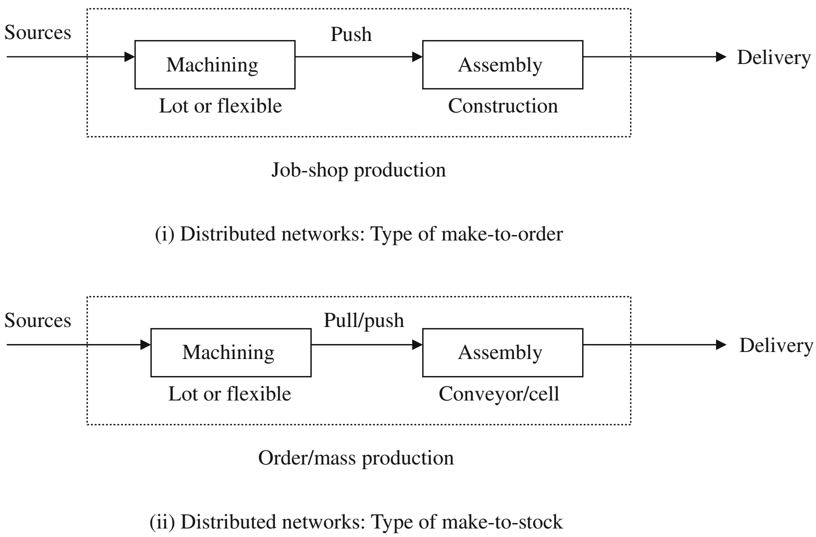
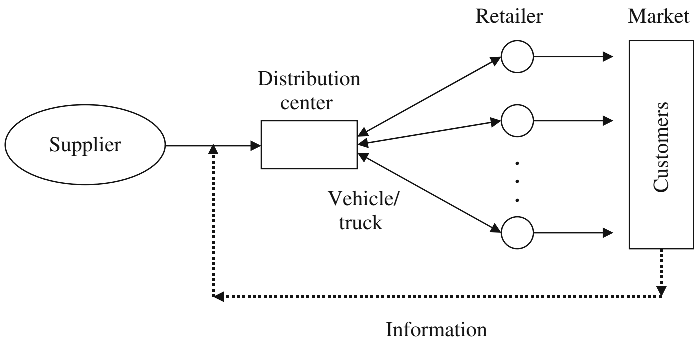
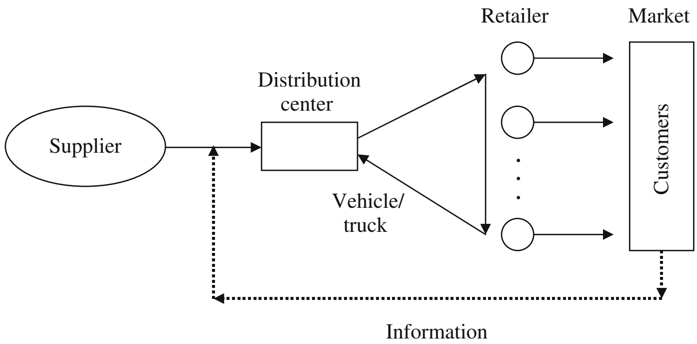


Fig. 1.2a Types of manufacturing processes



(i) Logistics: Tree type



(ii) Logistics: Cycle type

Fig. 1.2b Types of service processes

1.3 Management Goal and Risks

1.3.1 Game Approach to Profit

The important goal of enterprises is mainly related to the profit formula:

$$\text{Profit} = \text{Revenue–Cost}, \tag{1.1}$$

under global risks (constraints). The management goal is largely dependent on the market environment, and these relations and risks are summarized in Table 1.1.

The management game model (MGM) is based on the pair-gaming formulation of demand (orders) and supply (production/service), and is discussed later. Generally, the SCM networks can be regarded as the network of MGMs.

Our objective functions for the TAG goal are based on the unit-time criteria [8], and this criterion is similar to that of the river stream model (Fig. 1.3). The economic problem for the TAG is to exclude the various rocks (obstacles) and to increase the water (profit) flow.

Table 1.1 Goal and market views

Approach	Goal (focus)	Market	Risks
Traditional	Market sharing (full-cost pricing)	Demand > Supply	Limited supply
Toyota-like	Cost reduction (Kaizen)	Demand < Supply	Excess capacity, wasted
SCM	Throughput (TOC)	Demand = Supply	Quantitative imbalance
MGM	Total attainable goal (TAG) (pair-gaming)	Demand ≈ Supply	Strategic matching, challenge

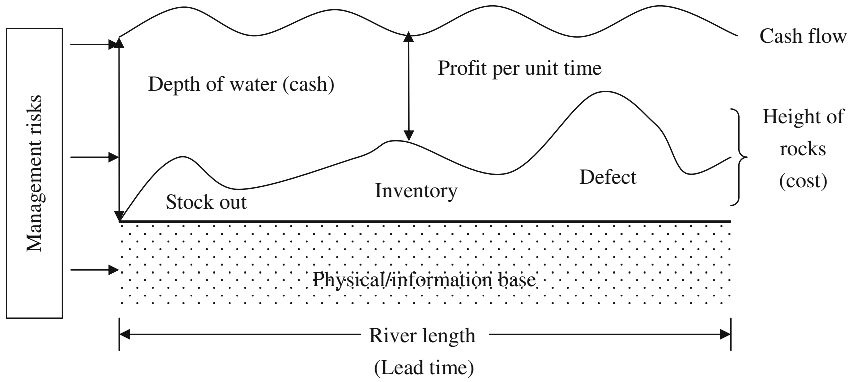


Fig. 1.3 River stream model

In a modern society, there is another problem involving time length from the order (upper part) until delivery (down part) in SCM (river). Thus, the reliability problem of lead time is incorporated here into our demand-to-supply management.

1.3.2 Management Risks

The systems such as product/service, enterprise, SCM and so on involve certain kinds of artifacts [11]. The risks always exist in the artifacts (Fig. 1.4), and it is important for managers to control the uncertainty (variability) of risks.

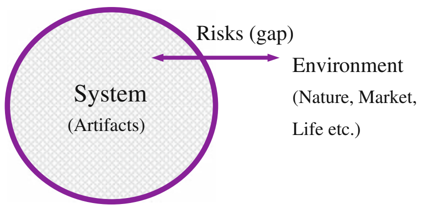


Fig. 1.4 Artifacts and risks

There are many risks (variabilities) that constrain the goal seeking in the enterprise environment. These management risks occur mainly in the market and operational environment, and are listed in Table 1.2. Then, the management problem is to maximize the goal Equation (1.1), under

$$\text{Market (outside) and Operational (inside) risks for Enterprise (systems)} \rightarrow \text{Minimize.} \tag{1.2}$$

Table 1.2 A list of management risks

Processes/level Risks	Manufacturing processes	Service processes	Enterprises Level
Market risks	Sales risk, Financial risk, Investment risk, Location risk, Calamity risk and so on.		Product defectives Social risk
Operational risks	Inventory risk Logistic risk Purchase risk Due-date risk Down risk and so on	Availability risk Distribution risk Buying risk Delivery risk Deteriorate risk and so on	Cash-rate risk Derivative risk Emergency affairs M&A risk and so on

In the distribution network, these risks are dependent and influence each other. Thus, collaborative/cooperative efforts and strategies are effective with risk complexity. The behaviors of risk complexity are often formulated by stochastic manners, and the queueing form is applied in this book.

1.4 Objectives of this Book

The objective of this book is to discuss and to show the Total Attainable Goal (TAG) and constraints for manufacturing and service enterprises, and to give the strategic/collaborative solution for the management with risks in heterogeneity. This unified approach to the enterprises would be valuable to the decision maker in the age of risk.

The organization of this book is shown in Fig. 1.5. After Part I, the management game module (MGM) is presented in Part II, and some variants of MGM and their relations are developed later in Parts III–VI. Part VII includes the collaborative map and emerging trends of this subject.

Risk involves chance. The risk management of artifacts is a movement toward the control of recent uncertainty, and it can be changed to focus on the concerns from the standpoint of amount to value. It is advantageous to exploit risk and to take advantage of uncertainty, as shown throughout this book.

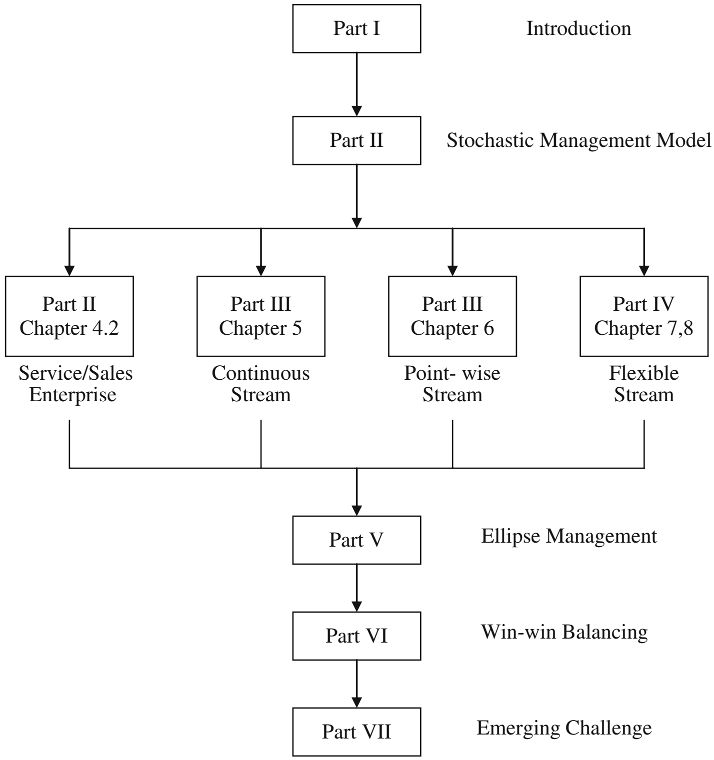


Fig. 1.5 Organization of this book

References

1. Beamon, B.M., Supply Chain Design and Analysis: Models and Methods, *International Journal of Production Economics*, 55, 281–294, 1998
2. Bernstein, P.L., *Against the Gods – The Remarkable Story of Risks*, Wiley, NY, 1996
3. Eliashberg, J. and Steinberg, R., Marketing-Production Joint Decision-Marketing, In: J. Eliashberg and G.L. Lilien (eds.), *Handbooks in Operations Research and Management Science*, Vol. 5 (Marketing), North-Holland, Amsterdam, pp. 827–880, 1993
4. Forrester, J.W., *Industrial Dynamics*, MIT Press, MA, 1961
5. Goldratt, E.M., *The Goal – A Process of Ongoing Improvement*, North River Press, MA, 1984
6. Minner, S., *Strategic Safety Stocks in Supply Chains*, Springer, Berlin, 2000
7. Nof, S.Y. (ed.), *Information and Collaboration Models of Integration*, Kluwer, Netherlands, 1994
8. Ross, S.M., *Applied Probability Models with Optimization Applications*, Holden-Day, San Francisco, 1970
9. Sahin, F. and Robinson, E.P., Flow Coordination and Information Sharing in Supply Chains: Review, Implications and Directions for Future Research, *Decision Sciences*, 33(4), 505–536, 2002
10. Shapiro, J.F., *Modeling the Supply Chain*, Duxbury, Australia, 2001
11. Simon, H.A., *The Sciences of the Artificial*, MIT Press, MA, 1969
12. Tayur, S., Ganeshhan, R. and Magazine, M. (eds.), *Quantitative Models for Supply Chain Management*, Kluwer, Boston, 1999

Chapter 2
Stochastic Management Approach

2.1 3M&I and Stochastic Approach

2.1.1 Introduction

F. W. Taylor, the father of scientific management, said in 1903 that management is an art [22]. By "an art" he meant the scientific law/technique (enterprise/factory) and the applicative "waza." Following that, this definition was further developed by Koontz and O'Donnell [9] and others.

About 100 years of the history of management has passed since F. W. Taylor established a theory of scientific management [22]. However, management theory regarding what management actually is still seems to be confusing [9] and that too at a static/statistical level. At this level, it would be limited to average theory.

This chapter is a preparation for the developing management theories through modeling experiments by a stochastic approach. Toward this purpose, we have developed a system approach to management modeling, and attempting to build a framework for the management research in the future [15].

2.1.2 Stochastic Management

2.1.2.1 3M&I System

As management is always facing environmental changes, it is natural to consider stochastic management by stochastic approaches [3, 4, 8, 10]. In stochastic management, the structure design theory is important for dispersing risk and for buffer design.

At the beginning, we present general management problems for a variety of 3M&I system. Next, we consider the structure design problem for the general management problem and present a new or unified approach for the art of variety.

The system is usually defined as the 3M&I system, consisting of huMan, Material/Machine, Money and Information as shown in Fig. 2.1.1. The use of 3M represents resources, while I represents methods. The possible states of the 3M&I system are usually numerous, and the state space of variety is our main concern.

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_2, © Springer Science+Business Media, LLC 2009

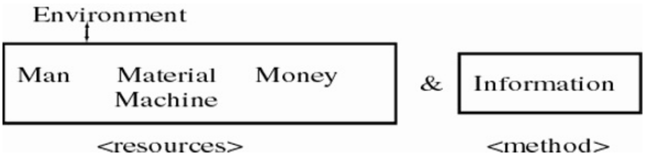


Fig. 2.1.1 3M&I system

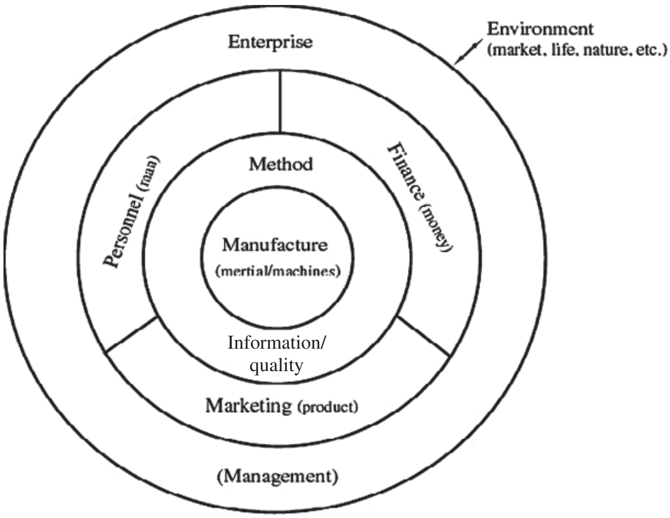


Fig. 2.1.2 3M&I and enterprise

Then, the management is regarded here as the management of the 3M&I system as shown in Fig. 2.1.2. The 3M&I manufacturing/enterprise is further divided into project and repetitive types, and the latter type is our object system and is treated below. Without loss of generality, the 3M system is assumed to vary stochastically in time processes under risks.

2.1.2.2 Variety and Structure

The management is now defined as an art of variety in a 3M&I system under the goal, and is called the general management problem. Individualization and uniformity are the opposite extremes of variety, and usual management (standardization) occurs between the extremes.

There is a law of requisite variety [1]. If the redundancy [1, 19] in information theory is introduced as the measure of management constraints, the degree of management standardization/structure can be shown. Recent globalization in the world is moving toward standardization, while manufacturing culture is moving toward individualization.

Table 2.1.1 Hundred years since Taylor

Since Taylor		Taylor	~	Today
Environment/object	Market/production environment	Economies of scale, division of labor	Economies of scope job enlargement	Economies of agility work cooperation
	Object system	Closed system	Open system	Complex system
Variety	Standardization	Work standardization	Standardization of production and quality	Globalization ISO standard
	Individualization	Human machinery	Human relations job design	Multiagent manufacturing culture
Structure	Management process	Separation of plan and administration	General management control/decision	Management strategy PDCA/CAPD
	Demand-to-supply	Functionization (plan)	CIM flexible	ERP/SCM agile/visible

Since there are various kinds of management, which are diversified, management also has a redundancy of structures for standardizations. According to past literature, the management process and demand-to-supply structures would be the two main types of management structures.

Each structure plays a vital role in preventing variety through the information/method (I) from disturbance. In our examination, we focus on the structures as a equilibrium system, and a significant amount of work on management problem is created through stochastic modeling.

Since Taylor published "Shop Management" in 1903, about 100 years have passed. With regard to environment/object, variety, and structure, the difference between Taylor's ideas and today's ideas are arranged in Table 2.1.1, as well as the flow of management principle.

2.1.3 Demand-to-Supply Management

2.1.3.1 Two-Center Problem

Recently, there is an increased emphasis on the integration of the separate functional areas of the firm. This phenomenon has been reflected in a number of recent textbooks addressing the integration issues between marketing and production management [5]. This problem was first pointed out by M. P. Follet et al. (1933) [7, 20], and it involves a class of heterogeneous agents.

Now, consider the two-center model, which enterprises use for sales and production centers (Fig. 2.1.3) [11]. The sales center would pursue the maximization of the demand price, while the production center would pursue the minimization of operating cost.

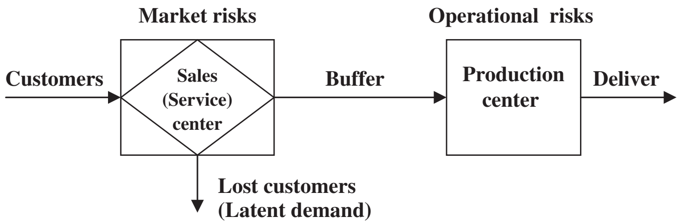
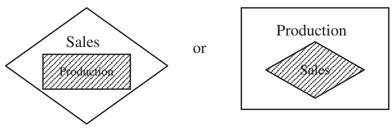
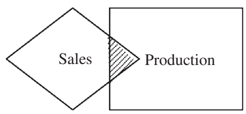
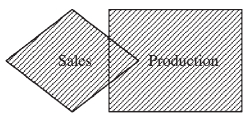
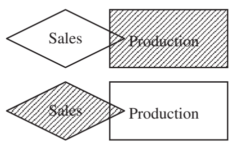


Fig. 2.1.3 Two-Center model

The problem of the two centers, that is, the goal of the factory/enterprise is to maximize the difference between reward and cost under the shorter lead time by the collaboration/cooperation of the two centers. There are the four types of two-center models in integration (Table 2.1.2).

We focus on the stochastic modeling and design for the demand-to-supply management type, and we present a framework theory for management design on the basis of two-center models [10].

Table 2.1.2 Four types of two-center models

Types	Patterns	Management
Domination		TOC/ divisionalization
Compromise		Trade/ distributed (non-cooperation)
Integration		Collaboration/ centralized (cooperation)
Sharing		VMI/ remote

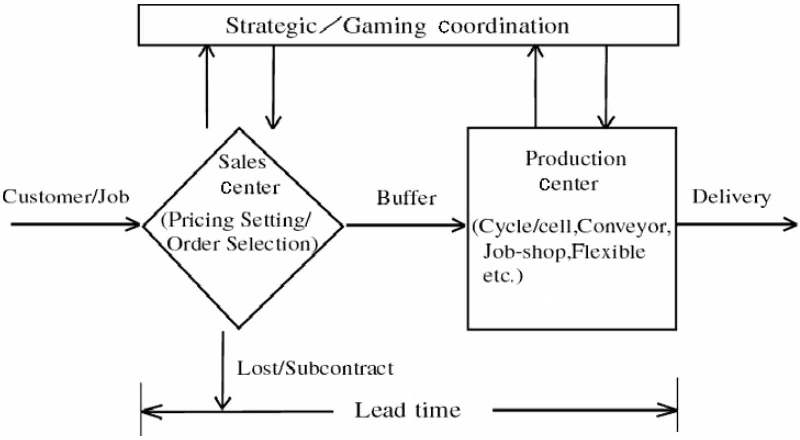
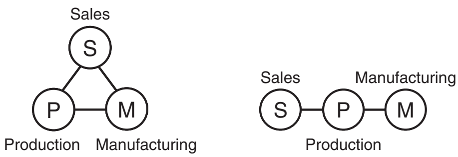


Fig. 2.1.4 General framework for demand-to-supply

A general framework for demand-to-supply management model is seen in Fig. 2.1.4 and is called the management game model (MGM) [12]. Based on this framework, some factory systems are distinguished such as stochastic systems, as lot/cell production, conveyor systems, job-shop production, flexible manufacturing and so on.

2.1.3.2 Toward Three-Center

In the three-center model [21], there is a triple relation of 3^2 (= 9) ways. Two major types are centralized and distributed (Fig. 2.1.5), and are compared in Table 2.1.3 [13]. This difference is similar to that of the ERP versus SCM type, and these would be contrasted to balancing issues.



(**a**) Centralized type (**b**) Distributed type

Fig. 2.1.5 Typical types of three-center

Table 2.1.3 Three-center problem: Centralized versus distributed

Comparison	Centralized	Distributed
Relation	Star	Series
Division of Work	Make	Buy
Package	ERP	SCM
Module	Vertical	Horizontal
Goal	Common	Individual

2.1.4 Process-Cycle Management

2.1.4.1 Two Problems of Cycles

This management process is characterized by a management cycle approach, in which functions of management are roughly divided into plan, organization, direction, and control [6]. Also, the management cycle is well known as a model of management process structure in industry.

As a typical case, the PDCA (Plan-Do-Check-Act) is commonly used in quality control etc. at the factory [17, 21]. It may be distinguished as the PDCA cycle, starting from plan, and the CAPD cycle, starting from check, in Fig. 2.1.6. For example, the plan corresponds to the setting of the control limit level.

The original version of PDCA is seen in the PDS, which consists of Plan (specification/hypothesis), Do (production/experiment) and See (inspection/judgment) in statistical quality control [17, 18]. Recently, the CAPD type has been issued.

2.1.4.2 PDCA versus CAPD

A comparison of PDCA and CAPD is seen in Fig. 2.1.7. The material and information flows are the same as those shown in Fig. 2.1.7a, while these are dual flows as shown in Fig. 2.1.7b. Generally, the difference would be smaller under larger due time, because the influence of the starting point would be diminished.

Also, alternatives of PDCA versus CAPD are classified in Table 2.1.4. An additional feature of PDCA versus CAPD would be seen in the shorter process cycles with due date barrier, and is treated stochastically as a management cycle model (MCM) with switching [13].

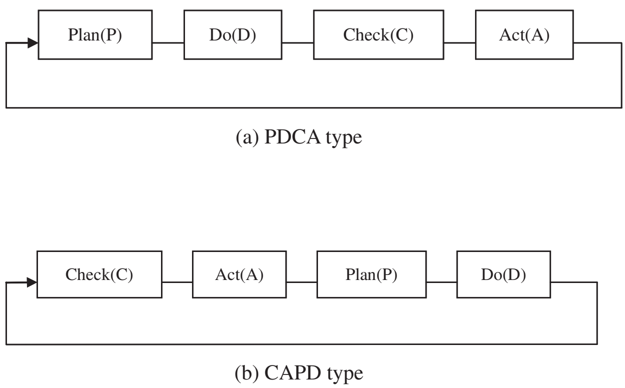


Fig. 2.1.6 Two-cycle model

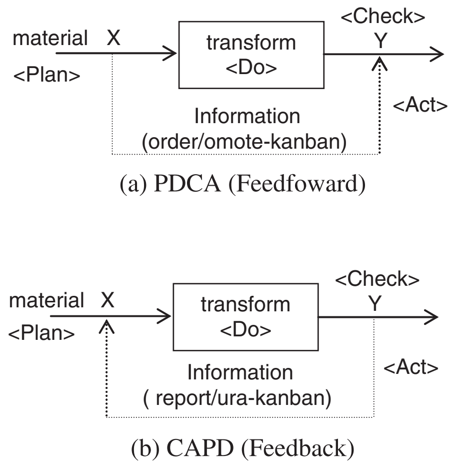


Fig. 2.1.7 PDCA versus CAPD

Table 2.1.4 Classification of management processes

Cycle type		PDCA	CAPD
Management	Approach	Design approach	Improvement approach
		Open approach	Closed approach
	Type	Future planning	Ex post facto action
		Goal seeking	Problem solving
		Top-down	Bottom-up
Object	Instruction form	Formal system	Informal system
	Control form	Feed forward	Feed back
	Trigger form	Push system	Pull system
	Retail form	"Goyoukiki"	Supermarket
	Medical-care form	Human dock	Doctor activity
Technique	Process control	Gantt chart(forward)	Backward
	Quality control	Control chart	Bayesian chart
	Inventory control	EOQ	Double-bin
	Production control	MRP	JIT
	Bottleneck control	MGM [12]	TOC/MGM
	Data control	Data mining	Data analysis
	Cost control	Standard cost system	Actual cost system

Remarks

In this chapter, the enterprise/factory is regarded as a 3M&I system, and is modeled by a not statistical but stochastic management approach. These include the demand-to-supply and process-cycle management models toward enterprise modeling and integration [11].

In the near future, these stochastic models will be formularized and designed for a stochastic/strategic management. In addition, this study would develop enterprise/factory science and management [2, 14], combined with a ERP/SCM balancing issue [16].

References

1. Ashby, W.R., *An Introduction to Cybernetics*, Wiley, NY, 1956
2. Binder, M. and Clegg, B., Enterprise Management: A New Frontier for Organizations, *International Journal of Production Economics*, 106, 409–430, 2007
3. Buzacott, J.A. and Shanthikumar, J.G., *Stochastic Models of Manufacturing Systems*, Prentice Hall, New Jersey, 1963
4. Crabill, T.B., Cross, D. and Manazine, M.J., A Classified Bibliography of Research on Optimal Design and Control of Queues, *Operations Research*, 25(2), 219–232, 1977
5. Eliashberg, J. and Steinberg, R., Marketing-Production Joint Decision-Making, In: J. Eliashberg and G.L. Lilien (eds.), *Marketing*, Elsevier, Amsterdam, 827–880, 1993
6. Fayol, H., Administration industrielle et Générale; *General and Industrial Management*, Pitman Publishing, NY, 1916
7. Follet, M.P., *Freedom & Coordination – Lecture in Business Organization*, L.H. Urwick (ed.), Pitman Publishing, London, 1949
8. Hopp, W.J. and Spearman, M.L., *Factory Physics – Foundations of Manufacturing Management*, 2nd ed., McGraw-Hill, Boston, 2000
9. Koontz, H. and O'Donnell, C., *Principles of Management – An Analysis of Managerial Functions*, McGraw-Hill, NY, 1959
10. Matsui, M., A Relationship of Average Criteria for Queueing Systems with Lost Units, *Symposium on Performance Models for Information communication Networks*, Shizuoka, Japan, 371–378, 1993
11. Matsui, M., An Introduction to Stochastic Management and Design, Part I: Management Problem and Structurization, 43–44, Part II: A General Management Problem and Stochastic Design, 62–63, *Preprints of Japan Industrial Management Association*, Fall Meeting, Japan, 1999 (in Japanese)
12. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
13. Matsui, M., A Management Cycle Model: Switching Control under Lot Processing and Time Span, *Journal of Japan Industrial Management Association*, 56(4), 256–264, 2005
14. Matsui, M., *Management of Manufacturing Enterprise–Profit Maximization and Factory Science*, Kyoritsu Shuppan, Tokyo, Japan, 2005 (in Japanese)
15. Matsui, M., Enterprise Modeling and Integration: A Stochastic Management Approach, *Proceedings of ICPR2007*, Chile, 2007 (on CD-ROM)
16. Matsui, M., Management Problem of Storategic MRP II/ERP/SCM – Sei-Han Collaboration and Pair-Strategic Map, *Management System*, 16(1), 43–46, 2006 (in Japanese)
17. Reid, R.A. and Cseko, G.C., Support Service Process Improvement: An Application within a University Health Sciences Center, *International Journal Productivity and Quality Management*, 1(4), 339–362, 2006
18. Schewhart, W.A., *Statistical Method from the Viewpoint of Quality Control*, The Graduate School, U.S. Department of Agriculture, Washington, 1939
19. Shannon, C.E. and Weaver, W., *The Mathematical Theory of Communication*, The University of Illinois Press, Urbana, 1964
20. Shapiro, B.P., Can Marketing and Manufacturing Coexist?, *Harvard Business Review*, Sep–Oct, 1977
21. Takahashi, T., Fundamental Concept of Quality Control and SQC/TQM, *Management System*, 9(1), 60–63, 1999 (in Japanese)
22. Taylor, F.W., Shop Management, In: *Scientific Management*, Harper & Brothers, NY, 1947, 1903
23. Yamato, J., Yamada, T., Matsui, M. and Nof, S.Y., A Cooperation/Collaboration Logic by Sharing Information in an ERP Model, *Proceedings of ICPR2000*, Blacksburg, VA, 2003 (on CD-ROM)

2.2 Risk Chains and Balancing

2.2.1 Introduction

In SCM, there are two main problems of the win-win strategy and bullwhip effect besides contracts. The former is formulated here under the perfect information-sharing/synchronization, and a theoretical step to its possibility issues is explored for later development.

For the study of the former, the station-centered approach in the CSP System (Conveyor-Serviced Production System) [8] is applied to the supply chain consisting of unit-enterprises. As the unit-enterprise stations (agents), Management Game Models [4, 7] are introduced in the place of generalized CSPS (Conveyor-Serviced Production Station) units [3] in the CSP System.

This chapter presents the integral balancing issues of cooperative/collaborative enterprises in SCM [5]. By integral balancing it is meant that both economics (profit) and reliability (lead time) are held in balance. First, the CSP System theory is prepared, and next, the MGM modelling is presented. Finally, the two-chain MGM of SCM is discussed in the integral balancing view.

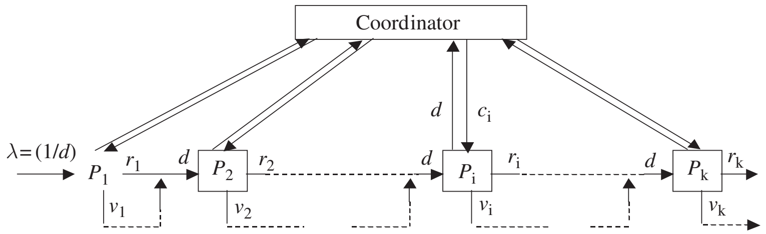
2.2.2 Fundamental Theory

2.2.2.1 Two CSP System Models

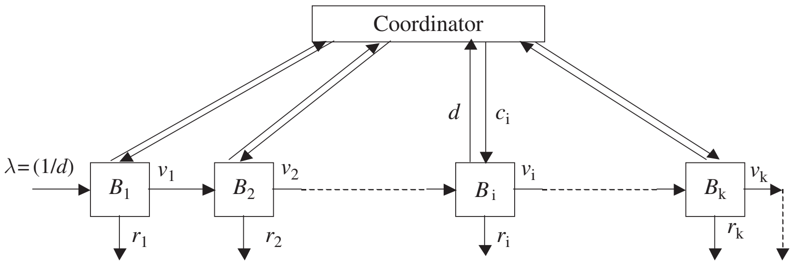
A great many of the links in modern production systems (or processes) are formed by conveyors. In the conveyor theory, two-production systems: (i) mechanical (or moving-belt) flowline system [14], and (ii) open-loop (or nonrecirculating) conveyor system [12] are especially distinguished from the viewpoint of material-flow and studied in terms of the operational setting. These systems are called the Conveyor-Serviced Production System (CSP System) in the sense of the mechanical material-flow system with variable arrival/service-time [2].

The research approach to the CSP System is classified into two types as given below. In particular, treatment such as the queueing system with ordered-entry or one that is a tandem type is called the system-centered approach. The treatment that

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_3, © Springer Science+Business Media, LLC 2009



(a) Model I: Coordinator and seriesí array of CSPS units



(b) Model II: Coordinator and ordered-entry array of CSPS units

Fig. 2.2.1 Two CSP System models

decomposes the CSP System to each independent station (queueing sub-system) is called the station-centered approach. The Conveyor-Serviced Production Station (CSPS) is pioneered in [13], and is a typical queueing sub-system in the case of fixed/removal items with delay [2, 6].

The CSP Systems, (i) and (ii), may be distinguished here as Models I and II, respectively, each composed of a decision maker and production process (or line) [8]. The production processes of Model I are a series array of K CSPSs (unloading and loading stations), while those of Model II are an ordered-entry array of K CSPSs (unloading stations). The relation between the production processes and decision maker is regarded as two levels of hierarchy: a CSPS unit (first level) and a coordinator balancing CSPS unit (second level) (see Fig. 2.2.1).

2.2.2.2 *Material Flow and Formulation*

(a) Balance of Material Flow

The mean input interval time is a design (or decision) variable of the coordinator, and is denoted by d $(0<d<\infty)$. The production rate, $r_i,\ i = 1, 2, \cdots, K$, is defined as an inverse of the mean interdeparture time, that is, the mean time between successive departures. The overflow rate, $v_i,\ i = 1, 2, \cdots, K$, is defined as an inverse of the mean inter-overflow time, that is, the mean time between successive overflows.

In the Models I and II, the following relations are generally satisfied:

$$\begin{aligned} r_{i-1} &= r_i + v_i, && \text{Model I}, i = 1, 2, \ldots, K \\ v_{i-1} &= r_i + v_i, && \text{Model II}, i = 1, 2, \ldots, K \end{aligned} \tag{2.2.1}$$

where $r_0 = v_0 = 1/d$. The value of d is communicated to each CSPS unit in the first level.

A practical assumption for the CSP System is introduced to produce the production quantity required in the planning period. This process is easy, if it is realized by providing a large enough buffer within stations. Thus,

$$\begin{aligned} \text{Assumption}: r_i + v_i &= 1/d, && \text{Model I}, \quad i = 1, 2, \ldots, K \\ \sum\nolimits_{i=1}^{K} ri + v_K &= 1/d, && \text{Model II}. \end{aligned} \tag{2.2.2}$$

Under this assumption, the input interval time, d, is called the cycle time. An estimated value of d, CT_c, is obtained from the planning period divided by the production quantity.

(b) Mathematical Formulation

General criteria for Models I and II are obtained from the queueing formula: λZ = M, in which the respective Z and M are the mean cycle time and mean number of departures in the system (see Appendix (A.3) [2, 6, 8, 9]).

Then, the respective targets Models I and II are taken from the production rate as follows:

$$R_I = r_K = (1/d) \prod\nolimits_{i=1}^{K} P_i, \tag{2.2.3}$$

$$R_{II} = d^2 v_K = d \prod\nolimits_{i=1}^{K} B_i, \tag{2.2.4}$$

where P and B are the probabilities of processing and loss, respectively, and

$$P = 1 - B = 1/(1 + \eta), \qquad 0 < P \leq 1 \tag{2.2.5}$$

in which η $(= M - 1)$ is the mean number of overflows per unit produced.

Also, the mean material-flow time, W, is given from the queueing formula: $W = ZL$ in Appendix (A.4) [2, 6, 8]. For Models I and II, the respective general criteria are as follows:

$$F_I = \sum\nolimits_{i=1}^{K} W_i, \tag{2.2.6}$$

$$F_{II} = \left(\sum\nolimits_{i=1}^{K} L_i\right) / (\lambda - v_K), \tag{2.2.7}$$

where $\lambda = 1/d$ and L indicate the mean number of units.

Then, a basic coordination problem of Models I and II is to maximize the functions R_1 and R_{II}, with respect to cycle time, d, in which each CSPS pursues the maximization of the probabilities P_i and B_i, respectively, with respect to the CSPS variable (look-ahead time, c_i). Under the constraint of F_I and F_{II}, the respective basic problems may be formularized by the two-level mathematical programming [1], and are dual.

2.2.3 SCM Models

2.2.3.1 CSP System versus SCM

Generally, the supply chain involves manufacturing, distribution, and sales. This chain is similar to the structure of Model I in Fig. 2.2.1a, if the CSPS units are replaced by the MGM units (agents).

Though the supply chain focuses on the series type, there are a few parallel types of MGMs, similar to the structure of Model II in Fig. 2.2.1b. These examples are seen in associated job-shops, retailer systems, and so on.

Table 2.2.1 shows the relation of the CSP system and supply chain in the modeling and balancing views. From Table 2.2.1, the station-centered approach to SCM would be useful and adopted.

Table 2.2.1 CSP System versus supply chain

	Approach	Stations	Problem
CSP System	System-centered	Points	Blocking
	Station-centered	Generalized CSPSs	System balancing
Supply chain	System-centered	Points	Resource balancing
	Station-centered	MGM agents	Integral balancing

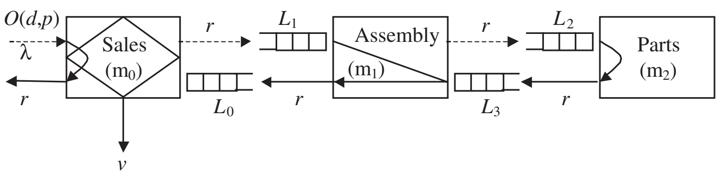
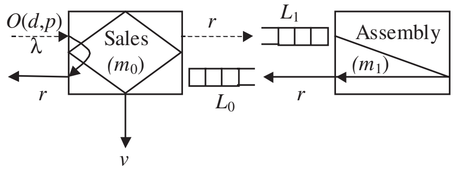
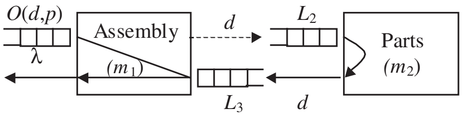


Fig. 2.2.2 SCM Model: A chain of MGMs



(a) Marketing-manufacturing SCM



(b) Build-to-order SCM

Fig. 2.2.3 Models of two-chain MGM

2.2.3.2 MGM Modeling

2.2.3.2.1 Series Type of MGMs

Examples of MGM modeling are classified into two types: series and parallel types of MGMs. The series type is seen in Fig. 2.2.2, and its formulation and an example of it are given in [11] under the *M/M* enterprise type.

This series type may be divided into the marketing-manufacturing (Fig. 2.2.3a) and build-to-order (Fig. 2.2.3b) SCMs. The former is a two-chain SCM of Service MGM [7] and manufacturing MGM [4], and the latter is a two-chain SCM of two manufacturing MGMs [6]. These treatments will be seen in Part VI under *M/M* enterprise type.

2.2.3.2.2 Parallel Type of MGMs

The parallel types are the make-or-buy type [10] and distributor type SCMs (Chapter 11.2), consisting of manufacturing MGMs or service MGMs. These are seen here in Figs. 2.2.4 and 2.2.5, respectively, and may be treated by queueing networks. Figure 2.2.5 is similar to that of the central server model of FMS in queueing.

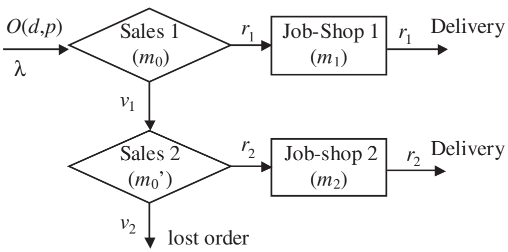


Fig. 2.2.4 Make-or-buy type SCM

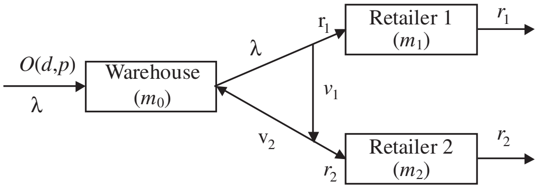


Fig. 2.2.5 Retailer type SCM

2.2.4 SCM Formulation

2.2.4.1 Goal-Seeking

For the SCM, the performance evaluation is useful for efficiency, but the economic evaluation would be further valuable to SCM managers. We consider here both the economics and reliability criteria for the integral balancing of SCM.

As the SCM goal, the alternative goals, MEN and DEN, for two-chain MGM are as follows:

$$\text{Main goal: } MEN = (ER_1 + ER_2) - (EC_1 + EC_2) \longrightarrow \max_d \tag{2.2.8}$$

$$\text{Dual goal : } DEN = (ER_1 - EC_1)^+ + (ER_2 - EC_2)^+ \longrightarrow \max_d \tag{2.2.9}$$

where $(a)^+ = \max\,(a,\ 0)$, and

ER_i: Mean revenue of enterprise i $(i = 1, 2)$,
EC_i: Mean operating cost of enterprise i $(i = 1, 2)$.

Now, let us denote the profits (net rewards), $EN_1 = ER_1 - EC_1$ and $EN_2 = ER_2 - EC_2$, by the functions, $f(d)$ and $g(d)$, respectively. Then, the following result generally holds in the dual goal (2.2.9):

$$f'(d) = 0 \text{ and } g'(d) = 0 \Longrightarrow f'(d) + g'(d) = 0 \tag{2.2.10}$$

as the optimal condition.

The condition (2.2.10) would derive the profit balancing for the win-win strategy, and attains the integral optimization in SCM. There is the balance point (cycle time) in the demand speed for profit maximization. Recently, a good example is found as shown in [11].

2.2.4.2 System balancing

In the SCM, another goal should be considered for the integral balancing. This would involve system balancing in reliability (lead time or loading, W) at the material-flow level. Figure 2.2.6 shows an example of system balancing in two lead times, $W_i,\ i = 1,\ 2$, for the demand speed (cycle time), d.

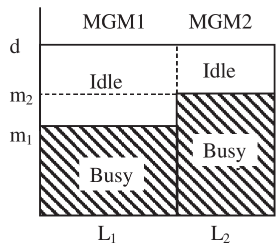


Fig. 2.2.6 Balancing in lead-time, W ($W = m_i L_i,\ i = 1, 2$)

In system balancing, it would be probable that W_1 should be equal to W_2. From Fig. 2.2.6, it is noted that there is a bottleneck or TOC problem in MGM2.

By integral balancing it is meant that the supply chain is balanced in both economics and reliability. Then, our purpose is to explore the possibility of the integral balancing of SCM. This totality would need to satisfy the constraints of management resources, contracts (price, inventory, risks, etc.), environment, and so on.

Remarks

Through the station-centred approach, this book presents the MGM modeling, discusses the two-chain MGM of SCM, and explores the win-win strategy in SCM. The research perspective moves toward generalization of the SCM theory in [11]. In this case, the hypothesis is considered that the profit maximization in cooperation is attainable in series and parallel types, even if each agent (enterprises) pursues the self goal in non-cooperation, then, the SCM balancing would be possible in not only economics but also reliability, simultaneously.

References

1. Geoffrion, A.M. and Hogan, W.W., Coordination of Two-Level Organization with Multiple Objectives, In: A.Y. Balakrishnan (ed.), *Techniques of Optimization*, Academic Press, NY, pp. 455–468, 1972
2. Matsui, M., *A Study on Optimal Operation Policies in Conveyor-Serviced Production System*, Doctoral Dissertation, Tokyo Institute of Technology, Japan, 1981 (in Japanese)
3. Matsui, M., A Generalized Model of Conveyor-Serviced Production Station, *Journal of Japan Industrial Management Association*, 44(1), 25–32, 1993 (in Japanese)
4. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
5. Matsui, M., MGM-Modeling and Balancing Problem in Supply Chain Management, *Proceedings of APIEMS 2004*, Gold Coast, Australia, 2004 (on CD-ROM)

6. Matsui, M., CSPS Model: Look-Ahead Controls and Physics, *International Journal of Production Research*, 43(10), 2001–2025, 2005
7. Matsui, M., Management Game Theory: Manufacturing vs. Service Enterprise Type, *International Journal of Productivity and Quality Management*, 1(1/2), 103–115, 2006
8. Matsui, M., Shingu, T. and Makabe, H., Conveyor-Serviced Production System: An Analytic Framework for Station-Centered Approach by Some Queueing Formulas, *Preliminary Report of the Operations Research Society of Japan*, Autumn, 104–107, 1977 (in Japanese)
9. Matsui, M., Shingu, T. and Makabe, H., An Analysis of Conveyor-Serviced Production Station by Queueing Theory, *Journal of Japan Industrial Management Association*, 28(4), 375–386, 1978 (in Japanese)
10. Matsui, M. and Omori, T., Parallel SCM: A Make-or-Buy Chain Model and Integral Optimization, *Workshop on Inventory Control and Production Planning & Management 2002*, Tokyo Institute of Technology, Japan, 2002
11. Matsui, M. and Ichihara, S., A Game Approach to SCM: Modeling, Formulation and Integral Optimization, Journal of Japan Society of Logistics Systems, 4(1), 67–80, 2003 (in Japanese); *Proceedings of ICPR 2003*, Blacksburg, VA, 2003 (on CD-ROM)
12. Muth, E.J. and White, J.A., Conveyor Theory: A Survey, *American Institute of Industrial Engineers Transactions*, 11(4), 270–277, 1999
13. Reis, L.L., Brennan, J. and Crisp, Jr. R.M., A Markovian Analysis for Delay of Conveyor-Serviced Production Stations, *International Journal of Production Research*, 5, 201–211, 1967
14. Wild, R., *Mass-Production Management, The Design and Operation of Production Flow-Line Systems*, John Wiley, London, 1972

Part II
Stochastic Management Model

Chapter 3
Management Cycle Model

3.1 Process Cycle Model

3.1.1 Introduction

A typical type of management cycle model is well-known in respective manufacturing processes [5]. The three main manufacturing processes include continuous, point-wise, and flexible streams. There are many kinds of cyclic regularities in the world of manufacturing. The process cycle problem is related to the cyclic structure in time processes. This chapter reviews the process cycle problem in manufacturing based on a stochastic management approach [1].

3.1.2 Manufacturing Process Cycle

In [2], the three aspects of the manufacturing system are observed: structural, transformational, and procedural. These are regarded as the layout, process, and management systems, respectively, in a manufacturing system.

Based upon the procedural aspects of the system, the management system is considered as a management system of production. This constitutes the so-called management cycle: planning, implementation, and control.

The Table 3.1.1 shows the management cycle for assembly line, job shop, and lot production types. These cycles may be standardized as the plan, do, check, and action in PDCA.

3.1.3 Single Cycle Models

3.1.3.1 CAPD Type: CSPS Model

Many studies have focused on stochastic/queueing models of a manufacturing system. The CSPS model, job-shop model, and flexible model can be applied as the main control models of a production/queueing type.

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_4, © Springer Science+Business Media, LLC 2009

Table 3.1.1 Management process for manufacturing system

Production system	Environment (market)	Management process			Control method
	Forecasting (F)	Plan (P)	Do (D)	Check (C) & Act (A)	Plan/ operation
Assembly line	Forecasting (demand/ price)	Cycle time/station	Line balancing (fixed/removal items)	Pitch diagram	MRP system
		Heijunka (sequencing)	Goal chasing/ Coordination	Stop rate	JIT system
		Ikko-Nagashi	Flexible/ mixed	Overflow	Ordered-entry
Job shop	Order-selection (accepted price)	Periodic/ Dynamic	Job/flow scheduling (Sequencing/ dispatching)	Loading/ leveling (Gantt chart)	MRP system
		Project plan	Project scheduling	Critical path	PERT & CPM
		Lot size	Lot scheduling (Sequencing/ dispatching)	Progressive figure diagram	MRP system
Lot production	Forecasting (demand/ price)	Heijunka (sequencing)	Number of Kanban (Production-ordering/ withdrawal)	Jidoka	JIT system
		Ikko-nagashi	Flexible (Fixed/dynamic/ ordered-entry)	Blocking	Central server

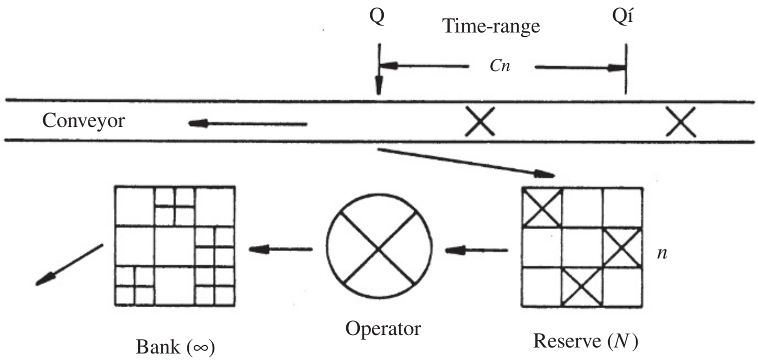


Fig. 3.1.1 Unloading station

A review of the CSPS model is seen in [6] and is as follows. The stations that take units from the conveyor for processing are called *unloading stations* (Fig. 3.1.1). An operator at the station performs productive activity cyclically, followed by operating policies.

The units that are suitable for utilization are called usables in Morris [7] and are followed by generally distributed interarrival times. For simplicity, Poisson arrivals are assumed as an introductory distribution. A reserve, in which usables are stored, has some capacity N, but a bank, in which the processed units are stored, is assumed to have infinite capacity for waiting.

The operator only looks ahead to the interval of the time-range (control variable) that is repeatedly set according to the operating policy. If an usable is there, he waits until it arrives at position Q (starting point of the time-range), and takes it just from the conveyor to reserve repeatedly (occurrence of delay). If there is no usable either in the time-range or in the reserve, he has to wait until the first usable arrives (occurrence of delay).

After the unloading activity is stopped subject to the rule, or a usable is not in the time-range but in reserve, the usable is taken out from the reserve and processed following the general distribution, $S(x)$. Then, the processed unit is stored in a bank, and the work cycle is finished. When the operator is busy (processing), the arrived usables overflow in (pass) the unloading station.

If the conveyor is a closed loop, the unloading station may be free to create the overflow (blocking), and, if it is an open loop, the station should be limited to allow the overflow (balking). The station may be controlled in accordance with the respective functions.

The CSPS model is a mathematical model for this unloading station in the M/G/m type mainly, and is the basic model that is common to the production station connected with the power conveyor. It has all the look-ahead times in ranges (control variables), and is here referred to as "*a queueing control model of a look-ahead type*."

This model may be regarded as the CAPD type. That is, this cycle consists of C (set time-range), A (remove usables), P (plan processing), and D (do processing).

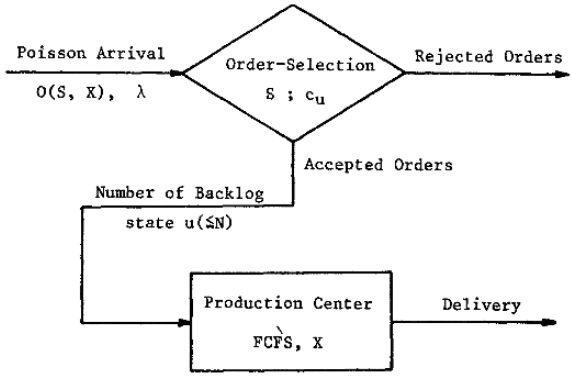


Fig. 3.1.2 Job-Shop Model

3.1.3.2 PDCA Type: JSPS Model

Now, consider the job shop (JSPS) that consists of job orders with marginal profits, a selection function with a backlog and a production center with fixed capacity (see Fig. 3.1.2) [4]. Now, suppose that the orders arrive according to a Poisson process with rate λ.

Also, the marginal profit, S, and processing time, X, of the orders are independent of the arrival process and assumed to be mutually independent, and they follow the distribution functions $G_1(s)$ and $G_2(x)$, $s,\ x \geq 0$, respectively.

The selection function with the backlog decides whether each arriving order is accepted or rejected under the constraint that the cumulated number of accepted orders is a finite or infinite integer, N. One realization of an order-selection process is seen in Fig. 3.1.3, in which the state of a system is given by the number of backlogs, $u\ (= 0,\ 1,\ 2, \ldots, N{-}1)$, at the instant after the ith order is processed.

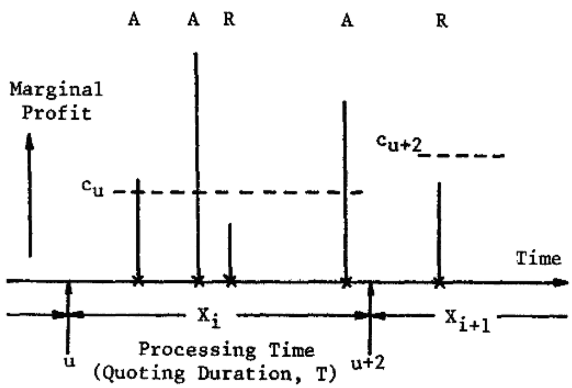


Fig. 3.1.3 An order-selection process: A (Accept) and R (Reject)

A selection criterion, c_u ($0 \leq c_u < \infty$), is a control variable depending on the amount of backlog, and an arriving order is accepted and rejected if $s \geq c_u$ and $s < c_u$, respectively.

The production center with fixed capacity processes one of the accepted orders under FCFS (First Come and First Service) discipline, and delivers the processed order to the customer.

The due date or time depends on both the service rate, μ, and the maximum backlog, N. The idle cost of the job shop is assumed to be $\beta(\geqq 0)$ per unit time.

This model is called "a queueing control model" of a selection type, and may be regarded as the PDCA type. This cycle consists of P (plan processing), D (process backlog), C (set criteria), and A (select job-set).

3.1.4 Single and Multiple Models

3.1.4.1 Multiple Cycle Models

For multiple stations, there are a series and parallel array of stations. For the latter, Fig. 3.1.4 shows the three types of multiple cyclic models. Table 3.1.2 gives a comparison of the three types by queueing theory.

Table 3.1.2 Parallel vs. Central

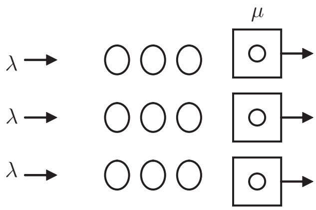
Cyclic type	Parallel	Central	
		Fork line	Flexible line
Waiting line	Shorter	Longer	Medium
Moving time	Shorter	Longer	Medium
Waiting time	shorter/longer	Average	Average
Profit	Individual	Social	

From Fig. 3.1.4 and Table 3.1.2, it is seen that the central type is better in social profit. The superiority of the flexible type is dependent on the efficiency of routing strategies as discussed later.

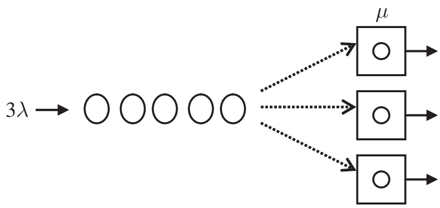
3.1.4.2 Optimal Cycle Policies

Two single cyclic models may be formulated by Markovian decision processes (MDP) [1]. In MDP, it is well known that the optimal policy exists in the stationary (cyclic) policies, and this can be seen in Table 3.1.3 for CSPS and job-shop models.

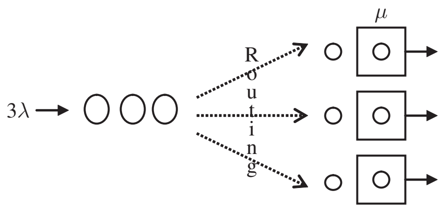
Also, the flexible line model is open, but its closed type is referred to as the Flexible Manufacturing System (FMS). There are the fixed, dynamic, ordered-entry, and hybrid routings, and these may be analyzed by the theory of closed queueing networks [3].



(a) Parallel type



(b) Central type: Fork line



(c) Central type: Flexible line

Fig. 3.1.4 Multiple cycle models

Table 3.1.3 Cyclic models: production/queueing control and operating policies

Model	Queue type	Objects	Optimal policy	Optimal property
CSPS	(Bus-type queus) Look-ahead control	Fixed item	Single unit policy	$d_1 \geq d_2 \geq \ldots$
		Removal item	Reserve-dependent and sequential range policy	$c_1 \leq c_2 \leq \ldots$
Job-Shop	(Channel-type queus) Order-selection control	Periodic type	Periodic selection policy	$c_1 \leq c_2 \leq \ldots$
		Dynamic type	Dynamic selection policy	$c_1 \leq c_2 \leq \ldots$
FMS	(Parallel-type queus) Flexible control	Machining	Fixed/ Dynamic routing	$\mu_1(q_1) \geq \mu_2(q_2) \geq \ldots$
		Machining/ Assembly	Ordered entry routing	$\mu_1 \geq \mu_2 \geq \ldots$

Remarks

In this chapter, the three-cyclic models in manufacturing were clarified from past research. Based on these models, the three main streams are studied and characterized as the respective queueing/strategic control systems in Parts III and IV by stochastic processes.

References

1. Derman, C., *Finite State Markovian Decision Processes*, Academic Press, NY, 1970
2. Hitomi, K., *Manufacturing Systems Engineering*, 2nd. ed., Taylor & Francis, London, 1996
3. Ma, J. and Matsui, M., Performance Evaluation of a Flexible Machining/Assembly System and Routing Comparisons, *International Journal of Production Research*, 40(7), 1713–1724, 2002
4. Matsui, M., Optimal Order-Selection Policies for a Job-Shop Production System, *International Journal of Production Research*, 23(1), 21–31, 1985
5. Matsui, M., Stochastic Management and Design of Manufacturing Systems: A Review, *Symposium on Performance Models for Information Communication Networks*, Sendai, Japan, 41–45, 2000 (in Japanese)
6. Matsui, M., CSPS Model: Look-Ahead Controls and Physics, *International Journal of Production Research*, 43(10), 2001–2025, 2005
7. Morris, W.T., *Analysis for Material Handling Management*, Richard D. Irwin, IL, 1962

3.2 Limit-Cycle Model

3.2.1 Introduction

A traditional approach to a management study is the so-called process management approach [4]. This approach is slightly different in terms of research areas of management. For example, it involves Planning-Organizing-Staffing-Direction-Control in general management [2], Planning-Implementation-Control in production management [8], and Plan-Do-Check-Act in quality management [11], and so on.

From the standpoint of stochastic management, we focus on the management cycle consisting of plan, do, check, and act phases. The management cycle is classified into two types of PDCA (Plan-Do-Check-Act) and CAPD (Check-Act-Plan-Do) cycles [3]. The PDCA and CAPD cycles are regarded here as the switching problem from plan ahead (look-ahead) to schedule backward (look-back) and from look-back to look-ahead, respectively, at the bottleneck. This chapter studies a mathematical modeling of this management cycle under lot processing.

This modeling is referred to as a type of $(t,\ k;\ T)$ switching policy [7]. Here, the switching policy has two processing rates (available speeds/capacities) and slow down or pick up speeds at the bottleneck, and the notations $t,\ k$, and T indicate the mean review period, control limit, and time span, respectively. An application to MRP (material requirements planning) [15]/APS (advanced planning and scheduling), and so on, is noted.

This chapter is organized as follows [6]. First, we present the cycle modeling by stochastic approach, corresponding to the trade-off problem of earliness and tardiness [1]. Next, the expected operating cost per unit time is given by mathematical formulation. Finally, we discuss the problem of optimal strategy numerically on the basis of a strategy map.

3.2.2 Management Cycle

3.2.2.1 Cycle Problem

Generally speaking, it is said that the purpose of management is to circulate the PDCA cycle in TQC. Both PDCA and CAPD cycles are involved in the management

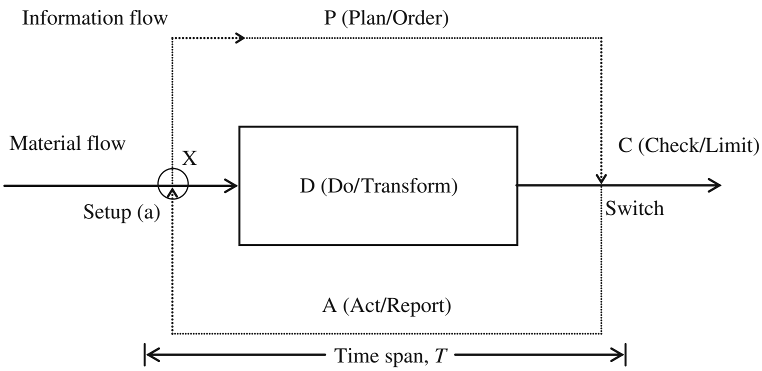
M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_5, © Springer Science+Business Media, LLC 2009

Table 3.2.1 Management cycle: PDCA versus CAPD

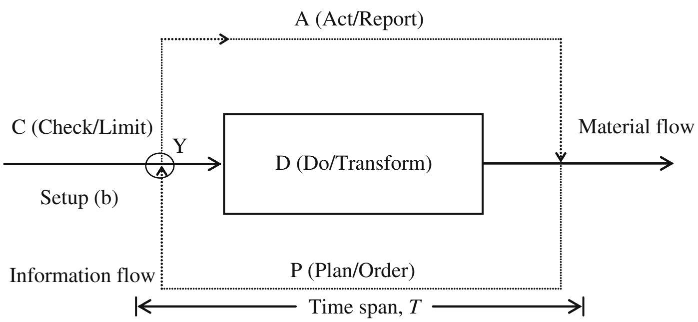
Types	PDCA	CAPD
Approach	Design approach	Improvement approach
System type	Open type	Closed type
Planning	Future planning	Action after fact
Processes	Goal seeking	Problem solving
Trigger	Push type	Pull type

processes. Two types of management cycles are compared and distinguished from five aspects in Table 3.2.1. Recently, the focus of the CAPD cycle has been on these kinds of pull types as the KANBAN system at Toyota.

The management recycling here is represented by the management cycle with the setup penalty as shown in Fig. 3.2.1. Then, management recycling becomes both PDCA and CAPD cycles, starting from X and Y, respectively.



(a) PDCA cycle



(b) CAPD cycle

Fig. 3.2.1 Management recycling

3.2.2.2 Focused Problem

The time bucket length and lot-size/splitting problems are involved in the production seat systems [14] and material requirements planning (MRP) systems [15]. These problems are similar to those of lot processing and the time span problem discussed in this book, and are illustrated in Fig. 3.2.2. A traditional approach is the usual DP-manner.

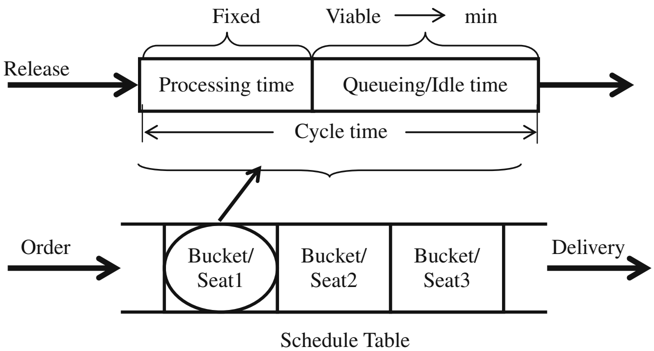


Fig. 3.2.2 APS model: single center case

However, there is no switching control during the time bucket (time span) [9]. Under the time span, there is the trade-off problem of earliness and tardiness in the MRP/APS system. This subproblem corresponds to the second stage in the two-stage design method [5] (Fig. 3.2.3).

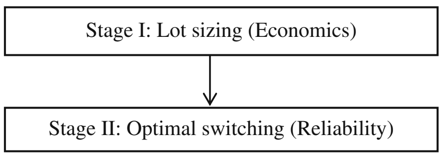


Fig. 3.2.3 APS problem: Two-stage design method

3.2.3 Mathematical Formulation

3.2.3.1 $(t, k; T)$-Switching Policy

The cycles of management recycling discussed here involve switching problems of look-ahead and look-back at bottlenecks. For the PDCA and CAPD cycles shown in Fig. 3.2.1, the corresponding recycling representations are shown as respective types (a) and (b) in Fig. 3.2.4. The look-ahead cycle (a) starts from the origin, 0, while that of the look-back cycle (b) starts from due time, T, inversely.

Then, the following assumptions are made as shown in Fig. 3.2.4: Any t and k indicate the timing of checks, cycles are infinitely repetitive, and setups are

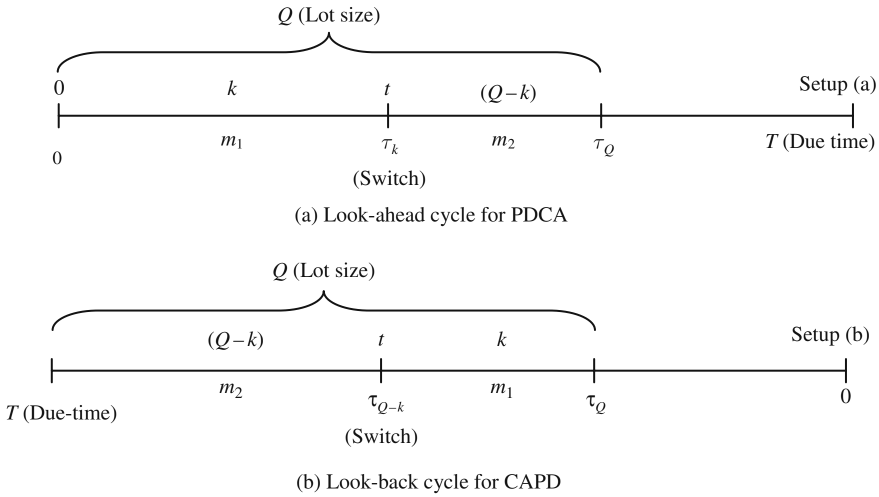


Fig. 3.2.4 $(t,\ k;\ T)$ switching policy in management recycling

completely renewed. The problem of management recycling then becomes a type of $(t,\ k;\ T)$ switching policy, and decides the control limits, t and k, under the time span (due time), T.

Now, suppose processing a lot of Q using the two available speeds, m_1 and m_2. For Fig. 3.2.4, the following notations are used

Q: Target (e.g, lot size)
T: Time span (due time/date)
t: Review or warm-up period for processes from start, if $k = 0$ in type (a), or $k = Q$ in type (b)
k: Number of pieces in processing Type 1 (control limit)
m_1: Mean processing time of Type 1 (lower speed/capacity)
m_2: Mean processing time of Type 2 (upper speed/capacity) $(m_1 > m_2)$
τ_k: Completion time of k pieces in type (a)
τ_{Q-k}: Completion time of $(Q - k)$ pieces in type (b)

$(m_1{>}m_2)$, during the finite due time, T. The $(t,\ k;\ T)$-switching policy is explained for the look-ahead (look-back) cycle as follows: Start at the mean processing time m_1 (m_2), and change the mean processing time m_2 (m_1) when k (or $Q - k$) pieces have been processed. Especially, if $k = 0$ (Q), the manager may decide the optimal review period, t^*, and use m_2 (m_1) only after time t^*.

If the cycle does not end during the finite due time, T, the processes are reset at the end of the due time. Also, if the cycle finishes during the finite due time, T, a buffer problem occurs. Here, the buffer problem is accompanied by an inventory-holding or earliness penalty. The type of switching policies are classified in Table 3.2.2.

Table 3.2.2 Four types of switching policies

	Switching policy ($t = 0$)	No switching ($t > 0;\ k = 0(a)$, or Q (b))
(a) Look-ahead cycle	Switch $(0,\ k;\ T)$	Only upper speed (use m_2 after t)
(b) Look-back cycle	Switch $(0,\ Q - k;\ T)$	Only lower speed (use m_1 after t)

This problem of switching policies is especially seen in material requirements planning (MRP), in which the due time corresponds to the time buckets. The time bucket/leadtime is fixed at MRP, but is variable in practical situations, such as APS. Also, the operating problem during time buckets is vague and should be discussed further.

3.2.3.2 Objective Function

In this section, we introduce a cost function as the objective of the cycle model. Suppose that the processing times are random variables and cycles are renewed under complete setup. The total expected operating cost per unit produced [10], *ECp*, is given by

$$EC_p = \frac{\text{E[cost per cycle]}}{\text{E[pieces per cycle]}} \tag{3.2.1}$$

In Eq. (3.2.1), the denominator is obtained by $E[N(T) \cdot I_Q(T)]$, in which the random variable $N(T)$ is the number of renewals up to time T, and the index function $I_Q(T)$ is $I_Q(T) = 1$ if $N(T) \leq Q$ and $I_Q(T) = 0$ if $N(T) > Q$. Then, the problem of minimizing the Eq. (3.2.1) is called the optimal switching problem, and is discussed below.

The cycle problem in lot processing is outlined in Fig. 3.2.5, where $\mu_i,\ i = 1$ and 2, are the mean processing rates of type i ($\mu_1 < \mu_2$). Then, the mean operating cycle cost is given by a newsboy-like formulation such as the trade-off between earliness and tardiness penalties.

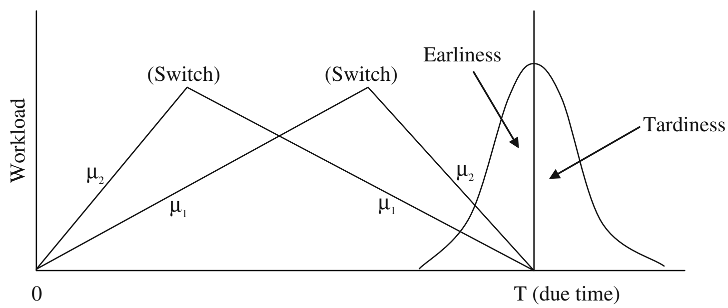


Fig. 3.2.5 Two service rates and penalties

Now, let us represent the completion time of i pieces by $\tau_{\mathrm{i}},\ i = 1, 2, \ldots,\ Q$. Also, let us represent the review cost, buffer cost, reset cost (risk) of the due date, holding cost of the due time, processing cost of Type 1, and processing cost of Type 2, by *A, B, D, H, P*, and *R*, respectively.

Then, the respective cost functions are given as follows:

$$A = \begin{cases} c_1 t, & \text{if } k = 0 \text{ in type (a), or } Q \text{ in type } (b) \\ 0, & \text{if } k \neq 0 \text{ or } Q \end{cases} \qquad \text{(Review cost)} \tag{3.2.2}$$

$$B = \begin{cases} c_2 E[\sum_{i=1}^{Q} (T - \tau_i)^+], & \text{Case with no-work-in-process (semi-WIP)} \quad (3.2.3a) \\ & \text{(Buffer cost)} \\ c_2 E[\min(\tau_Q, T)/2 + \sum_{i=1}^{Q} (T - \tau_i)^+], & \text{Case with work-in-process} \end{cases}$$

$$\text{(WIP)} \tag{3.2.3b}$$

$$D = c_3 \Pr(\tau_Q > T) \qquad \text{(Reset cost)} \tag{3.2.4}$$

$$H = c_4 T \qquad \text{(Holding cost)} \tag{3.2.5}$$

$$P = c_5 \mathrm{E}[\min(\tau_k, T)] \qquad \text{(Processing-1 cost)} \tag{3.2.6}$$

$$R = c_6 \mathrm{E}[(T - \tau_k)^+ - (T - \tau_Q)^+] \qquad \text{(Processing-2 cost)} \tag{3.2.7}$$

where $(\mathrm{X}\text{–a})^+$ is max(X–a, 0), and the parameters $c_1 \sim c_6$ are cost coefficients. The case of an earliness penalty may also be considered in the place of the inventory penalty in Eq. (3.2.3).

Thus, the mean operating cycle cost is given by the sum of each cost; that is, $A + B + D + H + P + R$. The minimization of this cost relates to the due-time problem of minimizing the sum of inventory and setup penalties. Alternatively, it is noted that the $B+H,\ P,\ A$ and $D+R$ correspond to the planning, doing, checking, and acting costs, respectively.

3.2.4 Numerical Considerations

3.2.4.1 A Numerical Example

In this section, we give a numerical example of exponential case using Mathematica. Some parameters are set as follows:

$Q = 3,\ T = 5$ or variable;
$m_1 = 2,\ m_2 = 1;$
$c_1 = 0.5,\ c_4 = 1,\ c_5 = 2,\ c_6 = 8;$
$c_2 = 2.5 \sim 25.0,\ c_3 = 0.25 \sim 2.50.$

Table 3.2.3 Numerical results for $(t,\ k;\ 5)$ policy $A \equiv 0,\ c_2 = 1.0,\ c_3 = 15.0$

(i) Case with semi-WIP							
k	B	D	H	P	R	E[N(T)]	ECp
0	3.262	0.661	1.768	0.000	8.000	2.828	13.691
1	2.849	1.656	2.011	1.477	5.046	2.486	13.039
2	2.737	2.827	2.259	2.947	2.107	2.213	12.876
3	2.746	3.909	2.396	4.000	0.000	2.087	13.050
(ii) Case with WIP							
k	B	D	H	P	R	E[N(T)]	ECp
0	3.762	0.661	1.768	0.000	8.000	2.828	14.191
1	3.533	1.656	2.011	1.477	5.046	2.486	13.723
2	3.606	2.827	2.259	2.947	2.107	2.213	13.745
3	3.746	3.909	2.396	4.000	0.000	2.087	14.050

Generally, there is the work-in-process (WIP) in lot production. Table 3.2.3 shows a numerical result for $(t,\ k;\ 5)$ policy in the case of not only semi-WIP, but also WIP. From Table 3.2.3, it is seen that an optimal control limit, k^*, exists.

Figure 3.2.6 shows the due time versus cycle cost in the semi-WIP case. From Fig. 3.2.6, it is found that there is an optimal due time under variables k and T.

3.2.4.2 Optimal Strategy

Using numerical considerations, we consider the structure of an optimal switching strategy. Tables 3.2.4 $\sim$ 3.2.7 show the strategic maps for the cost coefficients of buffer $c_2 = 2.5 \sim 25.0$, and the cost coefficients of setup $c_3 = 0.25 \sim 2.50$. Tables 3.2.4 and 3.2.5, and Tables 3.2.6 and 3.2.7 correspond to cases where the due time, T, is given and is variable, respectively.

From Tables 3.2.4–3.2.7, it is seen that the optimal strategy is different in terms of not only cost parameters, but also in due time, and so forth. The look-ahead cycle is better in the case of smaller c_2 and c_3 to larger c_2 and c_3. On the other

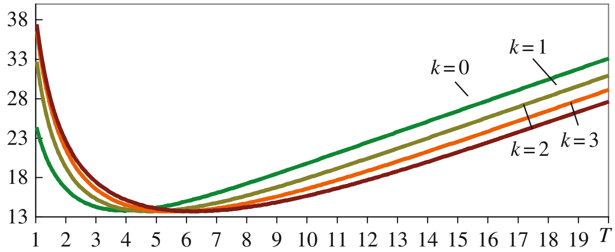


Fig. 3.2.6 Due Time versus cycle cost: Semi-WIP case

Table 3.2.4 A map of optimal strategy: $T = 5$, Case with semi-WIP

c3/ c2		0.250	0.500	0.750	1.000	1.250	1.500	[illegible]	[illegible]	[illegible]	[illegible]
2.5	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,4,3)	[illegible]	[illegible]	[illegible]	[illegible]
	ECp	[illegible]	[illegible]	[illegible]	[illegible]	10.479	11.130	[illegible]	[illegible]	[illegible]	[illegible]
5.0	(t,k)	[illegible]	[illegible]	[illegible]	[illegible]	(0,0,3)	(0,0,3)	(0,2,3)	(0,4,3)	(0,7,3)	(0,9,3)
	ECp	8.385	9.072	9.758	10.444	11.131	11.817	12.495	13.131	13.728	14.294
7.5	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,3,3)	(0,5,3)
	ECp	9.037	9.723	10.410	11.096	11.782	12.469	13.155	13.841	14.504	15.130
10.0	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,1,3)
	ECp	9.688	10.375	11.061	11.747	12.434	13.120	13.807	14.493	15.179	15.859
12.5	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,2)	(0,0,2)	(0,0,2)
	ECp	10.340	11.026	11.713	12.399	13.085	[illegible]	[illegible]	[illegible]	[illegible]	16.511
15.0	(t,k)	(0,0,2)	(0,0,2)	(0,0,2)	(0,0,2)	(0,0,2)	[illegible]	[illegible]	[illegible]	[illegible]	(0,0,2)
	ECp	10.823	11.508	12.192	12.876	13.561	14.245	14.929	15.614	16.298	16.982
17.5	(t,k)	(0,0,1)	(0,0,1)	(0,0,1)	(0,0,1)	(0,0,1)	(0,0,2)	(0,0,2)	(0,0,2)	(0,0,2)	(0,0,2)
	ECp	11.178	11.890	12.603	13.315	14.027	14.716	15.401	16.085	16.769	17.454
20.0	(t,k)	(0,0,1)	(0,0,1)	(0,0,1)	(0,0,1)	[illegible]	[illegible]	[illegible]	[illegible]	(0,0,1)	(0,0,1)
	ECp	11.454	12.166	12.879	13.591	[illegible]	[illegible]	[illegible]	[illegible]	17.152	17.864
22.5	(t,k)	(0,0,0)	(0,0,0)	(0,0,1)	(0,0,1)	[illegible]	[illegible]	[illegible]	[illegible]	(0,0,1)	(0,0,1)
	ECp	[illegible]	[illegible]	[illegible]	[illegible]	14.579	15.291	16.003	16.715	17.428	18.140
25.0	(t,k)	[illegible]	[illegible]	[illegible]	[illegible]	(0,0,1)	(0,0,1)	(0,0,1)	(0,0,1)	(0,0,1)	(0,0,1)
	ECp	[illegible]	[illegible]	[illegible]	[illegible]	14.855	15.567	16.279	16.991	17.704	18.416

Only lower speed
Look-ahead cycle
Look-ahead cycle
Look-ahead cycle (k*=1)
Look-back cycle (k*=0)

Table 3.2.5 A map of optimal strategy: $T = 5$, Case with WIP

c3/ c2		0.250	0.500	0.750	1.000	1.250	1.500	[illegible]	[illegible]	[illegible]	[illegible]
2.5	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,4,3)	[illegible]	[illegible]	[illegible]	[illegible]
	ECp	7.984	8.920	9.857	10.793	11.729	12.630	[illegible]	[illegible]	[illegible]	[illegible]
5.0	(t,k)	[illegible]	[illegible]	[illegible]	[illegible]	(0,0,3)	(0,0,3)	(0,2,3)	(0,4,3)	(0,7,3)	(0,9,3)
	ECp	[illegible]	[illegible]	[illegible]	[illegible]	12.381	13.317	14.245	15.131	15.978	16.794
7.5	(t,k)	[illegible]	[illegible]	[illegible]	[illegible]	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,3,3)	(2,0,0)
	ECp	9.287	10.223	11.160	12.096	13.032	13.969	14.905	15.841	16.754	17.455
10.0	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	[illegible]	[illegible]	[illegible]	[illegible]	(1,7,0)	(1,8,0)
	ECp	9.938	10.875	11.811	12.747	[illegible]	[illegible]	[illegible]	[illegible]	17.301	17.892
12.5	(t,k)	(0,0,2)	(0,0,2)	(0,0,2)	(0,0,2)	[illegible]	[illegible]	[illegible]	[illegible]	(1,5,0)	(1,7,0)
	ECp	10.570	11.471	12.373	13.274	14.176	15.077	15.979	16.880	17.650	18.273
15.0	(t,k)	(0,0,2)	(0,0,2)	(0,0,1)	[illegible]	[illegible]	[illegible]	[illegible]	(0,0,1)	(1,4,0)	(1,5,0)
	ECp	11.041	11.942	12.840	[illegible]	[illegible]	[illegible]	[illegible]	17.256	17.958	18.609
17.5	(t,k)	(0,0,1)	(0,0,1)	(0,0,1)	[illegible]	[illegible]	[illegible]	[illegible]	(1,1,0)	(1,2,0)	(1,4,0)
	ECp	11.349	12.233	13.116	13.999	14.882	15.766	16.649	17.527	18.234	18.914
20.0	(t,k)	(0,0,0)	(0,0,1)	(0,0,1)	(0,0,1)	(0,0,1)	(0,0,1)	(0,0,1)	(0,9,0)	(1,1,0)	(1,2,0)
	ECp	11.590	12.509	13.392	14.275	15.158	16.042	16.925	17.752	18.484	19.189
22.5	(t,k)	[illegible]	[illegible]	[illegible]	[illegible]	(0,0,1)	(0,0,1)	(0,6,0)	(0,8,0)	(1,0,0)	(1,1,0)
	ECp	[illegible]	[illegible]	[illegible]	[illegible]	15.434	16.318	[illegible]	[illegible]	[illegible]	[illegible]
25.0	(t,k)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,3,0)	[illegible]	[illegible]	[illegible]	[illegible]
	ECp	11.810	12.751	13.691	14.632	15.572	16.477	17.331	18.145	18.925	19.673

Only lower speed
Look-ahead cycle
Look-ahead cycle
Look-ahead cycle
Look-back cycle
Look-ahead cycle

hand, the look-back cycle is better in the case of smaller c_2 and larger c_3 or larger c_2 and smaller c_3. These look-ahead/back strategies are summarized and drawn in Figs. 3.2.7 and 3.2.8.

Also, the switching strategy (i.e., order launching and expediting in [15]) would be practical and better for some cases with a fixed due time (Tables 3.2.4 and 3.2.5). On the other hand, it is better to use the type $t = 0$ and no switching with a variable due time (Tables 3.2.6 and 3.2.7). That is, the look-ahead control with m_1 is only

Table 3.2.6 A map of optimal strategy: T-variable, Case with Semi-WIP

c3/ c2		0.250	0.500	0.750	1.000	1.250	1.500	1.750	2.000	2.250	2.500
2.5	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)
	T	4.4	3.7	3.3	3.0	2.7	2.5	2.3	2.2	2.1	2.0
	ECp	7.708	8.249	8.708	9.113	9.476	9.809	10.118	10.406	10.678	10.935
5.0	(t,k)	[illegible]	[illegible]	[illegible]	[illegible]	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)
	T	[illegible]	[illegible]	[illegible]	[illegible]	3.7	3.5	3.2	3.1	2.9	2.8
	ECp	8.333	9.072	9.706	10.270	10.781	11.251	11.688	12.097	12.482	12.849
7.5	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	[illegible]	[illegible]	[illegible]
	T	6.6	5.8	5.2	4.8	4.4	4.1	3.9	[illegible]	[illegible]	[illegible]
	ECp	8.760	9.640	10.403	11.085	11.705	12.277	12.811	[illegible]	[illegible]	[illegible]
10.0	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,2)	(0,0,2)	(0,0,1)	(0,0,1)
	T	7.2	6.4	5.8	5.3	5.0	4.7	4.0	3.9	3.2	3.1
	ECp	9.088	10.081	10.947	11.724	12.434	13.090	13.663	14.181	14.656	15.065
12.5	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,2)	(0,0,2)	[illegible]	[illegible]	[illegible]
	T	7.8	6.9	6.3	5.8	5.4	4.6	4.4	[illegible]	[illegible]	[illegible]
	ECp	9.355	10.442	11.396	12.254	13.040	13.725	14.329	[illegible]	[illegible]	[illegible]
15.0	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,2)	(0,0,2)	(0,0,1)	(0,0,1)	(0,0,0)	(0,0,0)
	T	8.2	7.3	6.7	6.2	5.2	4.9	4.1	3.9	3.1	3.0
	ECp	9.581	10.750	11.779	12.708	13.549	14.244	14.824	15.363	15.843	16.280
17.5	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,2)	(0,0,1)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
	T	8.6	7.7	7.0	6.5	5.5	4.5	3.5	3.4	3.3	3.2
	ECp	9.776	11.017	12.113	13.106	13.954	14.639	15.236	15.747	16.235	16.704
20.0	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,1)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
	T	8.9	8.0	7.4	6.9	4.9	3.9	3.7	3.6	3.4	3.3
	ECp	9.949	11.254	12.411	13.460	14.301	14.958	15.526	16.068	16.587	17.082
22.5	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,2)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
	T	9.2	8.3	7.6	6.3	4.2	4.0	[illegible]	[illegible]	[illegible]	[illegible]
	ECp	10.103	11.467	12.679	13.758	14.561	15.191	[illegible]	[illegible]	[illegible]	[illegible]
25.0	(t,k)	(0,0,3)	(0,0,3)	(0,0,3)	(0,0,2)	(0,0,0)	(0,0,0)	[illegible]	[illegible]	[illegible]	[illegible]
	T	9.5	8.6	7.9	6.5	4.3	4.1	4.0	3.8	3.7	3.6
	ECp	10.243	11.661	12.922	14.016	14.748	15.405	16.026	16.620	17.187	17.731

Look-ahead cycle

Look-ahead cycle

Look-ahead cycle

Look-back cycle (k*=0)

better in the case of smaller c_2 and larger c_3, or larger c_2 and smaller c_3, while the look-back control with m_2 is only better in the case of larger c_2 and c_3. Thus, the problem of no switching [16] is dependent on due time.

Finally, it is seen that the case of variable due time is better than that of fixed due time in terms of cost comparison. These results would be applicable to the variable problem of time buckets/lead times in production scheduling, such as MRP/APS, production seat [15, 16, etc.].

Remarks

This chapter introduces a management cycle model from the viewpoint of management processes, and discusses the optimal strategy for the $(t,\ k;\ T)$ switching policy. In addition, application to production scheduling, such as MRP/APS, production seat, and so on, is mentioned.

This model is also valuable for the research of push/pull systems [12] in the trigger type. Other modelings should be directed to the multi-period problem [16] in the limit-cycle, the control-chart version [13 etc.] in process control. Also, further research regarding modeling of the management cycle will be important for studying the management process approach.

Table 3.2.7 A map of optimal strategy: T-variable, Case with WIP

c3/ c2		0.250	0.500	0.750	1.000	1.250	[illegible]	[illegible]	[illegible]	[illegible]	2.500
2.5	(t,k)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.3)	[illegible]	[illegible]	[illegible]	[illegible]	(0.0.2)
	T	4.4	3.7	3.3	3.0	2.7	2.5	2.3	2.2	2.1	1.9
	ECp	7.958	8.749	9.458	10.113	10.726	11.309	11.868	12.406	12.928	13.407
5.0	(t,k)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.2)	(0.0.1)	(0.0.1)	(0.0.0)
	T	5.7	5.0	4.4	4.0	3.7	3.5	3.0	2.6	2.5	1.9
	ECp	8.583	9.572	10.456	11.270	12.031	12.751	13.404	13.986	14.482	14.923
7.5	(t,k)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.1)	(0.0.0)	(0.0.0)	(0.0.0)
	T	[illegible]	[illegible]	[illegible]	4.8	4.4	3.8	3.2	2.5	2.4	2.3
	ECp	[illegible]	[illegible]	[illegible]	[illegible]	12.955	[illegible]	[illegible]	[illegible]	[illegible]	15.797
10.0	(t,k)	[illegible]	[illegible]	[illegible]	[illegible]	(0.0.3)	[illegible]	[illegible]	[illegible]	[illegible]	(0.0.0)
	T	7.2	6.4	5.8	5.3	4.5	[illegible]	[illegible]	[illegible]	[illegible]	2.6
	ECp	9.338	10.581	11.697	12.724	13.634	14.360	14.962	15.487	15.993	16.481
12.5	(t,k)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.1)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)
	T	7.8	6.9	6.3	5.8	4.2	3.3	3.2	3.0	2.9	2.8
	ECp	9.605	10.942	12.146	13.254	14.134	14.813	15.406	15.973	16.519	17.046
15.0	(t,k)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.2)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)
	T	8.2	7.3	6.7	5.5	3.7	3.5	3.4	3.2	3.1	3.0
	ECp	9.831	11.250	12.529	13.668	14.491	15.152	15.782	16.387	16.968	17.530
17.5	(t,k)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.1)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)
	T	8.6	7.7	7.0	5.0	3.9	3.7	3.5	3.4	3.3	3.2
	ECp	10.026	11.517	12.863	13.999	14.751	15.446	16.111	16.747	17.360	17.954
20.0	(t,k)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)
	T	8.9	8.0	7.4	4.3	4.0	3.9	3.7	3.6	3.4	3.3
	ECp	10.199	11.754	13.161	14.215	14.981	15.708	16.401	17.068	17.712	18.332
22.5	(t,k)	(0.0.3)	(0.0.3)	(0.0.3)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)	(0.0.0)
	T	9.2	8.3	7.6	4.4	4.2	4.0	3.9	3.7	3.6	3.5
	ECp	10.353	11.967	13.429	14.391	15.186	15.941	16.665	17.356	18.025	18.672
25.0	(t,k)	(0.0.3)	(0.0.3)	(0.0.2)	(0.0.0)	(0.0.0)	(0.0.0)	[illegible]	[illegible]	[illegible]	[illegible]
	T	9.5	8.6	7.0	4.5	4.3	4.1	[illegible]	[illegible]	[illegible]	3.6
	ECp	10.493	12.161	13.663	14.552	15.373	16.155	16.901	17.620	18.312	18.981

Look-ahead cycle

Look-ahead cycle

Look-ahead cycle

Look-back cycle (k*=0)

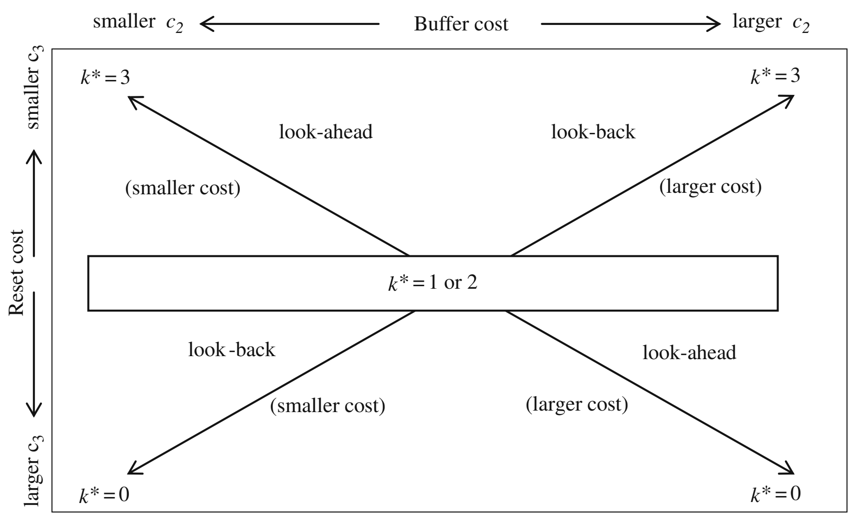


Fig. 3.2.7 Look-ahead/back strategy: Case of $T = 5$

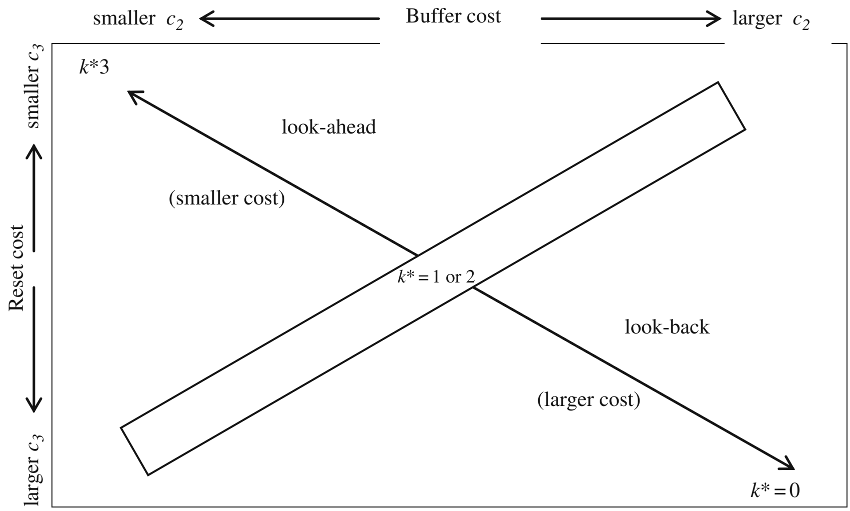


Fig. 3.2.8 Look-ahead/back strategy: T-variable case

References

1. Baker, K.R. and Scudder, G.D., Sequencing with Earliness and Tardiness Penalties: A Review, *Operations Research*, 38, 22–36, 1990
2. Fayol, H., *Administration industrielle et Générale; General and Industrial Management*, Pitman Publishing, NY, 1949
3. Ikegawa, T., I Have Learned from TQC, *Statistical Quality Control*, 36(9), 6–12, 1985(in Japanese)
4. Koontz, H. and O'Donnell, C., *Principles of Management: An Analysis of Managerial Functions*, McGraw-Hill, NY, 1959
5. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
6. Matsui, M., A Management Cycle Model: Switching Control under Lot Processing and Time Span, *Journal of Japan Industrial Management Association*, 56(4), 256–264, 2005
7. Matsui, M. and Yamaguchi, T., A Management Cycle Model: Type of $(t,\ k;\ T)$-Switching Policy, *Proceedings of 2nd Asia-Pacific Conference on Industrial Engineering and Management Systems (APIEMS)*, Kanazawa, Japan, 381–384, 1999
8. Montgomery, D.C. and Berry, W.L., *Production Planning, Scheduling, and Inventory Control: Concepts, Techniques, and Systems*, AIIE-PP&C, Georgia, 1974
9. Riezebos, J., Time Bucket Length and Lot-Splitting Approach, *International Journal of Production Research*, 42(12), 2325–2338, 2004
10. Ross, S.M., *Applied Probability Models with Optimization Applications*, Holden-Day, San Francisco, 1970
11. Shewhart, W.A., *Economic Control of quality of manufacturing Product*, Van Nostrand, New Jersey, 1931
12. Spearman, M.L. and Zazanis, M.A., Push and Pull Production Systems: Issues and Comparisons, *Operations Research*, 40(3), 521–532, 1992
13. Sun, J., Tsubaki, M. and Matsui, M., A Study of the PDCA and CAPD Economic Designs of the $\bar{x}$ Control Chart, *Industrial Engineering and Management Systems An International Journal*, 6(1), 11–21, 2007

14. Verzijl, J.J., *Production Planning and Information Systems*, Macmillan, London, pp. 16–17, 1976
15. Wight, O.W., *Production and Inventory Management in the Computer Age*, Van Nostrand, NY, 1974
16. Yamamoto, H. and Matsui, M., A Basic Study on a Limit-Cycle Problem with Multi-Periods and the Optimal Assignment Problem, *Journal of Japan Industrial Management Association*, 57(1), 23–31, 2006 (in Japanese)

Chapter 4
Management with Sales Risk

4.1 Management Game/Strategic View

4.1.1 Introduction

In modern enterprises, there are market (outside) and operational (inside) risks for management. The main risk factors of a market are price, quantity, quality, and speed of products. Most importantly, recent market risks require a flexible or a higher speed for enterprises or a shorter lead time for prompt delivery. However, a shorter lead time (reliability) may create a trade-off for a lower cost (economics). Our concern is with a management design methods, which will provide a shorter lead time for profit maximization under risks.

This chapter presents a new management view of enterprises under uncertainty, gives a design or decision-making method for the management using MGM (management game module), and discusses this module from the point of view of management strategy [13]. The theory of constraints (TOC) [7] is a non-cooperative improvement approach, but MGM is a cooperative design approach and superior to TOC in addressing collaboration.

The enterprise is assumed to consist of the sales center pursuing a maximum expected price with respect to demand speed, and the production center pursuing a minimum operating cost with respect to processing speed [10, 11]. The views of these two centers are developed in a random manner incorporating risks, and the operating cost is assumed to be the expected sum of inventory cost, busy cost, and idle cost. A relationship of marketing and manufacturing originates in Taylor's system [16], as pointed out in [4, 6] below, and is listed in [5].

4.1.2 Management View and Module

4.1.2.1 Assumptions and Notation

We propose a management view that gives an optimal relationship between economics and reliability. Suppose enterprises consist of sales and production centers (see Fig. 2.1.3). The sales center would typically pursue the maximization of

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_6,

expected sale price, and the production center would typically pursue the minimization of operating costs.

For this problem, which involves two centers, the goal of the enterprise is to maximize the difference between reward and cost under a shorter lead time by the collaboration of the two centers. The difference is regarded here as follows:

$$\text{(Marginal profit)} = \text{(Sales price)} - \text{(Variable cost)} \tag{4.1.1}$$

$$\longrightarrow \begin{cases} \text{(Market price)} - \text{(Operating cost)}, \\ \qquad\qquad \text{Make-to-stock type} \\ \text{(Accepted price)} - \text{(Operating cost)}, \\ \qquad\qquad \text{Make-to-order type} \end{cases} \tag{4.1.2}$$

The following assumption is generally added. At arrivals, all the orders/customers are specified by $O\,(p, m)$, in sales price p and processing time, m. When the market speed, d, becomes faster, the sales reward and thus marginal profit become larger. In practice, the market speed would have at least a constraint by pricing, p, and is denoted by $d\,(p)$. The production center performs the productive activity at the processing speed, m.

The view of the two centers is detailed in Fig. 4.1.1, and it is called the management game module (MGM). The following notation is listed and used below.

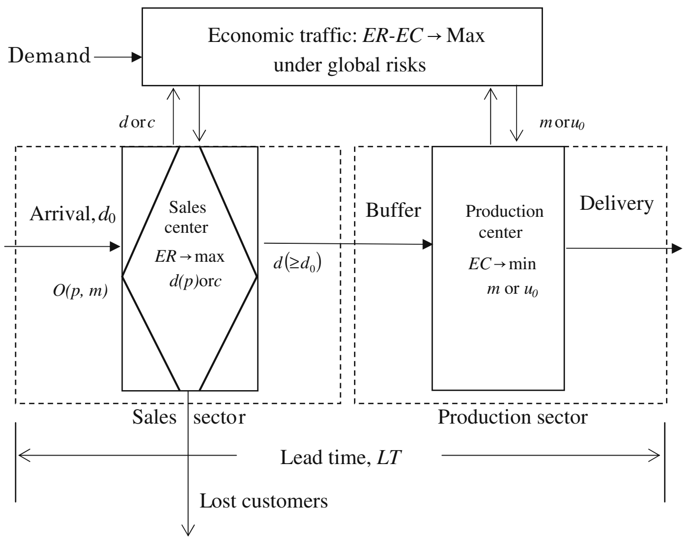


Fig. 4.1.1 Framework for management module

p: Sales price of products (items)
ER: Mean sales reward per unit time
EC: Mean operating cost per unit time
$EN(= ER - EC)$: Net reward (marginal profit)
ET: Mean lead time
PS: Pricing setting

MI: Mutual information (constraints)
λ: Mean arrival rate
μ: Mean processing rate
$d\left(= {}^{1}/_{\lambda}\right)$: Mean interarrival time
$m\left(= {}^{1}/_{\mu}\right)$: Mean processing time

$\rho\left(= {}^{m}/_{d}\right)$: Traffic intensity
Q: Queueing amount
B: Busy probability
I: Idle probability

$\alpha_i'(i = 1,\ 2,\ 3)$: Cost coefficients
a: Demand corresponding to a zero price
b: Price sensitivity of demand
c: Order-selection criterion
u_0: Switchover control level

4.1.2.2 Game/Strategic Approach

The relationship between the sales and production centers can be classified into domination, compromise, and integration in Table 2.12. Table 4.1.1 shows a classification of integration and a relational 2-centered view in a broad sense.

In Table 4.1.1, the notations A and B are a pair-set, $H\,(X)$ or $H\,(Y)$ is a negative entropy, indicating the degree of uncertainty, $I\,(X, Y)$ is mutual information, indicating the degree of constraints, and $H(X \otimes Y)$ is joint information by information theory [2, 14]. From Table 4.1.1, it is noted that the bottleneck concept is a special case of a 2-centered view.

The problem of two centers is characterized as a pair-matrix game form. This game form is a generalization of a dual-matrix game form [15], and thus, the proposed form is specifically called the management game module (MGM) in the sense of a pair-game form with constraints.

Now, let us define the pair-matrix in Fig. 4.1.2. This matrix consists of the pair subelements of mean reward and mean cost, $(ER,\ EC)$ in each (d, m) element. The relationship of pair- and dual-matrices is $(ER,\ EC)$ versus $(ER, -EC)$ in each element. Then, the pair-type game means the pair-type cooperative or

Table 4.1.1 Integration and Two-centered view

Integration	Demand/ supply	Sharing	Set relation	Constraints	2-centered view
Domination	Vertical	Occupancy	A ⊂ B or B ⊂ A	H(X) or H(Y)	Bottleneck (TOC)
Compromise	Trade	Sharing	A ∩ B	I(X,Y)	Strategic/ gaming
Integration	Collaborative	Sharing/ unification	A ∪ B	H(X ⊗ Y)*	MGM

* I(X, Y) = H(X) + H(Y) − H(X ⊗ Y)

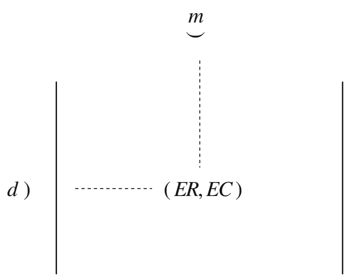


Fig. 4.1.2 Pair matrix concept

Table 4.1.2 TOC versus MGM

Item \ Module	TOC	MGM
Approach	Improvement	Collaborative Design
Goal	Contribution Margin, or ROA (per unit time)	Marginal Profit (per unit time)
Bottleneck (market/production)	Deterministic	Gaming
Lead time	Variable	Standerd, Variable

non-cooperative game of maximizing the throughput, that is, the marginal profit between the demand price and the operating cost, under a bottleneck of demand (market)/supply (production) (see Table 4.1.1).

The concept of TOC is different from the MGM in regard to two points (see Table 4.1.2), and both of these differences originated from the research around 1980. TOC is notably a noncooperative improvement approach, but the MGM is a cooperative design approach. Also, for the bottleneck problem, TOC is a deterministic approach in risks, but MGM is a gaming approach with the avoidance or management of risks.

4.1.3 Management Design Method

4.1.3.1 Economic Traffic

For the two centers, the economic objectives, *ER* and *EC*, are considered here. The objective for the sales center, *ER*, is generally given by

$$ER = \text{(mean sales reward between arrivals)/ (mean arrival time)} \tag{4.1.3}$$

The operating cost is regarded as the sum of the queueing (inventory) cost, busy cost, and idle cost, and from [12], it is the function of the mean arrival time, d,

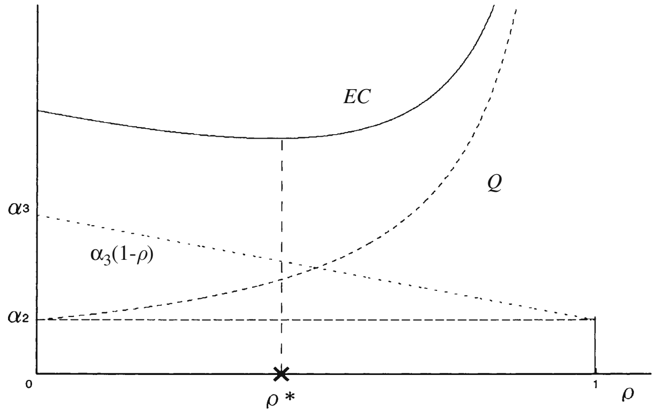


Fig. 4.1.3 Behavior of expected operating cost in production center

and mean processing time, m. Thus, the objective for the production center, *EC*, is given by

$$EC = \text{(queueing cost)} + \text{(busy cost)} + \text{(idle cost)}$$
$$EC = \alpha_1 Q + \alpha_2 B + \alpha_3 I, \tag{4.1.4}$$

and a pattern of the behavior in $GI/GI/1$ type can be seen in Figure 4.1.3.

The economic traffic at the first stage is as follows:

$$d^*(p),\ m^*,\ \text{or } \rho^* \text{ such that } EN = ER - EC - \text{max}, \tag{4.1.5}$$

subject to the constraints of traffic intensity, pricing/demand, and so on. We will consider a variety of economic traffic later.

4.1.3.2 Two-Stage Method

The management design means the simultaneous decision of the economic traffic, lead time, and pricing setting. For the purpose of this decision, we propose a graphical solution method, a two-stage design method [12], as shown in Fig. 4.1.4.

Generally, the problem of simultaneous decision is formulated in a two-level structure [8] as follows:

$$EN = ER - EC \to \underset{\rho}{Max} \qquad \text{(Economics)} \tag{4.1.6}$$

Subject to: Optimization of lead time (LT), Market/pricing (p),

$$\text{Traffic intensity } (\rho),\ \text{Buffer, and so on.} \quad \text{(Reliability)} \tag{4.1.7}$$

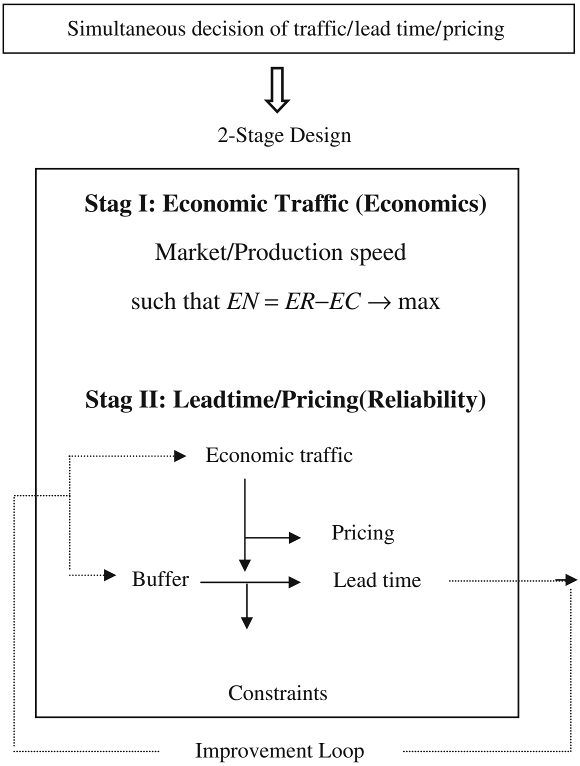


Fig. 4.1.4 Two-stage design method with incorporated

The two-stage method arranges or organizes the economic traffic of maximizing the marginal profit at the first stage (economics), and the economic lead time/pricing and mutual information under the economic traffic at the second stage (reliability) into two stages. At the second stage, this method includes an improvement loop for changing the economic lead time and for decreasing risks by buffers or traffic.

Finally, the economic constraints of management design are evaluated. For this purpose, the mutual information [2, 14] is introduced and examined.

4.1.4 Simple Enterprise type

4.1.4.1 Criteria and Formulation

Now, let us regard the manufacturing and service enterprises, for simplicity as a $M/M/1$ system [3] in a push-type system. In this type, the mean sales reward, *ER*, and mean operating cost, *EC*, are shown respectively as follows:

$$ER = p/d, \tag{4.1.8}$$

$$\begin{aligned} EC &= \alpha_1\rho/(1-\rho) + \alpha_2\rho + \alpha_3(1-\rho) \\ &= \alpha_1\rho/(1-\rho) + \alpha_2 + (\alpha_3 - \alpha_2)(1-\rho), \quad \alpha_3 - \alpha_2 \geq \alpha_1 \end{aligned} \tag{4.1.9}$$

In addition, the respective probability density functions of interdeparture times, Y, and lead times, T, are given by [3]

$$\alpha(\tau) = \lambda \exp(-\lambda\tau), \tau \geq 0 \tag{4.1.10}$$

$$f(t) = (\mu - \lambda)\exp\{-(\mu - \lambda)t\}, \quad t \geq 0 \tag{4.1.11}$$

The mean lead time, *ET*, and negative entropy, H, [9] are then obtained, respectively, as follows:

$$ET = m/(1-\rho), \tag{4.1.12}$$

$$H = 1 + \ln 1/\beta, \tag{4.1.13}$$

where β is a parameter of the exponential distribution.

Thus, a typical example of mathematical formulation in this MGM case is given from Eq (4.1.6), (4.1.7), and (4.1.9) as follows:

$$EN = p/d - EC \rightarrow \underset{d,\ m}{Max} \qquad \text{(Throughput)} \tag{4.1.14}$$

subject to

$$m/(1-\rho) \leq LT_0, \qquad \text{(Lead time)} \tag{4.1.15}$$

$$d^{-1} \leq a - bp, \qquad \text{(Price/demand)} \tag{4.1.16}$$

$$d \geq m. \qquad \text{(Traffic)} \tag{4.1.17}$$

where $a,\ b,\ LT_0$ are constants.

4.1.4.2 Two-Stage Solution Example

From the Formulations (4.1.14)–(4.1.17), an optimal solution would be obtained easily by a usual method. This problem here may be treated by the graphical solution method proposed.

For an $M/M/1$ operation, we apply the two-stage design method in Fig. 4.1.5. The special results are seen in Figs. 4.1.5 and 4.1.6 as follows:

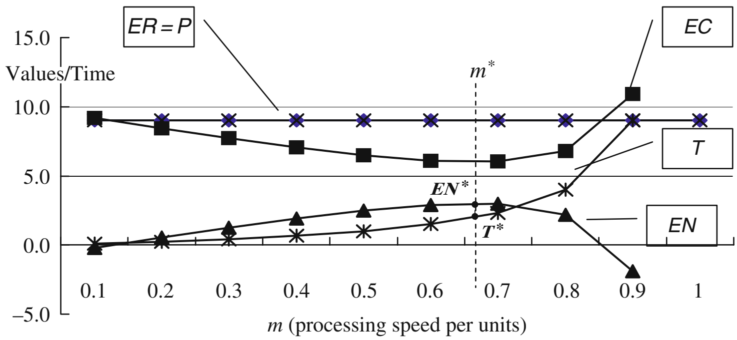


Fig. 4.1.5 Two-Stage design: Market bottleneck case (demand speed, $d = 1.0$)

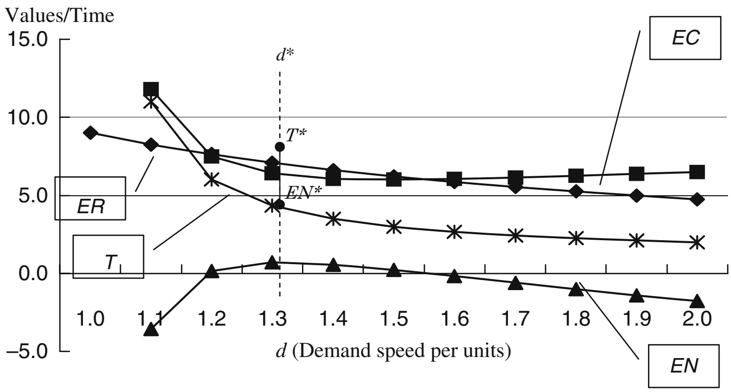


Fig. 4.1.6 Two-Stage design: Production bottleneck case (proceeding speed, $m = 1.0$)

Stage 1: Determination of economic traffic

$$d^* = m \bigg/ \left\{ 1 - \sqrt{\frac{\alpha_1 m}{p - (\alpha_3 - \alpha_2)\, m}} \right\}, \text{ for a given } m \tag{4.1.18}$$

$$m^* = d \left\{ 1 - \sqrt{\frac{\alpha_1}{\alpha_3 - \alpha_2}} \right\}, \text{ for a given } d \tag{4.1.19}$$

Stage 2: Lead time/pricing setting

$$ET^* = m^* \big/ \left(1 - \rho^*\right), \tag{4.1.20}$$

$$p^* = \left(\alpha - 1\big/d^*\right)\big/b. \tag{4.1.21}$$

Moreover, the mutual information (constraints) of this system, *MI*, is obtained from (4.1.10), (4.1.11), and (4.1.13) at the second stage. That is, from (4.1.10), (4.1.11), and (4.1.13),

$$MI = 1 + \ln\ d - \ln\ \rho \big/ (1 - \rho), \tag{4.1.22}$$

where the *MI* means $I\ (X, Y)$, and

$$MI = 2\int_0^{\infty} a(\tau)\log a(\tau)d\tau - \int_0^{\infty} f(t)\log f(t)dt. \tag{4.1.23}$$

Finally, it is noted that this type is a simple case of infinite buffer in *M/M/*1, and thus, the lead time may be changed not only by the buffer but also by the traffic. For example, the lead time is shorter if the buffer is smaller and the traffic is lighter.

4.1.5 Management Strategy

4.1.5.1 Pair-Matrix Tables (Maps)

The management strategy map is helpful to managers under global risks, and is obtained here by the pair-matrix method in the form of a matrix table. A design example/strategy for the simplified *M/M/*1 enterprise of the push type is given here and is numerically discussed. Some parameters in the enterprise are set as follows:

$$\alpha_1 = \alpha_2 = 1,\ \alpha_3 = 10;\ p = 9,\ \alpha = 10,\ b = 1$$

Then, an optimal solution/strategy would be given by solving the Formulations (4.1.14)–(4.1.17), if necessary. However, it is limited to only a solution value, and thus is not useful as a strategy map corresponding to a mariner's compass. Here, we use the two-stage method (shown in Fig. 4.1.5), and obtain a few pair-matrix tables (maps) by giving a combination of d and m. Table 4.1.3 shows the result of a pair-matrix map in such a case.

In addition, the mean net reward, *EN*, mean leadtime, *ET*, pricing setting, *PI*, and mutual information (constraints), *MI*, are calculated from Formulations (4.1.14), (4.1.20), (4.1.21), and (4.1.22) respectively under each (*d, m*) element, and are indicated in the matrix. The under zone in Table 4.1.3 shows the feasible region under the conditions of $\rho < 1$ (traffic) and $d^{-1} \leq a - bp$ (price/demand).

In addition, a pair-matrix table (map) for the make-to-order type is obtained by a slight change from Table 1 in [10], and is again seen in Table 4.1.4. In this example, the Markovian $M/ < M, M > /1$ (4) queueing system with order reward is treated under order-selection and switch-over capacity, and the traffic variables are an order-selection criterion, c, and a switch-over level, u_0. More technical details are discussed in [10], and an extension of the pair-matrix theory is available in Chapter 10.1.

Table 4.1.3 Strategy map: Simple enterprise and ellipse shape

d (Market speed)		*m* (Production speed) 0.4	0.5	0.6	0.7	0.8	0.9	1	1.1	1.2
0.9	*ER*	9.8765	9.8765	9.8765	9.8765	9.8765	9.8765	9.8765	9.8765	9.8765
	EC	6.8	6.25	6	6.5	10	–	–10	–6.5	–6
	EN	3.0765	3.6265	3.8765	3.3765	–0.123	–	19.877	16.377	15.877
	LT	0.72	1.125	1.8	3.15	7.2	–	–9	–4.95	–3.6
	MI	1.1178	0.6715	0.2015	–0.358	–1.185	–	–	–	–
	PS	8.8889	8.8889	8.8889	8.8889	8.8889	8.8889	8.8889	8.8889	8.8889
1	*ER*	9	9	9	***9***	9	9	9	9	9
	EC	7.0667	6.5	6.1	6.0333	6.8	10.9	–	–10.9	–6.8
	EN	1.9333	2.5	2.9	***2.9667***	2.2	–1.9	–	19.9	15.8
	LT	0.6667	1	1.5	2.3333	4	9	–	–11	–6
	MI	1.4055	1	0.5945	0.1527	–0.386	–1.197	–	–	–
	PS	9	9	9	9	9	9	9	9	9
1.1	*ER*	8.2645	8.2645	8.2645	8.2645	8.2645	8.2645	8.2645	8.2645	8.2645
	EC	7.2987	6.7424	6.2909	6.0227	6.1212	7.1364	11.818	–	–11.82
	EN	0.9658	1.522	1.9736	2.2417	2.1433	1.1281	–3.554	–	20.083
	LT	0.6286	0.9167	1.32	1.925	2.9333	4.95	11	–	–13.2
	MI	1.6549	1.2776	0.913	0.5357	0.1145	–0.409	–1.207	–	–
	PS	9.0909	9.0909	9.0909	9.0909	9.0909	9.0909	9.0909	9.0909	9.0909
1.2	*ER*	7.6389	7.6389	7.6389	7.6389	7.6389	7.6389	7.6389	7.6389	7.6389
	EC	7.5	6.9643	6.5	6.15	***6***	6.25	7.5	12.75	–
	EN	0.1389	0.6746	1.1389	1.4889	1.6389	1.3889	0.1389	–5.111	–
	LT	0.6	0.8571	1.2	1.68	2.4	3.6	6	13.2	–
	MI	1.8755	1.5188	1.1823	0.8458	0.4892	0.0837	–0.427	–1.216	–
	PS	9.1667	9.1667	9.1667	9.1667	9.1667	9.1667	9.1667	9.1667	9.1667
1.3	*ER*	7.1006	7.1006	7.1006	7.1006	7.1006	7.1006	7.1006	7.1006	7.1006
	EC	7.6752	7.1635	6.7033	6.3205	6.0615	6.0192	6.4103	7.8846	13.692
	EN	-0.575	–0.063	0.3973	0.7801	1.0391	1.0814	0.6903	–0.784	–6.592
	LT	0.5778	0.8125	1.1143	1.5167	2.08	2.925	4.3333	7.15	15.6
	MI	2.0733	1.7324	1.4165	1.1082	0.7924	0.4514	0.0584	–0.442	–1.223
	PS	9.2308	9.2308	9.2308	9.2308	9.2308	9.2308	9.2308	9.2308	9.2308
1.4	*ER*	6.6327	6.6327	6.6327	6.6327	6.6327	6.6327	6.6327	6.6327	6.6327
	EC	7.8286	7.3413	6.8929	6.5	6.1905	6.0143	6.0714	6.5952	8.2857
	EN	–1.196	–0.709	–0.26	0.1327	0.4422	0.6184	0.5612	0.0374	–1.653
	LT	0.56	0.7778	1.05	1.4	1.8667	2.52	3.5	5.1333	8.4
	MI	2.2528	1.9243	1.6242	1.3365	1.0488	0.7487	0.4202	0.0372	–0.455
	PS	9.2857	9.2857	9.2857	9.2857	9.2857	9.2857	9.2857	9.2857	9.2857

feasible

4.1.5.2 Management Solutions/Strategy

The MGM module is referred to as an ellipse shape consisting of two centers (poles). Effective management solution/strategy such as profit maximization, $(d, m) = (1, 0.7)$ in Table 4.1.3, would usually lie between the sales-maximization pole ("American" company) and cost-minimization pole (the "Japanese" company).

From Table 4.1.3, Fig. 4.1.5 and 4.1.6 are first obtained in the case of a market/production bottleneck. Figures 4.1.5 and 4.1.6 show examples of a two-stage management design for marketing $d = 1.0$ and production $m = 1.0$, respectively. Next, a variety of feasible solutions/strategies in Table 4.1.3 is summarized in Table 4.1.5. The Nash or Stackelberg's solution is the optimal/equilibrium strategy in non-cooperative 2-center gaming shown in Table 4.1.3 or 4.1.4.

From Table 4.1.5, the best solution can be found, and a better management strategy can be obtained. In addition, a variety of feasible solutions in a make-to-order type are obtained from a pair-matrix map as shown in Table 4.1.4, and are summarized in Table 4.1.6.

Table 4.1.4 Strategy map in make-to-order case: demand speed $d = 0.5$, and available production speeds, $m = 1$ or 0.5

Production

Market c	u_0	−1	0	1	2	3
0.6	*ER*	**1.7408**	1.6110	1.5472	1.4558	1.3268
	EC	0.9125	0.7916	0.7320	0.6853	0.6339
	EN	0.8283	0.8195	0.8151	0.7705	0.6929
0.7	*ER*	1.7250	1.5968	1.5382	1.4596	1.3524
	EC	0.8898	0.7625	0.7042	0.6630	0.6214
	EN	0.8352	0.8344	0.8340	0.7966	0.7310
0.8	*ER*	1.7035	1.5761	1.5219	1.4551	1.3676
	EC	0.8693	0.7354	0.6784	0.6423	0.6088
	EN	0.8342	0.8407	0.8434	0.8128	0.7589
0.9	*ER*	1.6780	1.5502	1.4996	1.4433	1.3732
	EC	0.8510	0.7105	0.6549	0.6231	0.5964
	EN	0.8271	0.8397	**0.8447**	0.8201	0.7768
1.0	*ER*	1.6498	1.5202	1.4726	1.4253	1.3702
	EC	0.8346	0.6875	0.6336	0.6056	0.5845
	EN	0.8153	0.8327	0.8391	0.8197	0.7857
1.1	*ER*	1.6199	1.4872	1.4421	1.4025	1.3596
	EC	0.8220	0.6665	0.6143	0.5898	0.5731
	EN	0.8000	0.8207	0.8278	0.8127	0.7866
1.2	*ER*	1.5892	1.4521	1.4090	1.3759	1.3430
	EC	0.8070	0.6473	0.5970	0.5755	**0.5624**
	EN	0.7822	0.8049	0.8120	0.8004	0.7806

Table 4.1.5 A variety of management solutions: Simple enterprise

		(d,m)	Economics	Reliability	Risk in EN^*
Optimal solution / strategy	Production, min in *EC*	(1.2,0.8)	*ER* 7.6389 *EC* 6 *EN* 1.6389	*LT* 2.4 *MI* 0.4892 *PS* 9.1667	1.3278
	Sales, max in *ER*	(1.0,0.7)	*ER* 9 *EC* 6.0333 *EN* 2.9667	*LT* 2.3333 *MI* 1.8473 *PS* 9	0
	Overall (cooperative)	(1.0,0.7)	*ER* 9 *EC* 6.0333 EN^* 2.9667	*LT* 2.3333 *MI* 1.8473 *PS* 9	0
Nash's Solution Stackelberg's Solution		(1.0,0.7)	*ER* 9 *EC* 6.0333 *EN* 2.9667	*LT* 2.3333 *MI* 1.8473 *PS* 9	0

Table 4.1.6 A variety of management solutions: Make-to-order enterprise

		(d,m)	Economics		Risk in EN^*
Optimal solution / strategy	Production, min in *EC*	(1.2, 3)	*EN* 0.7806	*ER* 1.3430 *EC* 0.5624	0.0641
	Sales, max in *ER*	(0.6, -1)	*EN* 0.8283	*ER* 1.7408 *EC* 0.9125	0.0164
	Overall (cooperative)	(0.9, 1)	EN^* 0.8447	*ER* 1.4996 *EC* 0.6549	0
Nash's solution Stackelberg's solution		(0.9, 3)	*EN* 0.7768	*ER* 1.3732 *EC* 0.5964	0.0679

By the improvement loop, we now are able to shorten the lead time at the expense of maximal net reward $EN = 2.9667$ shown in Table 4.1.5. A feasible solution would be the market $d = 1.0$ and production $m = 0.5$, if a customer requires a reduction of about $LT = 1$.

The risk in each strategy is evaluated by the difference from the EN^* at the right column in Tables 4.1.5 and 4.1.6. In addition, the condition for independence is noted: $MI = 0$ may be necessary, but it is not sufficient to achieve profit maximization. This independence condition would be associated with the law of requisite variety by Ashby [1], meaning that the variety of the output is equal to that of input.

Remarks

This chapter presents a theoretical framework of a management design/strategy for enterprises, develops a two-stage design method for the simultaneous, collaborative determination of economic traffic and lead time/pricing, and proposes a cooperative design approach in contrast to the theory of constraints (TOC), and in contrast to other non-cooperative planning methods for management strategy.

With the strategy map obtained by the pair-matrix method, we can attain a collaborative solution from strategy to action under global risks. This approach would be helpful to users by accompanying the analysis with market and operational risks evaluation. The next chapter focuses on the development of MGM theory including service type ($\alpha_2 > \alpha_3$).

References

1. Ashby, W.R., *Introduction to Cybernetics*, Chapman & Hall, London, 1956
2. Attneave, F., *Applications of Information Theory to Psychology*, Holt, Rinehart and Winston, Inc., NY, 1959
3. Cox, D.R. and Smith, W.L., *Queues*, Chapnan & Hall, London, 1961
4. Davis, K.R., The Process of Problem Finding: A Production-Marketing Example, *Interfaces*, 8(1), 82–86, 1977

5. Eliashberg, J. and Steinberg, R., Marketing-Production Joint Decision-Making, In: J. Elishberq and G.L. Lilien (eds.), *Marketing*, North-Holland, Amsterdam, 1993
6. Follet, M.P., *Freedom & Coordination –Lecture in Business Organization*, L.H. Urwick (ed.), Pitman Publishing, London, 1949
7. Goldratt, E.M., *The Goal – A Process of Ongoing Improvement*, North River Press, MA, 1984
8. Lasdon, L.S., *Optimization Theory for Large Systems*, Macmillan, New York, 1970
9. Matsui, M., A Note on Entropy of Erlang Distribution, *The Keiei-Kogaku (Industrial Engineering)*, Hiroshima University, Japan, 19(2), 67–75, 1971 (in Japanese)
10. Matsui, M., A Game-Theoretic Consideration of Order-Selection and Switch-Over Policy, *Preprints of Japan Industrial Management Association*, Fall Meeting, 48–49, 1983 (in Japanese)
11. Matsui, M., On a Joint Policy of Order-Selection and Switch-Over, *Journal of Japan Industrial Management Association*, 39(2), 83–87, 1988 (in Japanese)
12. Matsui, M., An Optimal Design Problem of Production and Queueing Systems, *Symposium on Performance Models for Information Communication Networks*, Hakone, Japan, 77–85, 1994 (in Japanese); Optimal Economic Design of Production and Queueing Systems, *Abstracts of APORS'94*, Fukuoka, Japan, 266, 1994
13. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Industrial Management Association*, 53(1), 1–9, 2002
14. Shannon, C.E. and Weaver, W., *The Mathematical Theory of Communication*, The University of Illinois Press, Urbana, 1964
15. Suzuki, M., *An Introduction to Game Theory*, Kyouritsu Shuppan, Tokyo, Japan, 1981 (in Japanese)
16. Taylor, F.W., *Scientific Management*, Harper & Row, NY, 1911

4.2 Service Versus Manufacturing Model

4.2.1 Introduction

Traditionally, there has been a noncooperative problem of marketing and manufacturing since M. P. Follet [15]. Marketing (sales center) is concerned with sales, whereas the manufacturing (production center) is concerned with costs. This factor often falls in the theory of constraints [4], and it is not necessarily directed to profit maximization.

This two-center problem is first discussed in a job-shop model with order-selection [8, 9]. Recently, this two-center model has been developed into a Management Game Model (MGM) [11], and the ellipse theory with pair-pole has also been found in the pair-matrix table in FMS [14] and in job-shop [12] types.

However, the discussion involves a somewhat limited manufacturing type. In modern society, the service economy [3] is growing, and service management has become important. Some contribution [1, 5, 6, 7, 16 etc.] to this subject have been made, but their magnitude is not generally known.

Here we examine the basic model (MGM), which consists of sales and production centers, which works for generalization of the service system type [11]. The service (manufacturing) type involves the case in which the idle (busy) cost is the constant with respect to the traffic/utilization rate.

First, the service-type MGM versus manufacturing-type MGM is defined, and the traffic accounting is introduced. Next, the service-type MGM is discussed for the existence of optimal traffic. Finally, the common ellipse theory is ascertained on the pair-matrix table, and its common usage is discussed under a strategic goal. Throughout the chapter, the service versus manufacturing system type is noted.

4.2.2 Management Game Model

4.2.2.1 Explanation of the Model

In Chapter 4.1, we proposed the basic model, MGM, which gives an optimal relationship between economics (profit) and reliability (lead time). The MGM consists

M. Matsui, *Manufacturing and Service Enterprise with Risks*, 63
DOI 10.1007/978-0-387-84804-4_7, © Springer Science+Business Media, LLC 2009

of the sales (demand) center pursuing profit maximization and the production (supply) center pursuing cost minimization. The problem involves maximization of the difference (profit) under a shorter lead time, but it is dependent on the cooperation of the two-center model.

This enterprise model is formulated in the queueing form. For simplicity, let us consider an enterprise model of *M/M/*1 type. In this type, the mean operating cost, EC, per unit time is given by

$$EC = \alpha_1 \frac{\rho}{1-\rho} + \alpha_2 \rho + \alpha_3 (1-\rho), \quad \rho < 1 \tag{4.2.1}$$

This cost system is based on the traffic/utilization rate, ρ, and is called here the traffic accounting. Generally, the traffic/utilization rate, ρ, is obtained from the work sampling in IE, or from the occupation divided by the capacity of the system.

In the traffic accounting, Eq. (4.2.1) is transformed in two ways as follows:

$$EC = \begin{cases} \alpha_1 \frac{\rho}{1-\rho} + \{\alpha_2 + (\alpha_3 - \alpha_2)(1-\rho)\}, & \alpha_2 \le \alpha_3. \quad (4.2.2a) \\ \alpha_1 \frac{\rho}{1-\rho} + \{\alpha_3 + (\alpha_2 - \alpha_3)\rho\}, & \alpha_2 > \alpha_3. \quad (4.2.2b) \end{cases}$$

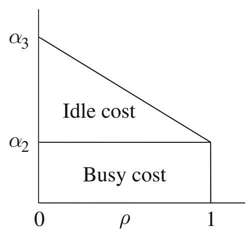
The Eq. (4.2.2a) is the case of manufacturing-type MGM (Fig. 4.2.1a), and the Eq. (4.2.2b) is the case of service-type MGM (Fig. 4.2.1b). In the manufacturing type, the busy time occurrence becomes larger, and thus, the production availability becomes larger in the case of $\alpha_2 \le \alpha_3$. From Fig. 4.2.1a, the busy cost is fixed, and the idle cost is variable with respect to traffic/utilization rate, ρ.

In the service type, the idle time occurrence becomes larger, and thus, the customer availability becomes larger in the case of $\alpha_2 > \alpha_3$. From Fig. 4.2.1b, it is noted that the idle cost is fixed, and the busy cost is variable with respect to ρ:

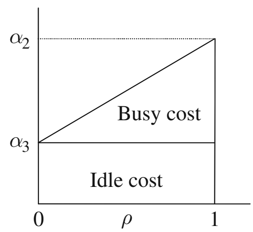
4.2.2.2 Objective Functions

Generally, the mean sales reward, ER, per unit time is given by

$$ER = \frac{p}{d}. \tag{4.2.3}$$



(a) Manufacturing-type ($\alpha_2 \le \alpha_3$)



(b) Service-type ($\alpha_2 \le \alpha_3$)

Fig. 4.2.1 Cost structure of MGM

Then, the net reward (economics), EN, is from Eqs. (4.2.1) and (4.2.3) as follows:

$$EN = \frac{p}{d} - \left\{\alpha_1 \frac{\rho}{1-\rho} + \alpha_2\rho + \alpha_3(1-\rho)\right\}. \tag{4.2.4}$$

Also, the mean leadtime (reliability), ET, is from Little's formula as follows:

$$ET = \frac{m}{1-\rho}. \tag{4.2.5}$$

Generally, the ET is an increasing function of ρ.

For the case of $\rho > 1$, the exchange of d and m is considered here in Eq. (4.2.4). The case would be seen in the produce-to-stock type.

Thus, the EN and ET are represented by EN' and ET', respectively, as follows:

$$EN' = \frac{p}{m} - \left\{\alpha_1 \frac{\rho'}{1-\rho'} + \alpha_2\rho' + \alpha_3(1-\rho')\right\}. \tag{4.2.6}$$

$$ET' = \frac{d}{1-\rho'}. \tag{4.2.7}$$

where $\rho' = d/m < 1$.

Then, the functions EN and EN' are dual to d and m, and the functions ET and ET' are dual to d and m. This factor means the duality of produce-to-order and produce-to-stock service systems. In addition, the return-on-asset (ROA) is given by the output (4.2.4) and input (4.2.5) as return-on-wait $(ROW) = EN/ET$.

Furthermore, *ROW* is decomposed into the production (P) and management (M) efficiencies as follows:

$$ROW = \frac{EN}{ET} = \frac{m}{ET} \times \frac{EN}{m}. \tag{4.2.8}$$

If necessary, the optimal *ROW* is computed by the DEA [2].

4.2.3 Service Type MGM

4.2.3.1 Operating Cost Coefficient

Generally, there is no optimal traffic in the function of Eq. (4.2.2b) of service type MGM. However, the busy cost coefficient, α_2, would not be the linear function of processing (m), but the higher-order function of m. This manipulation would explore the management treatment similar to that of the manufacturing type.

Then, the mean-operating cost, EC, is expressed in spite of Eq. (4.2.2b) as follows:

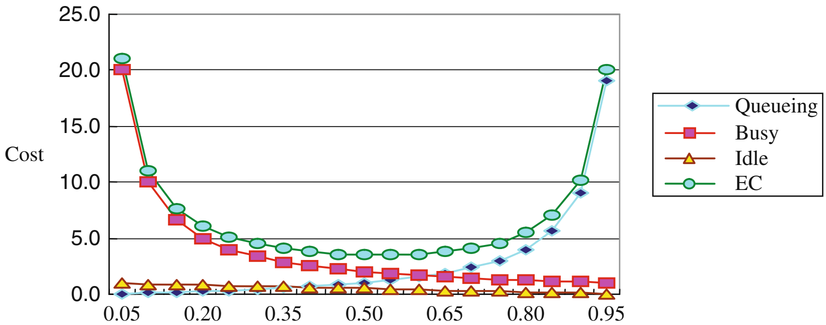


Fig. 4.2.2 Behavior of EC under $d = 1(\alpha_1 = 1, \alpha_2 = 1/m^2, \alpha_3 = 1)$

$$EC = \alpha_1 \frac{\rho}{1-\rho} + [\alpha_3 + \{\alpha_2(m) - \alpha_3\}\rho],\ \ \alpha_2 \geq \alpha_3 \tag{4.2.9}$$

where α_2 is of the type:

$$\alpha_2(m) = \frac{\varepsilon}{m^2}, \tag{4.2.10}$$

in which ε is a busy constant.

The behavior of EC is seen in Fig. 4.2.2, and the optimal traffic exists in EC'.

In the case of $\rho > 1$, the mean operating cost, EC', is given by

$$EC' = \alpha_1 \frac{\rho'}{1-\rho'} + \alpha_2(d)\rho' + \alpha_3(1-\rho'), \tag{4.2.11}$$

where $\alpha_2(d) = \varepsilon/d^2$. Thus, the functions EC and EC' are dual with respect to d and m.

4.2.3.2 Produce-to-Order/Stock

The behavior of objective functions are considered with a numerical example. The parameters are set to $\alpha_1 = 1,\ \varepsilon = 1,\ \alpha_3 = 1$ and $p = 9$. The simple service cases are obtained from Eqs. (4.2.9) and (4.2.10), and are seen in Figs. 4.2.3 and 4.2.4 This case is similar to that of produce-to-order service systems.

A case of the produce-to-stock service systems is obtained from Eq. 4.2.11 and seen in Figs. 4.2.5 and 4.2.6.

From Figs. 4.2.3–4.2.6, it is seen that the EN and ROW have respective maximums. Also, the production efficiency is a monotone function, but the management efficiency has the maximum.

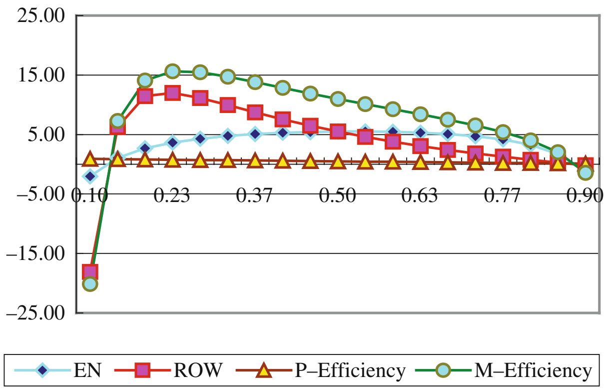


Fig. 4.2.3 Simple service case: $d = 1$

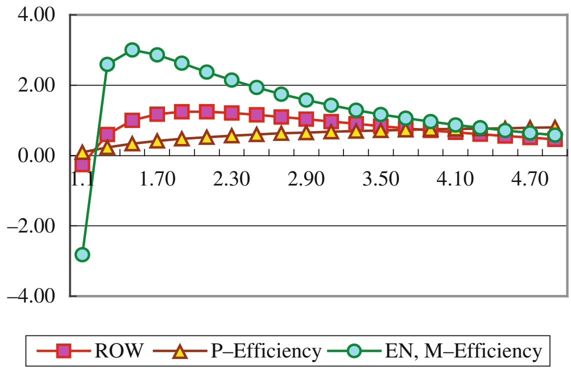


Fig. 4.2.4 Simple service case: $m = 1$

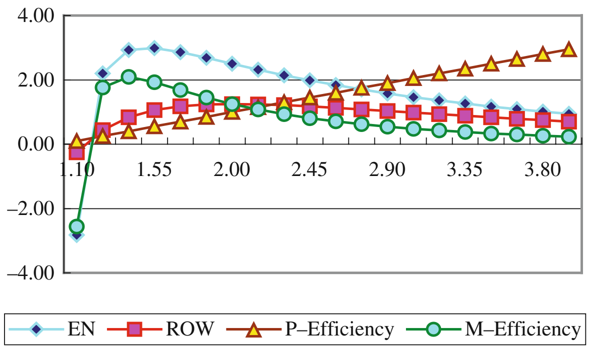


Fig. 4.2.5 Produce-to-stock service case: $d = 1$

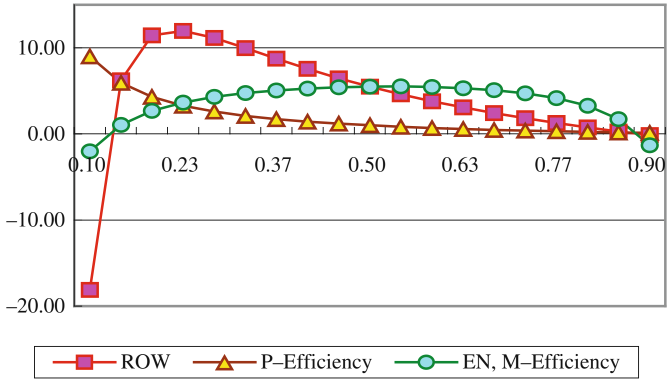


Fig. 4.2.6 Produce-to-stock service case: $m = 1$

4.2.4 Pair-Matrix Table

4.2.4.1 Ellipse Theory

The pair-matrix table is introduced in [10], and is here developed for both the types. The pair-matrix table is composed of the cells with the pair-element of economics and reliability. Also, the ellipse theory is referred to as an ellipse shape consisting of two centers (poles), and the profit maximization usually lies between the sales maximization and cost minimization poles on the pair-matrix table.

An example of the pair-matrix table and ellipse shape is seen in Fig. 4.2.7. Figure 4.2.7 is the case of the manufacturing type ($\alpha_2 \leq \alpha_3$), the gray elements are the extreme poles, and the white zone is the case of $\rho \approx 1$. Also, the northwest zone is infeasible for the constraints of d and m. It is noted that this table is symmetric with respect to the axis of $\rho = 1$ from the Section 4.2.2, and is similar to the case of service type ($\alpha_2 > \alpha_3$).

4.2.4.2 Strategic Goal Example

Under a strategic goal, the ellipse theory is applied to the management strategy for service systems. There is some trajectory to the strategic goal, and a sketch of strategic trajectory is seen in Fig. 4.2.8.

For the manufacturing type, let the strategic goal (target) be the maximal profit, EN^* in the cell (1.00, 0.65), and the two initial (present) states be the cells L (1.35, 0.45) in the shorter lead time and R(1.30, 0.85) in the shorter cost, respectively. The former state indicates the case of lower demand and excess capacity (shorter lead

			m							
			0.6	0.7	0.8	0.9	1.0	1.1	1.2	1.3
d	0.6	*ER*		12.86	11.25	10.00	9.00	8.18	7.50	6.92
		EC		8.29	6.25	6.00	6.10	6.29	6.50	6.70
		EN		4.57	5.00	4.00	2.90	1.89	1.00	0.22
		ET		4.20	2.40	1.80	1.50	1.32	1.20	1.11
		ROW		1.09	2.08	2.22	1.93	1.43	0.83	0.20
	0.7	*ER*	12.86		11.25	10.00	9.00	8.18	7.50	6.92
		EC	8.29		9.13	6.50	6.03	6.02	6.15	6.32
		EN	4.57		2.13	3.50	2.97	2.16	1.35	0.60
		ET	4.20		5.60	3.15	2.33	1.93	1.68	1.52
		ROW	1.09		0.38	1.11	1.27	1.12	0.80	0.40
	0.8	*ER*	11.25	11.25		10.00	9.00	8.18	7.50	6.92
		EC	6.25	9.13		10.00	6.80	6.12	6.00	6.06
		EN	5.00	2.13		0.00	2.20	2.06	1.50	0.86
		ET	2.40	5.60		7.20	4.00	2.93	2.40	2.08
		ROW	2.08	0.38		0.00	0.55	0.70	0.63	0.41
	0.9	*ER*	10.00	10.00	10.00		9.00	8.18	7.50	6.92
		EC	6.00	6.50	10.00		10.90	7.14	6.25	6.02
		EN	4.00	3.50	0.00		–1.90	1.05	1.25	0.90
		ET	1.80	3.15	7.20		9.00	4.95	3.60	2.93
		ROW	2.22	1.11	0.00		–0.21	0.21	0.35	0.31
	1.0	*ER*	9.00	9.00	9.00	9.00		8.18	7.50	6.92
		EC	6.10	6.03	6.80	10.90		11.82	7.50	6.41
		EN	2.90	2.97	2.20	–1.90		–3.64	0.00	0.51
		ET	1.50	2.33	4.00	9.00		11.00	6.00	4.33
		ROW	1.93	1.27	0.55	–0.21		–0.33	0.00	0.12
	1.1	*ER*	8.18	8.18	8.18	8.18	8.18		7.50	6.92
		EC	6.29	6.02	6.12	7.14	11.82		12.75	7.88
		EN	1.89	2.16	2.06	1.05	–3.64		–5.25	–0.96
		ET	1.32	1.93	2.93	4.95	11.00		13.20	7.15
		ROW	1.43	1.12	0.70	0.21	–0.33		–0.40	–0.13
	1.2	*ER*	7.50	7.50	7.50	7.50	7.50	7.50		6.92
		EC	6.50	6.15	6.00	6.25	7.50	12.75		13.69
		EN	1.00	1.35	1.50	1.25	0.00	–5.25		–6.77
		ET	1.20	1.68	2.40	3.60	6.00	13.20		15.60
		ROW	0.83	0.80	0.63	0.35	0.00	–0.40		–0.43
	1.3	*ER*	6.92	6.92	6.92	6.92	6.92	6.92	6.92	
		EC	6.70	6.32	6.06	6.02	6.41	7.88	13.69	
		EN	0.22	0.60	0.86	0.90	0.51	–0.96	–6.77	
		ET	1.11	1.52	2.08	2.93	4.33	7.15	15.60	
		ROW	0.20	0.40	0.41	0.31	0.12	–0.13	–0.43	

Fig. 4.2.7 Dual pair-matrix table: Manufacturing type ($\alpha_1 = \alpha_2 = 1,\ \alpha_3 = 10,\ p = 9$)

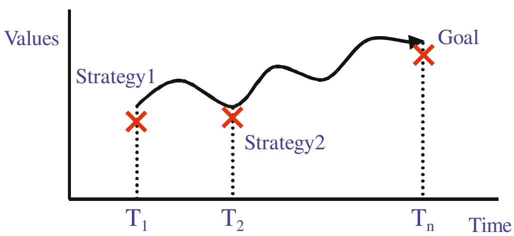


Fig. 4.2.8 A sketch of strategic trajectory

d		m: 0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90
0.95	*ER*	9.47	9.47	9.47	9.47	9.47	9.47	9.47	9.47	9.47	9.47	9.47
	EC	6.94	6.64	6.37	[illegible]	[illegible]	[illegible]	[illegible]	6.64	7.75	10.45	19.47
	EN	2.54	2.84	3.10	[illegible]	[illegible]	[illegible]	[illegible]	2.83	1.72	–0.97	–10.00
	ET	0.69	0.86	1.06	[illegible]	[illegible]	[illegible]	[illegible]	3.56	5.07	8.08	17.10
	ROW	3.67	3.32	2.94	[illegible]	[illegible]	[illegible]	[illegible]	0.79	0.34	–0.12	–0.58
1.00	*ER*	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00
	EC	7.07	6.77	6.50	6.27	6.10	6.01	6.03	6.25	6.80	8.02	10.90
	EN	1.93	2.23	2.50	2.73	2.90	2.99	2.97	2.75	[illegible]	0.98	–1.90
	ET	0.67	0.82	1.00	1.22	1.50	1.86	2.33	3.00	[illegible]	5.67	9.00
	ROW	2.90	2.73	2.50	2.23	1.93	1.61	1.27	0.92	0.55	0.17	–0.21
1.05	*ER*	8.57	8.57	8.57	8.57	8.57	[illegible]	8.57	8.57	8.57	8.57	8.57
	EC	7.19	6.89	6.62	6.39	6.19	6.05	6.00	6.07	6.34	6.96	8.29
	EN	1.38	1.68	1.95	2.19	2.38	[illegible]	2.57	[illegible]	2.23	1.61	0.29
	ET	0.65	0.79	0.95	1.16	1.40	1.71	2.10	[illegible]	3.36	4.46	6.30
	ROW	[illegible]	2.13	2.04	1.89	1.70	1.48	1.22	[illegible]	0.66	0.36	0.05
1.10	*ER*	[illegible]	8.18	8.18	8.18	8.18	[illegible]	8.18	8.18	8.18	8.18	8.18
	EC	7.30	7.01	6.74	6.50	6.29	6.13	6.02	6.01	6.12	6.45	7.14
	EN	0.88	1.17	1.44	1.68	1.89	[illegible]	2.16	2.18	2.06	1.74	1.05
	ET	0.63	0.76	0.92	1.10	1.32	1.59	1.93	2.36	2.93	3.74	4.95
	ROW	1.40	1.54	1.57	1.53	1.43	1.29	1.12	0.92	0.70	0.46	0.21
1.15	*ER*	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83
	EC	7.40	7.12	6.86	6.61	6.40	6.21	6.08	6.01	6.02	6.18	6.56
	EN	0.42	0.70	0.97	1.21	1.43	1.61	1.75	1.82	1.80	1.64	1.27
	ET	0.61	0.74	0.88	1.05	1.25	1.50	1.79	2.16	2.63	3.26	4.14
	ROW	0.69	0.95	1.10	1.15	1.14	1.08	[illegible]	0.84	0.69	0.50	0.31
1.20	*ER*	7.50	7.50	7.50	7.50	7.50	7.50	[illegible]	7.50	7.50	7.50	7.50
	EC	7.50	7.23	6.96	6.72	6.50	6.31	6.15	6.04	6.00	6.05	6.25
	EN	0.00	0.27	0.54	0.78	1.00	1.19	1.35	1.46	1.50	1.45	1.25
	ET	0.60	0.72	0.86	1.02	1.20	1.42	1.68	2.00	2.40	2.91	3.60
	ROW	0.00	0.38	0.62	0.77	0.83	0.84	0.80	0.73	0.62	0.50	0.35
1.25	*ER*	7.20	7.20	7.20	[illegible]	7.20	7.20	7.20	7.20	7.20	7.20	7.20
	EC	7.59	7.32	7.07	[illegible]	6.60	[illegible]	6.23	6.10	6.02	6.01	6.09
	EN	- 0.39	- 0.12	0.13	0.37	0.60	[illegible]	0.97	1.10	1.18	1.20	1.11
	ET	0.59	0.70	0.83	0.98	1.15	1.35	1.59	1.88	2.22	2.66	3.21
	ROW	- 0.66	- 0.17	0.16	0.38	0.52	0.59	0.61	0.59	0.53	0.45	0.34
1.30	*ER*	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92
	EC	[illegible]	[illegible]	[illegible]	6.93	6.70	6.50	6.32	[illegible]	[illegible]	[illegible]	6.02
	EN	[illegible]	[illegible]	[illegible]	0.00	0.22	0.42	0.60	[illegible]	[illegible]	[illegible]	0.90
	ET	[illegible]	[illegible]	[illegible]	0.95	1.11	1.30	1.52	[illegible]	[illegible]	[illegible]	2.93
	ROW	[illegible]	[illegible]	- 0.30	0.00	0.20	0.33	0.40	0.42	[illegible]	[illegible]	0.31

EN* (Goal) · State L · State R · L1 · L2 · R1 · R2 · R3 · R4

Fig. 4.2.9 Ellipse strategy example: manufacturing type ($\alpha_1 = \alpha_2 = 1, \alpha_3 = 10,\ p = 9$)

time), and the latter state indicates the case of lower demand and utilized capacity (lower cost).

There are some main routes from the respective states, and six trajectories from cell-to-cell as shown in Fig. 4.2.9. The best routes are L1 and R2, respectively, in ROW. Especially, the route L1 is seen in the Dell model.

For the service type, let the strategic goal (target) be the maximal profit, EN^*, in the cell (1.00, 0.65), and the two initial (present) states be the cells, L(1.30, 0.35) in the shorter lead time, and R(1.30, 0.75) in the smaller cost, respectively. There are some main routes from the respective states, and seven trajectories from cell-to-cell as shown in Fig. 4.2.10.

From Fig. 4.2.10, the optimal routes are the L1 and R1, respectively, in ROW. There is a small difference in the manufacturing and service types, but the difference is not substantial.

		m (d)										
d (m)		0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80
0.95	ER	9.47	9.47	9.47	[illegible]	[illegible]	[illegible]	[illegible]	9.47	9.47	9.47	9.47
	EC	4.65	4.22	3.94	[illegible]	[illegible]	[illegible]	[illegible]	4.10	4.57	5.36	6.81
	EN	4.82	5.25	5.54	[illegible]	[illegible]	[illegible]	[illegible]	5.37	4.91	4.11	2.67
	ET	0.44	0.55	0.69	[illegible]	[illegible]	[illegible]	[illegible]	2.06	2.66	3.56	5.07
	ROW	10.99	9.48	8.01	6.68	5.48	4.41	3.46	2.61	1.84	1.15	0.53
1.00	ER	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00
	EC	4.46	4.05	3.77	3.59	[illegible]	3.49	3.57	3.75	4.06	4.58	5.45
	EN	4.54	4.95	5.23	5.41	[illegible]	5.51	5.43	5.25	4.94	4.42	3.55
	ET	0.43	0.54	0.67	0.82	1.00	1.22	1.50	1.86	2.33	3.00	4.00
	ROW	[illegible]	9.20	[illegible]	6.61	5.50	4.51	3.62	[illegible]	2.12	[illegible]	0.89
1.05	ER	8.57	8.57	8.57	8.57	8.57	[illegible]	8.57	8.57	8.57	[illegible]	8.57
	EC	4.29	3.89	3.62	3.44	3.34	3.31	3.35	3.47	3.69	4.06	4.63
	EN	4.28	4.68	4.96	5.13	5.23	5.26	5.22	5.10	4.88	4.52	3.94
	ET	0.42	0.53	0.65	0.79	0.95	1.16	1.40	1.71	2.10	2.63	3.36
	ROW	10.20	8.92	7.67	6.52	5.48	4.56	3.73	2.99	2.32	1.72	1.17
1.10	ER	8.18	8.18	8.18	8.18	8.18	8.18	8.18	8.18	8.18	8.18	8.18
	EC	4.13	3.75	3.48	3.30	3.20	3.15	3.17	3.25	3.41	3.67	4.08
	EN	4.05	4.44	4.70	4.88	4.98	5.03	5.01	4.93	4.77	4.51	4.11
	ET	0.41	0.51	0.63	0.76	0.92	1.10	1.32	1.59	1.93	2.36	2.93
	ROW	9.82	8.64	7.48	6.41	5.44	4.57	3.80	3.10	2.48	1.91	1.40
1.15	ER	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83
	EC	3.99	3.62	3.36	3.18	3.07	3.02	3.02	3.07	3.19	3.38	3.68
	EN	3.84	4.21	4.47	4.64	4.75	4.81	4.81	4.75	4.64	4.44	4.15
	ET	0.41	0.50	0.61	0.74	0.88	1.05	1.25	1.50	1.79	2.16	2.63
	ROW	9.45	8.36	7.28	6.28	5.37	4.56	3.83	3.18	2.59	2.06	1.58
1.20	ER	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50
	EC	3.86	3.50	3.25	3.08	2.96	2.90	[illegible]	2.92	3.01	3.15	3.38
	EN	3.64	4.00	4.25	4.42	4.54	4.60	[illegible]	4.58	4.49	4.35	4.13
	ET	0.40	0.49	0.60	0.72	0.86	1.02	1.20	1.42	1.68	2.00	2.40
	ROW	9.10	8.09	7.08	6.14	5.29	4.53	3.84	3.23	2.67	2.17	1.72
1.25	ER	7.20	7.20	7.20	7.20	7.20	7.20	7.20	7.20	7.20	7.20	7.20
	EC	3.74	3.39	3.15	2.98	[illegible]	[illegible]	2.78	2.79	2.86	2.97	3.14
	EN	3.46	3.81	4.05	4.22	[illegible]	[illegible]	4.42	4.41	4.34	4.23	4.06
	ET	0.39	0.49	0.59	0.70	0.83	0.98	1.15	1.35	1.59	1.88	2.22
	ROW	8.76	7.83	6.88	6.00	5.20	4.48	3.83	3.25	2.73	2.26	1.83
1.30	ER	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92
	EC	3.63	3.30	3.06	2.89	2.78	2.71	2.68	2.68	2.73	2.81	2.95
	EN	3.29	3.63	3.86	4.03	4.14	4.21	4.25	4.24	4.20	4.11	3.98
	ET	[illegible]	[illegible]	0.58	0.69	0.81	0.95	1.11	1.30	[illegible]	[illegible]	2.08
	ROW	[illegible]	[illegible]	6.69	5.86	5.10	4.42	3.81	3.26	[illegible]	[illegible]	1.91
1.35	ER	[illegible]	[illegible]	6.67	6.67	6.67	6.67	6.67	6.67	[illegible]	[illegible]	6.67
	EC	[illegible]	[illegible]	2.98	2.81	2.70	2.63	2.59	2.59	[illegible]	[illegible]	2.79
	EN	3.13	3.46	3.69	3.85	3.97	4.04	4.08	4.08	4.05	3.98	3.88
	ET	0.39	0.47	0.57	0.68	0.79	0.93	1.08	1.25	1.45	1.69	1.96
	ROW	8.13	7.32	6.49	5.71	5.00	4.35	3.77	3.25	2.79	2.36	1.98

EN* (Goal)

L1 L2 L3 R1 R2 R3 R4

State L

State R

Fig. 4.2.10 Ellipse strategy example: service type ($\alpha_1 = 1, \alpha_2 = 1/m^2$ or $1/d^2,\ \alpha_3 = 1$)

Remarks

The service-type MGM versus the manufacturing-type MGM was introduced into the study for increasing service enterprises and SCM, and the ellipse theory/strategy was numerically shown. This result would show the collaborative logic of marketing (d) and manufacturing (m), although the given examples are simpler. Further discussions are seen in Chapter 13 [13].

In addition, the new definition of service systems is based on traffic accounting and should be considerable, and the duality of produce-to-order and produce-to-stock systems is noted.

References

1. Buffa, E.S. and Sarin, R.K., *Modern Production/Operations Management*, 8th ed., John Wiley, NY, 1987
2. Charnes, A., Cooper, W.W. and Rhodes, E., Measuring the Efficiency of Decision Making Units, *European Journal of Operational Research*, 2, 429–444, 1978
3. Fuchs, V.R., *The Service Economy*, National Bureau of Economic Research, NY, 1968
4. Goldratt, E.M., *The Goal – A Process of On-Going Improvement*, Nerth River Press, MA, 1984
5. Heskett, J.L., *Managing in the Service Economy*, Harvard Business School Press, Boston, MA, 1986
6. Johnston, R. and Clark, G., *Service Operations Management*, Prentice-Hall, Harlow, UK, 2001
7. Lovelock, C.H., *Managing Services – Marketing, Operations and Human Resources*, 2nd ed., Prentice Hall, New Jersey, 1992
8. Matsui, M., A Game-Theoretic Consideration of Order-Selection and Switch-Over Policy, *Preprints of Japan Industrial Management Association*, Fall Meeting, 48–49, 1983 (in Japanese)
9. Matsui, M., On a Joint Policy of Order-Selection and Switch-Over, *Journal of Japan Industrial Management Association*, 39(2), 83–87, 1988 (in Japanese)
10. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
11. Matsui, M., Management Game Theory: Manufacturing vs. Service Enterprise Type, *International Journal of Productivity and Quality Management*, 1(1/2), 103–115, 2006
12. Matsui, M. and Nakada, Y., Strategic Management/Design Approach to a Job-shop Production System, *International Journal of Production Research*, 41(14), 3257–3271, 2003
13. Matsui, M. and Fujikawa, H., Selling and Manufacturing can Collaborate Profitably, *DIAMOND Harvard Business Review*, 30(1), 72–83, 2005 (in Japanese)
14. Matsui, M. and Wang, L., An Economic/Lend-Time Design Comparison and Map for Central Server Systems including FMS, *International Journal of Automation Technology*, 1(1), 35–44, 2007
15. Urwick, L.H. (ed.), *Freedom & Coordination – Lectures in Business Organization, by Mary Parker Follet*, Pitman Publishing, London, 1949
16. Verma, R., Fitzsimmons, J. and Heineke, J., New Issues and Opportunities in Service Design Research, *Journal of Operations Management*, 20, 2(Special issue), 117–202, 2002

Part III
Stream Risk Processes

Chapter 5
Continuous Risk Stream

5.1 Line Design Without Stoppers

5.1.1 Introduction

Assembly systems in manufacturing often consist of multiple production stations connected by conveyors to transport and store materials [15]. There are the two major types of arrays of unit stations: line type and flexible type.

They differ in material flows of processed and overflow items. The line type [12] is usually known as the line-production system in which items are continuously processed in a series of stations and become finished products in the last station. We call it Assembly Line Systems (ALSs) based on a station-centered approach [7, 11].

The ALS has two cases with or without stoppers, which prevent the overflow of items. The former system is known as free-flow lines (e.g., [13]), in which usables wait in each station until their processing is over, and only processed items are outputted. The latter system is known as the case with conveyor pace [5]. In that case, the usables are continuously transported by power conveyors, and the overflows that have not been finished arise inevitably.

In designing the ALS, the assembly line balancing (ALB) problem [3, 15] occurs. The problem involves assigning the element tasks work to stations satisfying the precedence relation among the tasks and optimizing an objective function. In the cases with stochastic variations, such as the arrival/service times, the problem is called the stochastic ALB problem.

A usable, which is processed on the ALS, often requires more than the cycle time under the stochastic variations. The ALS design needs two determinations of not only cycle time but also buffer design for absorbing the variations. In the traditional ALS design, there is a (simple) two-step procedure (e.g., [1]), but it is not a simultaneous design procedure with feedback and costs.

This chapter applies a framework of a two-stage design method [9, 10], and proposes a two-stage design method, which unifies the combinatorial line-balancing problem and stochastic buffer-design problem [16]. This method is applied here to the ALS without stoppers in which the unit station is regarded as the Generalized Conveyor-Serviced Production Station (CSPS) [1, 8].

The design problem of the ALS without stoppers is then considered as a coordination problem between the unit stations (Generalized CSPSs). By simulation

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_8, © Springer Science+Business Media, LLC 2009

optimization, the station-centered approach is first prepared. Next, the two-stage design method is developed. Finally, the design procedure is established.

5.1.2 Explanation of the Model

5.1.2.1 Two-Level Approach

For the assembly line, the Generalized Conveyor-Serviced Production Station (Generalized CSPS) is used as a unit station based on a station-centered approach. We regard the ALS without stoppers as a series array of Generalized CSPSs (Fig. 5.1.1). In Fig. 5.1.1, it is considered that the assembly line system has the two-level structure: the buffer-design problem of each station in the lower level and the coordination problem of buffers by the cycle time in the upper level.

It is assumed that the usables flow is according to a regular arrival with the inter-arrival time d. The service time in each station is supposed to follow the Erlang distribution with mean $\overline{x}_i$. Under these assumptions, each station individually decides the buffer (look-ahead time) c_i in order to minimize the total expected cost, which is the sum of buffer cost and delay-and-overflow cost.

Processed items, which are outputs from the prestation or are serviced by the relief workers because of overflows, become inputs into the poststation. After being serviced in all the stations from the head station to the last station, they become finished products.

Then, the traditional line balancing procedure may be changed as shown in Fig. 5.1.2.

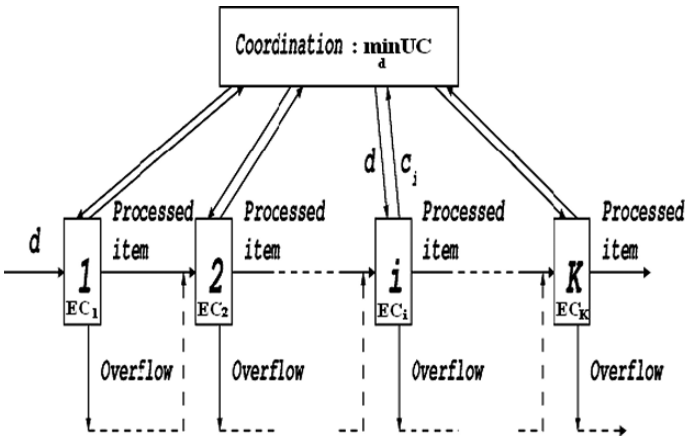


Fig. 5.1.1 Two-level structure of the assembly line system

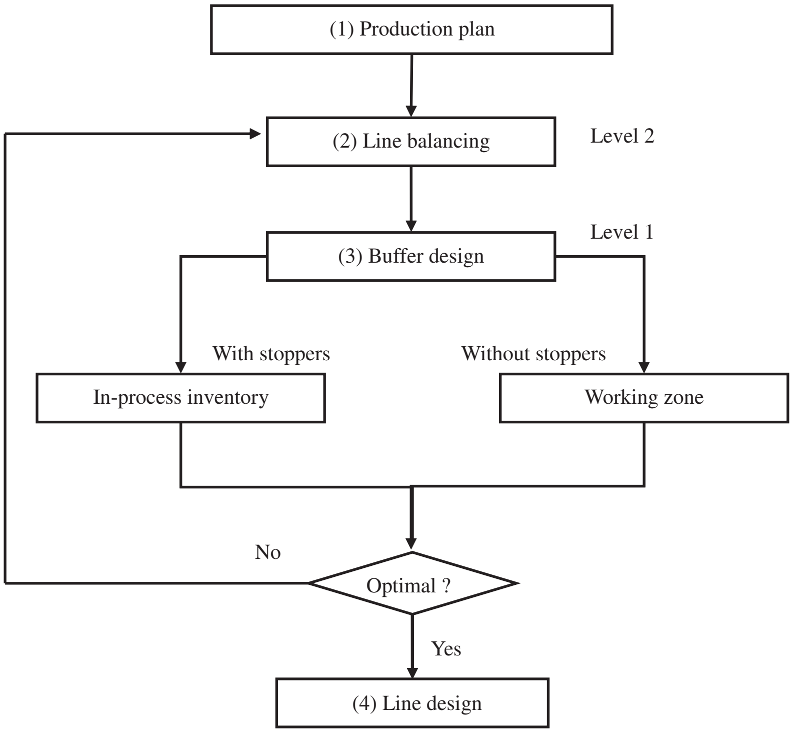


Fig. 5.1.2 Two-level balancing

5.1.2.2 Unit Station and Objective

The Generalized CSPS is introduced as a model of unit stations. From recent research [4], the Single Unit Policy (SUP), in which usables are serviced whenever they are taken on conveyors, is the optimal policy in the case of the regular arrivals. Therefore, it is sufficient for the fixed item case (Fig. 5.1.3) to be the only one to be considered.

In the Generalized CSPS model, the operating rule for Fixed item case (FIC) is as seen in Fig. 5.1.4, and the terminology, such as, delay, D_i, overflow, η_i, look-ahead time c_i, and design factor, ε_i, are introduced. It is noted that the look-ahead time, which is a part of the working zone, is considered as a (time) buffer.

The productive cycle-time per unit produced is the sum of service time and delay time, that is, $z_i = \bar{x}_i + D_i$ on average at station i. The mean delay time, D, are a linear relation to the mean number of overflows, η, such as $\lambda D = 1 + \eta - \rho$ in Appendix (A.3).

The objective function of the system is the total expected cost, TC, given by the sum of each station cost EC_i. The station cost at station i, EC_i, is the total expected operating cost, and is the sum of the buffer cost and delay-and-overflow cost for production planning period T_0.

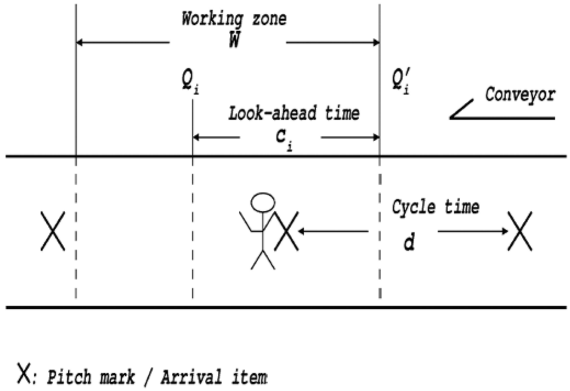


Fig. 5.1.3 Generalized CSPS: fixed item case

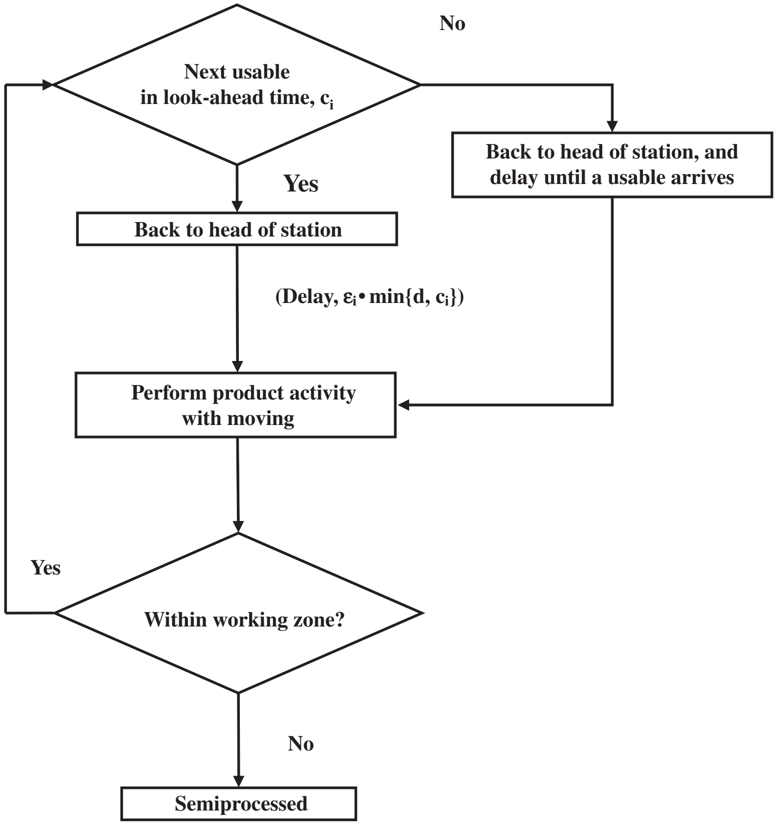


Fig. 5.1.4 Flowchart of generalized CSPS under FIC

That is, the EC_i is given from [1] as follows:

$$EC_i = \alpha_i c_i + Y_i, \tag{5.1.1}$$

where α_i is cost efficient of buffer, and the delay-and-overflow cost, Y_i, is given by

$$Y_i = \frac{T_0}{\overline{x_i} + D_i}(\beta_{1i} D_i + \lambda_i \beta_{2i} \eta_i) = \frac{T_0}{1 + \eta_i}\{\beta_{1i}(1 - \rho_i) + (\beta_{1i} + \lambda_i \beta_{2i})\eta_i\} \tag{5.1.2}$$

in which, and β_{1i} and β_{2i} are cost efficients of delay and overflow, respectively.

Finally, the problem of ALS may be generally formulated as a two-level mathematical program [14]. Under d, the buffer, c_i, is then decided in order to minimize EC_i of each station. Our overall problem is formulated in the two levels as follows:

$$\begin{aligned}
&\min_d UC = \min_d \sum_{i=1}^{K} \overline{EC}_i(d, \breve{c}_i(d)) && \text{(Unit cost)} && (5.1.3a)\\
&s.t. \quad 0 < d \le CT && \text{(Cycle time)} && (5.1.3b)\\
&\qquad \text{Constraints of line-balancing} && \text{(Line-balance)} && (5.1.3c)\\
&s.t. \quad EC_i(d, \breve{c}_i(d)) = \min_{c_i} EC_i(d, c_i) && \text{(Station cost)} && (5.1.3d)\\
&\qquad s.t. \quad 0 \le c_i \le W_i && \text{(Working zone)} && (5.1.3e)\\
&\qquad i = 1, \cdots, K.
\end{aligned}$$

where $\overline{EC}_i(\cdot)$ and UC are the expected operating cost per unit produced at single and all stations, respectively.

Then, the two-stage method is applied later to this Formulation (5.1.3)–(5.1.8) in the place of typical mathematical programming methods.

5.1.3 Total Line Balancing

5.1.3.1 Station Versus System

We adopt the station-centered approach instead of the traditional system-centered approach. The merits of this are to transform the multistage problem to a unit-station problem, and also, to decrease the large computational time.

Generally, the following inequality holds:

$$\sum_{i=1}^{K} \min_{c_i} EC_i \ge \min_{c_i} TC \tag{5.1.4}$$

Then, it is assumed that the minimum total cost of the system approximately equals the cost individually minimized on each station. That is,

$$TC^* = \sum_{i=1}^{K} \min_{c_i} EC_i \tag{5.1.5}$$

The discussion is processed through a numerical example in the case of three stations. For optimization methods by simulation, the complex method [6] is used in the station-centered approach, and the Genetic Algorithm [2] is used in the system-centered approach.

Figure 5.1.5 shows the behavior of the total cost per unit produced, UC, at the unit station, and it attains the optimal arrival time d^*, which minimizes UC. That is, the $d = 0.9$, $UC = 0.42$ are optimal as shown in Fig. 5.1.5. We will also choose the optimal cycle time $d = 0.9$, later.

Then, the difference in total cost TC is seen in Table 5.1.1. From Table 5.1.1, it can be seen that the station-centered approach is more effective than the system-centered approach. Table 5.1.2 shows a comparison in the computational time of the station versus the system-centered approach. It is seen that the station-centered approach is also superior to the system-centered approach, and this approach seems to be more effective in the case of additional multiple stations.

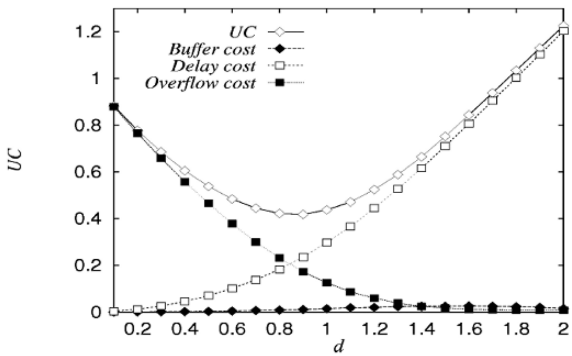


Fig. 5.1.5 The Behavior of total cost per unit produced at the unit station

Table 5.1.1 Station-versus system-centered design: *d – viable* case

$\bar{x}_1$	$\bar{x}_2$	$\bar{x}_3$	d^*	c_1^*	c_2^*	c_3^*	TC^*	difference %
0.8	0.8	0.8	0.9	1.06	1.35	2.03	13,640	0.5
0.4	1.0	1.0	0.7	0.97	1.06	2.32	19,964	2.6
0.4	0.8	1.2	0.7	0.97	0.77	1.74	18,345	2.3
0.6	0.6	1.2	0.8	0.97	0.97	1.42	14,132	0.7

Table 5.1.2 A comparison of computational time: $d = 0.9,\ \overline{x}_1 = \overline{x}_2 = \overline{x}_3 = 0.8$

	TC^*	Computational time
System-c	13,640	22′33″
Station-c	13,709	1′35″
Different	0.5%	about 1/14

5.1.3.2 Two-Stage Design Method

The two-stage design method is proposed as an optimal design method for the assembly line system. This method unifies the combinatorial line-balancing problem and stochastic buffer-design problem, which have been dealt with separately in past research.

For simplicity, the design problem of the assembly line system in this chapter is primarily considered as the operational design under existing production facility. Thus, the design problem is first treated under a given number of stations.

Then, the first stage is to decide the economical cycle time as the input/output variable, and the second stage is to decide the economical buffers, which minimize the expected operating cost under the economical cycle time. In addition, the first and second stages are repeated. The details are as follows:

Step 1 (Preliminary stage): Parameters setting

In Step 1, the traditional line balancing is utilized as the setting of initial variables. Thus, it starts by calculating the limited (maximum) value of cycle time.

(i) Maximum cycle time

From the production-planning quantity N_0 and production-planning period T_0, the maximum cycle time is initially set by the following equation:

$$CT = \frac{T_0}{N_0} \tag{5.1.6}$$

This is used as an initial value d_0 for the interarrival time to the system.

(ii) Line-balancing

Under the number of workstations, K and the maximum cycle time, CT in Eq. (5.1.6), the element task, Uj, is assigned to each station, satisfying the precedence relation of the element tasks, and the mean service times, $\overline{x}_i' s$, are decided.

Then, the element task Uj can be assigned to each station under the cycle time CT, and it is assumed that $K \geq K_0$, when the mean of total assembly time S_0 is given. Here, K_0 is the minimum number of workstations as follows:

$$K_0 = \left\lceil \frac{S_0}{CT} \right\rceil, \tag{5.1.7}$$

in which $\lceil A \rceil$ is the minimum value of integers, which is equal to or no smaller than A.

Step 2 (First stage): Economic cycle time

At this stage, the cycle-time improvement is carried out by the change of the parameter in Step 1. That is, the interarrival time d is improved from the initial value, d_0. as the d is viable and may be changed under this circumstance.

Step 3 (Second stage): Economic buffers

Based on the station-centered approach, the buffer variable c_i, which minimizes the cost of each station is first decided, and then the feedback to Step 2 is carried out in order to search for the sum of the minimum total cost for minimization.

(i) Decision of buffers c_i

Under the design factor ε_i, given in the preliminary stage, the optimum buffer c_i for $EC_i^*(d, c_i)$, which minimizes the total cost in each station, $EC_i\ (d, c_i)$, is decided by using the simulation optimization (e.g., complex method [6]).

(ii) Calculation of cost

The total cost $TC\ (d;\ c_1,\ c_2, \ldots,\ c_K)$ of the system is the sum of the minimum total cost $EC_i^*(d, c_i)$ required in each station. And, the cost UC per unit produced is given below:

$$UC = (d; c_1, c_2, \cdots, c_K) = \frac{TC}{NI}, \tag{5.1.8}$$

where NI is the total artical usables in (0, T_0].

(iii) Termination condition

If the change of d is finished, it ends. If not, d is changed from d to $d = 0.1$, then it returns to the Step 2 again, and the minimum UC is searched.

5.1.4 Optimal Design Example

5.1.4.1 A Design Problem

The precedence relation during element tasks is shown in Fig. 5.1.6, and the two-stage design method is applied to the example [3], in which the service times have stochastic variations.

The parameters are set as follows:

Regular arrival, Erlang service ($k = 3$), $K = 5$, $T_0 = 8,400$, $N_0 = 8,400$, $\varepsilon_i = 0.5$, $\alpha_i = 100$, $\beta_{1i} = 1$, $\beta_{2i} = 1$, number of simulation runs 10,000.

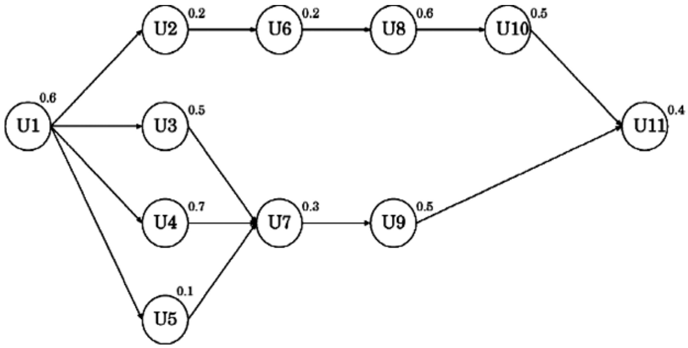


Fig. 5.1.6 A precedence relation [3]

Table 5.1.3 Optimal design example

d	c_1	c_2	c_3	c_4	c_5	UC	BL
$d_0 = 1.0$	1.14	1.19	1.14	1.14	1.14	2.307	0.080
$d^* = 0.9$	0.91	1.10	0.91	0.91	1.05	2.285	–0.022

Following the procedure, it was optimally designed as shown in Table 5.1.3. And, the balance loss, *BL* was obtained by the following expression:

$$BL = \frac{K \times d - S_0}{K \times d}. \tag{5.1.9}$$

In the simple two-stage procedure, it is designed only at the initial value $d_0 = 1$ for the interarrival time. Now, we are able to obtain the economic traffic d^* and economic buffers c_i by repeating the first and second stages, in the two-stage method. The relative reduction of the cost UC^* is 0.95%, which has been improved slightly.

Also, the balance loss is shown in Table 5.1.3. From Table 5.1.3, it can be seen as good from the view of the balance loss in the traditional evaluation. Thus, we were able to reconfirm the effectiveness of the two-stage design method proposed.

5.1.4.2 Cycle Time Problem

In Step 1, the line-balancing is carried out using some production information. Then, the line-balancing problem is classified into two types of problems: (1) deciding the cycle time under the given number of stations (a given production facility), and (2) deciding the number of the necessary stations under the cycle time given (a given demand speed of the market for the product).

Table 5.1.4 shows the number of stations and the cost under the cycle time given. As the cycle time *CT* decreases and the number of stations increases, the total cost *TC* of the system increases monotonically. Under the decided number of stations,

Table 5.1.4 Number and cost of station under the cycle time given

		CT		d^*		
CT(given)	*K*	*TC*	*UC*	d^*	TC^*	UC^*
2.0	3	9,938	2.37	1.2	12,318	1.76
1.2	4	14,469	2.07	1.1	15,544	2.04
1.1	5	18,313	2.40	1.0	19,582	2.33
1.0	5	19,377	2.31	0.9	21,322	2.28
0.9	6	24,276	2.60	0.8	26,637	2.54
0.8	7	29,484	2.81	0.7	33,005	2.75
0.7	8	34,357	2.86	0.7	34,357	2.86

the economic cycle time d is further studied. However, the minimum TC^* and UC^* also increase as the number of stations increases.

The installation cost of stations seems to be a problem for consideration. Also, the cycle time has not been calculated based on production-planning quantity and production-planning period. Therefore, the schedule in which the production volume is not satisfied arises in the case of $CT \geq d_0$ and $d \geq d_0$. The problem under the production quantity is considered later in Chapter 9.

References

1. Feyzbakhsh, S.A., Matsui, M. and Itai, K., Optimal Design of a Generalized Conveyor-Serviced Production Station: Fixed and Removal Item Cases, *International Journal of Production Economics*, 55, 177–189, 1998
2. Gen, M. and Cheng, R., *Genetic Algorithms & Engineering Design*, Wiley, NY, 1997
3. Ignall, E.J., A Review of Assembly Line Balancing, *The Journal of Industrial Engineering*, 16(4), 244–254, 1965
4. Itai, K. and Matsui, M., Optimal Arrival Schedule to a Generalized Conveyor-Serviced Production Station, *Journal of Japan Industrial Management Association*, 46(3), 194–203, 1995 (in Japanese)
5. Kottas, J.F. and Lau, H.-S., A Total Operating Cost Model for Paced Lines with Stochastic Task Times, *American Institute of Industrial Engineers Transactions*, 8(2), 234–240, 1976
6. Kowailk, J. and Osborne, M.R., *Methods for Unconstrained Optimization Problems*, Elsevier, NY, 1968
7. Matsui, M., *A Study on Optimal Operating Policies in Conveyor-Serviced Production Systems*, Doctoral Dissertation, Tokyo Institute of Technology, Japan, 1981 (in Japanese)
8. Matsui, M., A Generalized Model of Conveyor-Serviced Production Station (CSPS), *Journal of Japan Industrial Management Association*, 44(1), 25–32, 1993 (in Japanese)
9. Matsui, M., Optimal Economic Design of Production and Queueing Systems, *Abstracts of APORS'94*, Fukuoka, Japan, 266, 1994
10. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002

11. Matsui, M., Shingu, T. and Makabe, H., Conveyor-Serviced Production System : An Analytic Framework for Station-Centered Approach by Some Queueing Formulas, *Preliminary Reports of the Operations Research Society of Japan*, Autumn, 104–107, 1977 (in Japanese)
12. Muramatsu, R., *New Principles of Production Management*, Kunimotoshobo, Tokyo, Japan, 169–182, 1979 (in Japanese)
13. Muramatsu, R., Kasugai, H. and Kuroda, M., A Study of the Dynamic Characteristic of an Assembly System, *Industrial Engineering*, 5(6), 539–548, 1963 (in Japanese)
14. Shimizu, K., Ishizuka, Y. and Bard, J.F., *Non Differentiable and Two-Level Mathematical Programming*, Kluwer, Boston, 1997
15. Wild, R., *Mass-Production Management – The Design and Operation of Production Flow-line Systems*, Wiley, London, 1972
16. Yamada, T. and Matsui, M., 2-Stage Design Method for Assembly Line System: A Unified Approach, *Journal of Japan Industrial Management Association*, 51(6), 538–549, 2001 (in Japanese)

5.2 Line Design with Stoppers

5.2.1 Introduction

The ALS (assembly line system) can be without or with stoppers, which prevent the overflow of items. The latter system is known as a free-flow line (e.g., [9, 10]), in which the arrival items are controlled (stopped or proceeded) by a stopper at each station.

For the stochastic design of ALS with stoppers, many papers have already been published. This design problem has both the line-balancing problem, such as, combinatorics and the buffer-design problem under stochastic arrival/service times, and it is usually called the stochastic line-balancing problem. Our approach is basically more systematic than that of the past studies [3, 11].

In this chapter, we apply the two-stage design method [7, 8] to this case, and consider the stochastic design problem as a simultaneous decision of the economic traffic (cycle time) and the buffers [13], as well as the case without stoppers in Chapter 5.1 [12]. By using this method, the first stage decides the economic cycle time that minimizes the expected operating cost, and the second stage decides the number of pallets that minimizes the costs relating to buffers in the system under the economic cycle time.

First, the objective function for the station-centered approach is considered, and a simple case of $D/M/1$ type by queueing approach and a typical case of $D/E_k/1$ type by simulation are introduced. Next, the two-stage design procedure for the ALS with stoppers is presented, and the two cases of ALS with and without stoppers are unified. Finally, an optimal design example is shown by applying this procedure, and the two cases are compared numerically.

5.2.2 Station-Centered Approach

5.2.2.1 Explanation of Model

In this chapter, we treat assembly line systems with stoppers at each station $i,\ i = 1, 2, \dots,\ K$ (Figure 5.2.1). It is assumed that the items flow according to a regular

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_9, © Springer Science+Business Media, LLC 2009

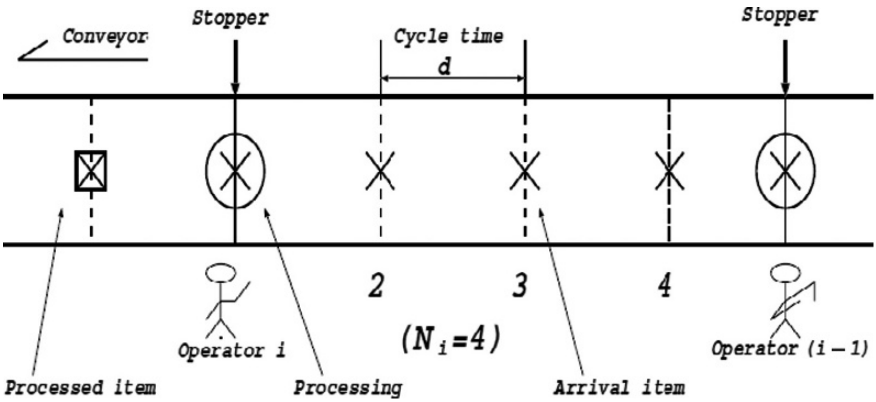


Fig. 5.2.1 Unit station

arrival at the cycle time d, and the service time $\bar{x}_i$, in each station, i follows the Erlang distribution with phase k. So, each station is regarded as a $D/E_k/1$ type of queueing system.

If a station is busy, arrivals wait in front of the station as buffers. Under these assumptions, the problem is to decide simultaneously both the cycle time, d, and the capacity of in-process inventory, N_i, at each station i in view of the operating costs. Similar to Chapter 5.1, we adopt not the system-centered approach, but the station-centered approach.

5.2.2.2 Two-Stage Design Method

Similar to Chapter 5.1, the ALS with stoppers is regarded as a two-level structure, and is considered as the decision-making problem of the economic traffic (cycle time) in the upper level and the buffer-design problem of each station in the lower level. This problem is here formulated as a problem not of mathematical programming [1], but of a two-stage design method [7, 8].

The two-stage design method is seen in Fig. 5.2.2. The first stage is to decide the optimal interarrival time (cycle time), d^*, that minimizes the sum of the total

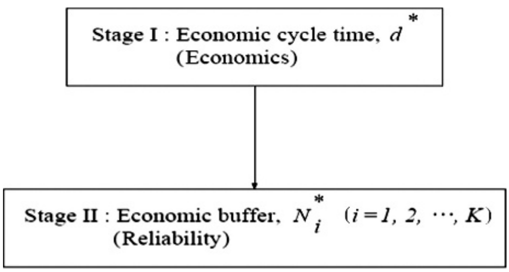


Fig. 5.2.2 Two-stage design method

expected operating cost, EC_i. The cost at station i, EC_i, is the sum of the in-process inventory cost, busy cost, and idle cost per unit time.

In *D/G/*1 type, the busy and idle rate per unit time are ρ_i and $1 - \rho_i$, respectively [6]. Then, the total expected operating cost at station, i, EC_i, is similar to MGM, and is as follows:

$$EC_i = \alpha_{1i} L_i + \alpha_2 \rho_i + \alpha_{3i}(1 - \rho_i). \tag{5.2.1}$$

Then, the objective function at the first stage is set as follows:

$$TC = \sum_{i=1}^{K} EC_i. \tag{5.2.2}$$

Under the optimal cycle time, d^*, at the first stage, the second stage is to decide the number of pallets, $N_i{}^*$, that minimizes the sum of buffer-and-overflow cost, BC_i. Here, the buffer-and-overflow cost at station i, BC_i, is as follows:

$$BC_i = \beta_{1i} N_i + \beta_{2i} B_i, \quad i = 1, 2, \ldots, K \tag{5.2.3}$$

where B_i is the probability of overflows, and β_{1i} and β_{2i} are cost efficiencies.

An analytical result for the unit station is obtained from [6] as follows: In the case of $D/M/1$ type, which is the same as $D/E_1/1$, the total expected operating cost, EC_i, is given by

$$EC_i = \alpha_{1i} \frac{\rho_i}{1 - \delta_i} + \alpha_2 \rho_i + \alpha_{3i}(1 - \rho_i), \quad i = 1, 2, \ldots, K \tag{5.2.4}$$

where δ_i is the root of the equation

$$\delta_\mathrm{i} = \exp\{-\frac{1 - \delta_\mathrm{i}}{\rho_\mathrm{i}}\}, \quad i = 1, 2, \ldots, K \tag{5.2.5}$$

in which is restricted to $0 < \delta_i < 1$.

Figure 5.2.3 shows the behavior of the objective function, EC_1, at the first stage. From Fig. 5.2.3, the optimal cycle time d^*, which minimizes EC_1 exists, and $EC_1{}^* = 3.47$ at $d^* = 1.6$.

Figure 5.2.4 shows the behavior of the throughput, Th_i $(= \lambda(1 - B_i))$, under $N_1 = 1, 2, \ldots, 7$. From Fig. 5.2.4, it is shown that the throughput increases when N_i increases. At the second stage, the optimal capacity of in-process inventory at station 1, N_i, is $N_\mathrm{i}{}^* = 5$ from Eq. (5.2.3), and the throughput is maximized when $d^{**} = 1.3$.

A similar behavior is found by simulation in the case of $D/E_k/1$ type. Therefore, it is noted that the optimal values of d, $d^* = 1.6$, and $d^{**} = 1.3$, would generally differ because of cost consideration.

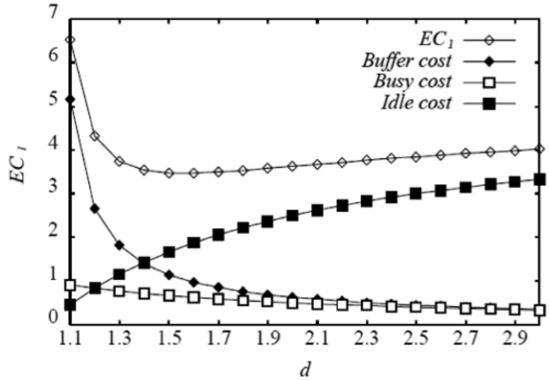


Fig. 5.2.3 Behavior of cost: Exponential service

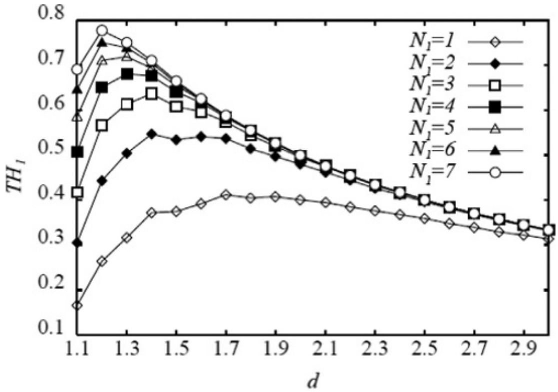


Fig. 5.2.4 Behavior of throughput: Exponential service

5.2.3 Numerical Consideration

5.2.3.1 Two-Stage Design Procedure

For the design of ALS, both types of existing and installation problems of production facilities occur. In the former problem, the cycle time, which is the demand speed of the market, is chosen under the given number of stations in the existing production facilities (leader). Similar to Chapter 5.1, we consider the former case of the given number of stations. Following Fig. 5.2.2, the two-stage design procedure for ALS with stoppers is seen in Fig. 5.2.5. The details are as follows:

Step 1 (Preliminary stage): Parameter setting

In Step 1, the traditional line balancing is introduced as the setting of initial variables. Thus, this step starts by calculating the maximal value of cycle time.

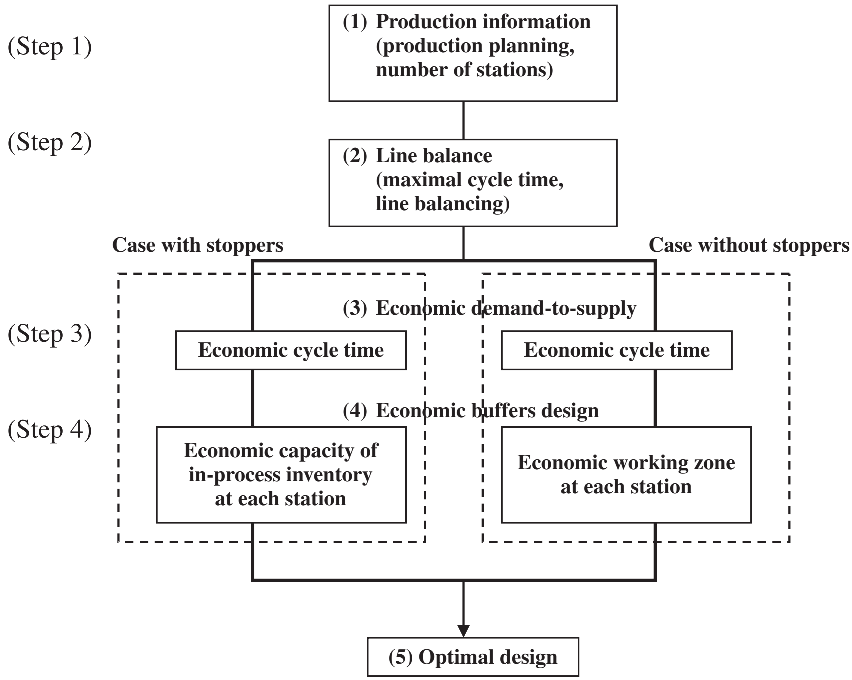


Fig. 5.2.5 A summary of the design framework for ALS

(i) Maximal cycle time
From the production planning quantity N_0 and the production planning period T_0, the maximal cycle time is initially set by the following expression:

$$CT = T_0/N_0 \tag{5.2.6}$$

(ii) Condition on the number of stations
Under the maximal cycle time CT in (5.2.6) and total assembly time S_0 given, the number of stations K given must be restricted to $K \geq K_0$. Here, K_0 is the minimal number of stations as follows:

$$K_0 = \left\lceil \frac{S_0}{CT} \right\rceil,$$

in which $\lceil A \rceil$ is the minimal value of integers, which is equal to or no smaller than A. (If this is not possible, the production planning is infeasible.)

(iii) Line balancing
Under the given number of workstations K and the maximal cycle time CT in (5.2.6), the element tasks Uj satisfying the precedence relation

are assigned to each station by using the Jackson Method. In addition, the mean service times $x_i's$ are decided.

(iv) Queueing condition ($\rho i < 1$)
Satisfying $\rho_i < 1$, the cycle time CT must be restricted to $CT > \bar{x}_i$. (If this is not possible, the production planning is infeasible.)

Step 2 First stage: Economic cycle time
At this stage, the economic cycle time minimizing the expected operation cost is decided.

(i) Decision of cycle time
By simulation, the total cost TC at the system is given as the sum of minimal total cost $EC_i{}^*$ (given by Eq. (5.2.1)) required in each of the station. There is an attempt to change the interarrival time d from $\bar{x}_i$ to CT in order to improve the cost.
Thus, the optimal cycle time d^*, which minimizes the system cost TC is decided.

Step 3 Second stage: Optimal buffers
Under the economic cycle time d^* at the first stage, the buffers in each station and the minimizing costs related to buffers are decided.

(i) Decision of buffers N_i
Under the interarrival time d^* obtained at the first stage, the optimal buffer $N_i{}^*$, which minimizes the buffer-and-overflow cost at station i, BC_i (in Eq. (5.2.3)), is decided. Thus, the optimal design is achieved.

5.2.4 Further Consideration

5.2.4.1 Summary of ALS Design

For the given number of stations, the two-stage design procedure for ALS is unified from Chapter 5.1 in this chapter, and it is seen in Fig. 5.2.5. For the case without stoppers, it is noted that the two-step method in [2] may be introduced to Steps 3 and 4 in Fig. 5.2.5 instead of iterative steps in [12].

Now, the two-stage design procedure is applied to an example of a line-balancing problem in Fig. 5.2.5 [5], and its optimal design is seen in Table 5.2.1. The parameters are set as follows:

Regular arrival, Erlang service ($k = 3$), $K = 5$, $T_0 = 8,400$, $N_0 = 5,600$, $\alpha_{1i} = \alpha_{2i} = 1$, $\alpha_{3i} = 5$, $\beta_{1i} = 1$, $\beta_{2i} = 100$.

Table 5.2.1 Optimal design example: ALS with stoppers

d	N_1	N_2	N_3	N_4	N_5	TC	Difference
$d_0 = 1.5$	3	2	3	3	2	16.16	–
$d^* = 1.2$	5	2	5	5	4	15.28	5.5%
$\overline{x}_i$	1.0	0.7	1.0	1.0	0.9		

5.2.4.2 Comparison with and Without Stoppers

For the ALS with stoppers, the Generalized CSPS [2] is introduced as a model of unit stations. The expected cost per unit produced, UC, is used as the objective function, and the two-stage design procedure in Chapter 5.1 is applied to this example.

The first stage is to decide the interarrival time d^* minimizing the UC. The second stage is to decide the buffer (look-ahead time) c_i at each station, which is part of the working zone and minimizes the UC.

Similar to Table 5.2.1, Table 5.2.2 shows the case of ALS without stoppers. From Tables 5.2.1 and 5.2.2, the difference between d_0 and d^* is slightly improved by 5.5% in the case with stoppers, but it is significantly improved at 22.1% in the case without stoppers.

Finally, we focus on the relationship between service times and buffers (Table 5.2.3) in view of bottleneck theory [4]. From Table 5.2.3, it is supposed that the space-buffers in the bottleneck increase in the case with stoppers, while the time-buffers in the nonbottleneck are the largest in the case without stoppers.

Table 5.2.2 Optimal design example: ALS without stoppers

d	c_1	c_2	c_3	c_4	c_5	UC	Difference
$d_0 = 1.5$	1.57	1.47	1.57	1.57	1.59	3.62	–
$d^* = 1.1$	1.30	1.35	1.30	1.30	1.21	2.82	22.1%
$\overline{x}_i$	1.0	0.7	1.0	1.0	0.9		

Table 5.2.3 Relationship between service times and buffers: Under the economic cycle time

Under the economic cycle time

Stoppers	d^*	$\overline{x}_2 = 0.7$	$<$	$\overline{x}_5 = 0.9$	$<$	$\overline{x}_1 = 1.0$
With	$d^* = 1.2$	$N_2 = 2$	$<$	$N_5 = 4$	$<$	$N_1 = 5$
Without	$d^* = 1.1$	$c_2 = 1.35$	$>$	$c_5 = 1.21$	$<$	$c_1 = 1.30$

References

1. Aiyoshi, E. and Shimizu, K., Hierarchical Decentralized Systems and its New Solution by a Barrier Method, *IEEE Transactions on Systems, Man & Cybernetics*, 11(6), 444–449, 1981
2. Feyzbakhsh, S.A., Matsui, M. and Itai, K., Optimal Design of a Generalized Conveyor-Serviced Production Station: Fixed and Removal Item Cases, *International Journal of Production Economics*, 55, 177–189, 1998
3. Ghosh, S. and Gagnon, R.J., A Comprehensive Literature Review and Analysis of the Design, Balancing and Scheduling of Assembly Line Systems, *International Journal of Production Research*, 27(4), 637–670, 1989
4. Goldratt, E.M. and Cox, J., *The Goal: A Process of Ongoing Improvement*, North River Press, Inc., MA, 1992
5. Ignall, E.J., A Review of Assembly Line Balancing, *The Journal of Industrial Engineering*, 16(4), 244–254, 1965
6. Jansson, B., Choosing a Good Appointment System – A Study of Queues of the Type (D,M,1), *Operations Research*, 14, 292–312, 1966
7. Matsui, M., An Optimal Design Problem of Production and Queueing Systems, *Symposium on Performance Models for Information Communication Networks*, Hakone, Japan, 77–85, 1994 (in Japanese)
8. Matsui, M., A Management Game Model: Economic Traffic, Lead time and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
9. Muramatsu, R., *New Principles of Production Management*, Kunimotoshobo, Tokyo, Japan, 169–182, 1979 (in Japanese)
10. Muramatsu, R., Kasugai, H. and Kuroda, M., A Study of the Dynamic Characteristic of An Assembly System, *Industrial Engineering*, 5(6), 539–548, 1963 (in Japanese)
11. Sarin, S.C., Erel, E. and Dar-El, E.M., A Methodology for Solving Single-Model, Stochastic Assembly Line Balancing Problem, *Omega*, 27(5), 525–535, 1999
12. Yamada, T. and Matsui, M., 2-Stage Design Method for Assembly Line Systems: A Unified Approach, *Journal of Japan Industrial Management Association*, 51(6), 538–549, 2001 (in Japanese)
13. Yamada, T. and Matsui, M., 2-Stage Design Method for Assembly Line System with Stoppers, *Journal of Japan Industrial Management Association*, 51(6), 594–602, 2001

Chapter 6
Point-Wise Risk Processes

6.1 Periodic Type Strategy

6.1.1 Introduction

A macro-level (or economic) problem for job-shop production in Matsui [2, 3] is extended here to the case of changeable production capacity. Job orders have variable estimated prices and arrive frequently at irregular or random intervals. The problem of selecting the orders according to the periodic selection policy (PSP) is discussed under changeable production capacity.

The macro-level problem considered is summarized as follows: Accepting all orders is not always the best option due to changeable capacity considerations. The manager of the job shop is faced with the problem of selecting and processing orders according to some decision rule and according to the problem of increasing the idle (opportunity) cost of the job shop. We will decide here the structure for the best decision rule under a periodic type system.

A simple problem of the job-shop production system consisting of a sales center with order-selection and a production center with changeable capacity is first treated under no switch-over cost by Matsui [4]. For fixed switch over costs, Tijms [9–12] studied the problem of how to switch over some processing rates to minimize the mean operating cost. The optimality of a switch-over policy is showed in [9], and a continuous model is seen in [1, 10].

Tijms' stochastic model [11] is extended to treat together the problem of how to select the job orders arriving irregularly to maximize the mean accepted price. Both problems are interrelated, and thus better understanding of the structure of optimal order-selection policies would be very interesting. Also, the cooperative and non-cooperative control problems of sales and production centers is discussed here, since complete cooperation would be practically impossible.

This chapter generalizes and discusses the control problem of maximizing the marginal profit (= accepted price-operating cost) of a job-shop production system of a periodic type with order-selection and switch-over [5]. First, a generalized stochastic model with fixed switching costs is proposed to derive the two subobjective functions: the mean accepted price and mean operating cost.

Next, the generalized model is formulated in two ways, as the cooperative versus the noncooperative control problems of sales and production centers. Finally, the

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_10,

nonmonotonic structure of optimal order-selection criteria is found, and the demerit of noncooperative control is numerically considered.

6.1.2 Stochastic Model

6.1.2.1 Assumptions and Notations

Generally, job-shop production systems consist of a sales center with order-selection and a production center with scheduling. Muramatsu [7] and Kate [8] discussed a relationship of order-selection and scheduling, and presented production-planning systems of two types: periodic versus dynamic.

These studies illustrate the outline of the problems, but lack qualitative or quantitative considerations. For this study, we introduce a stochastic model of the job-shop production system consisting of a sales center with order-selection and a production center with switch-over (see Fig. 6.1.1). This method is basically a queueing system with one production center, which is modeled as a single server queue under order-selection. No due times are explicitly considered except that the backlog is controllable finitely.

Suppose that job orders have an independent estimated price, S, and processing time, X, and arrive according to Poisson processes with rate λ at a steady state. It is then assumed that all job orders have a processing time drawn from the same distribution independent of estimated price. Also, suppose the arriving job orders are accepted or rejected by using one of the two selection criteria, and next, the accepted job orders are processed by using one or two available processing rates. Any job orders, which are rejected are assumed to be lost or transferred to the subcontractor without comeback.

Now, the distribution functions, $G_1(s)$, of random variables, S, is given by $G_1\ (s) = \Pr\{S \leq s\},\ s \geq 0$. In the sales center, arriving job orders are accepted

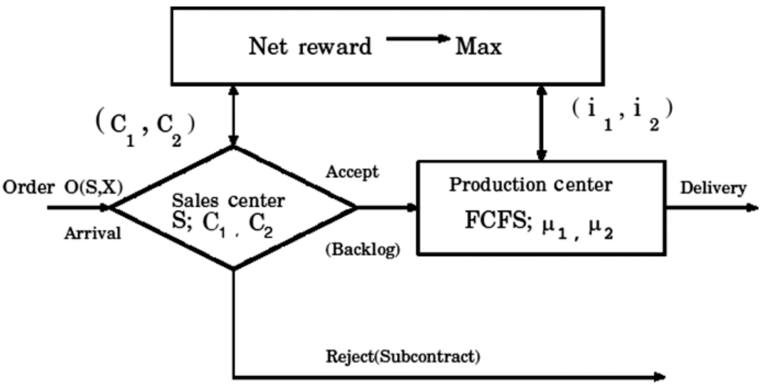


Fig. 6.1.1 A job-shop production system

or rejected by using one of the two selection criteria: c_1 and c_2, depending on the backlog. When the sales center accepts job orders with an estimated price larger than c_k, the mean accepted price of the orders $\alpha^{-1}(c_k)$ is given by

$$\alpha^{-1}(c_k) = \int_{c_k}^{\infty} s d\left[G_1(s)/\overline{G}_1(c_k)\right], 0 \le c_k \le \infty, \tag{6.1.1}$$

where

$$\overline{G}_1(c_k) = \Pr\{S > c_k\} = 1 - G_1(c_k),\ 0 \le c_k \le \infty. \tag{6.1.2}$$

The production center has two types of available processing rates and processes, the job order accepted by the sales center by processing the rate on a first-come first-served basis (FCFS). The distribution function of the processing time of each type k $(= 1,\ 2)$, X_k, is given by $G_2^{(k)}(x) = \Pr\{X_k \le x\},\ x \ge 0$. Similar to Tijms [11], it is assumed that

$$G_2^{(1)}(x) \le G_2^{(2)}(x), \tag{6.1.3}$$

so that processing Type 2 is faster than processing Type 1.

Denote by μ_k^{-1} the first moment of processing time, X_k, and for $j \ge 2$, denote $\mu_k^{(j)}$ the jth moment of X_k. We assume that $\mu_k^{(2)} < \infty$ and $\mu_k^{(3)} < \infty$. Also, under Poisson arrival, the arrival rate of job orders with an estimated price larger than c_k is, $\lambda(c_k)$, where $\lambda(c_k)$ is given by, $\lambda(c_k) = \lambda\bar{G}_1(c_k)$. To avoid the system being uncontrollable, we assume that $\lambda(c_2) < \mu_2$.

Both the selection criteria, c_k $(k = 1,\ 2)$, used in selected job orders and the switch-over of the two processing types are operated according to the size of the backlog, i, at a time just after processing is finished. The size of the backlog is controlled on two-control levels (control variables): $i_1, i_2 (0 \le i_2 \le i_1, i_1 \ge 1)$.

The operating cost of the system consists of the fixed switch-over cost, K_k $(k = 1,\ 2)$, and the variable costs: processing cost at rate r_k, holding cost at rate h, and idle cost at rate β. The fixed switch-over cost, $K_{1\ (2)}$, occurs in the production center when processing Type 1 (Type 2) is changed to Type 2 (Type 1). Here, we assume $K_1 = K_2 = K$, since the average will be the same over a long time. In addition, the switch-over time is assumed to be zero for simplicity.

6.1.2.2 Periodic Type Model

Corresponding to the two main order-selection policies, there are two periodic type models and dynamic type models of a job shop. Here we consider a periodic type model (see Fig. 6.1.2).

Immediately after the completion of an order, a decision is made about the selection criteria, $c_k,\ k = 1,\ 2$; and about the processing mode, $k = 1,\ 2$, to be used for the next order. The decision is based on the size of the backlog of accepted orders,

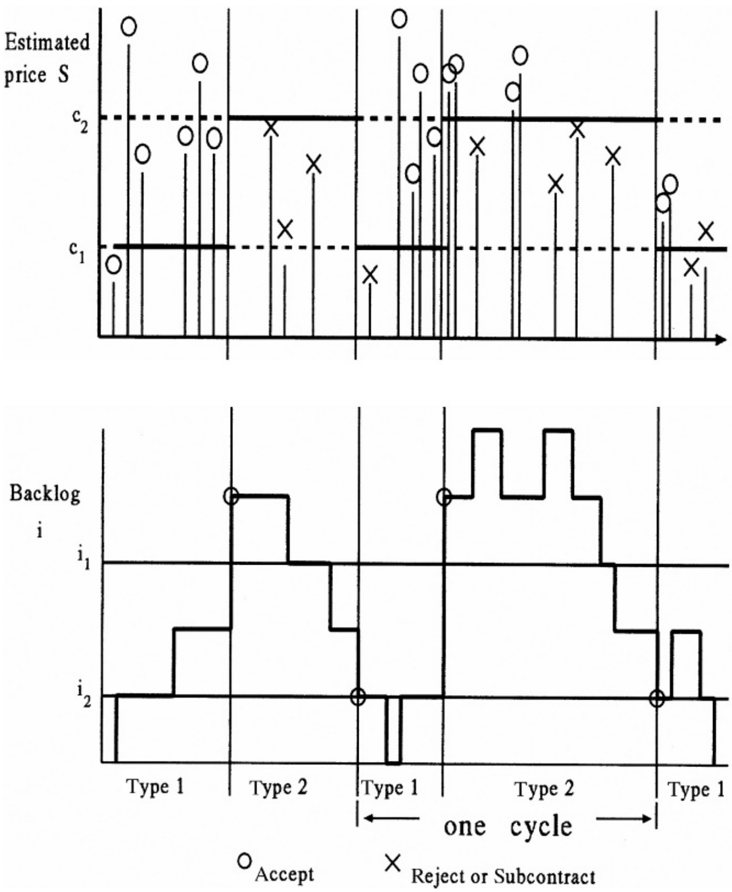


Fig. 6.1.2 Time processes of periodic type

i, in relation to the control levels, i_1 and i_2. Orders that arrive during processing of an order are selected or rejected at the end of processing, and after that, the decision about selection criterion and the processing mode is made.

If the backlog, i, is zero after the completion of an order, the decision $k = 1$ is made and the system will wait (idling) for the arrival of an order. After completion of an order with $k = 1$, if $0 \leq i_2 \leq i_1$, k remains 1 and the sales center will only accept job orders larger than c_1 and the production center will continue to process in Mode 1; if $i > i_1$, the decision $k = 2$ is made and the sales center will only accept job orders larger than c_1 and will continue processing in Mode 2 (the switch incurs the cost of K).

Sales center will accept job orders larger than c_1 and will continue processing in Mode 1 (this switch also incurs the cost of K). The interval time between order arrival and job acceptance is called the *quoting time*.

6.1.3 Objective Functions

6.1.3.1 Embedded Approach

In this section, we give the two sub-objective functions: mean accepted price and mean operating cost. Here we use the embedded approach by Tijms [11] (see Fig. 6.1.3).

This periodic type model can be represented by semi-Markov decision processes in which the decision epochs are given by the service completion epochs, and at any decision epoch the system can be classified into one of the states of denumerable state space $I = \{i|i = 0, 1, \ldots\} \bigcup \{i'|i' = 0, 1, \ldots\}$.

Here state i (i') corresponds to the situation in which the number of customers present is i and service type μ_i was 1(2), and a set of available actions is given by $A\ (i) = \{1, 2\}$, where action k prescribes to use service type, k, for the next service and selection criteria, c_k, for selection of orders set just before the decision epochs.

From the assumption of Poisson arrival, the probability, $P_k\ (n, c_k)$, that n orders are accepted only when the estimated price S is larger than or equal to c_k during a processing time X_k, is given by,

$$P_k(n, c_k) = \int_n^{\infty} \left[\left\{\lambda \overline{G}_1(c_k)x\right\}^n \Big/ n!\right] \times \exp\left\{-\lambda \overline{G}_1(c_k)x\right\} dG_2^{(k)}(x),\ n = 1, 2, \ldots. \tag{6.1.4}$$

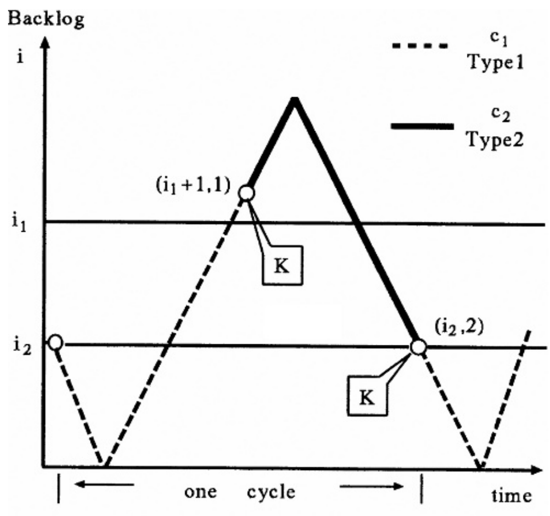


Fig. 6.1.3 Stochastic model: periodic type

Let $a_{ij}(k)$ be the transition probability that when the state is, i and an action, $k \in A(i)$, is used, the next state equals, j. From Eq. (6.1.4),

$$a_{ij}(k) = P_k(j + 1 - u, c_k),\ j \geq u. \tag{6.1.5}$$

The expected sojourn time from the decision epoch with state, i, and action, $k \in A(i)$, to the next epoch, $\tau(i, k)$, is given clearly by

$$\begin{aligned} &\tau(i, k) = \tau(i', k) = \mu_k^{-1}, \\ &\tau(0, k) = \tau(0', k) = \lambda^{-1} + \mu_1^{-1},\ k = 1, 2, \ldots. \end{aligned} \tag{6.1.6}$$

At such a problem if the state of the system is infinity, we choose a finite set (embedded set), $A_f = \{i|i = 0, \ldots i1\} \bigcup \{i_2'\}$. Thus, we consider the embedded Markov chain such that state, i, at the decision epoch is, $i \in A_f$, for any, f^∞. The probabilities, $\tilde{a}_{if}(f)$, that starting when the state is i, the first entry state in A_f is state j $(j \in A_f)$ are, from Eq. (6.1.4), as follows:

$$\begin{aligned} &\tilde{a}_{ii_2'}(f) = \tilde{a}_{i'i_2'}(f) = 1, && i > i_1, \\ &\tilde{a}_{ij}(f) = P_1(j + 1 - i, c_1), && 1 \leq i \leq i_1, i - 1 \leq j \leq i_1, \\ &\tilde{a}_{ii_2'}(f) = 1 - \sum_{j=0}^{i_1 - i + 1} P_1(j, c_1), && 1 \leq i \leq i_1, \\ &\tilde{a}_{i'j}(f) = \tilde{a}_{ij}(f), && 0 \leq i \leq i_2, \\ &\tilde{a}_{0j}(f) = \tilde{a}_{1j}(f). \end{aligned} \tag{6.1.7}$$

Also, we need the following: Now let $\tilde{\tau}$ (i, f), be the total expected sojourn time until the first entry state is in the embedded set, A_f, starting when the system is, i. Then, the total expected sojourn time $\tilde{\tau}$ (i', f) that the first entry state in the embedded set A_f becomes i_2, starting when the system is $i'(i > i_2)$, is as follows:

$$\tilde{\tau}(i', f) = \tau(i - i_2), \quad i > i_2. \tag{6.1.8}$$

Further, using Eq. (6.1.6)

$$\begin{aligned} &\tilde{\tau}(i, f) = \tilde{\tau}(i', f), \quad i > i_1, \\ &\tilde{\tau}(i, f) = \tau(i, 1) + \sum_{j=i_1-i+2}^{\infty} \tau(i - 1 + j - i_2)\mathrm{P}_1(j, c_2), \quad 1 \leq i \leq i_1 \\ &\tilde{\tau}(0, f) = \lambda^{-1} + \tilde{\tau}(1, f) \end{aligned} \tag{6.1.9}$$

6.1.3.2 Accepted Price and Operating Cost

Now, assume that the operating cost corresponding to transitions between states consists of a fixed switch-over cost and some variable costs. That is,

$$\text{Operating cost} = \text{Fixed switch-over cost} + \text{Variable costs,} \tag{6.1.10}$$

where variable costs are the opportunity cost, the processing cost, and the idle cost.

We consider the two subobjective functions: the mean accepted price and the mean operating cost of the long-run average per unit time. First, let the total expected sojourn time, the total expected price, and the total expected operating cost until the state of the system becomes i'_2, starting from when the system is i, be denoted by $T(i, f)$, $L(i, f)$ and $G(i, f)$, respectively.

Next, we let the two subobjective functions $F_1(f)$ and $F_2(f)$ be

$$\begin{aligned} F_1(f) &= \mathrm{L}(i'_2, f)/T(i'_2, f), \\ F_2(f) &= \mathrm{G}(i'_2, f)/\mathrm{T}(i'_2, f) \end{aligned} \tag{6.1.11}$$

The functions $F_1(f)$ and $F_2(f)$ represent the mean accepted price and mean operating cost of the long-run average, respectively [13].

6.1.4 Cooperative Case

6.1.4.1 Two-Level Formulation

The job shop that consists of sales and production centers under a distribution environment can be classified into a two-level approach of two types: cooperative and noncooperative. In this section, we consider the cooperative type. First, we examine the following relation, using Formula (6.1.11), towards this problem.

$$\text{Net reward rate } F = \text{Mean accepted price } F_1 - \text{Mean operating cost } F_2.$$

The problem that causes this net reward rate F to maximize under the distribution environment is called Problem 1 (cooperative). That is, Problem 1 should be the following:

$$\begin{aligned} &\max_{\mathrm{c}} F(c; \hat{i}(c)), \\ &\quad \text{s.t. } 0 \le c \le c_0 \\ &\qquad F(c; \hat{i}(c)) = \max_{\mathrm{i}} F(c; i), \\ &\qquad \text{s.t. } 0 \le i \le i_0,\ i_2 - i_1 \le 0, \end{aligned} \tag{6.1.12}$$

where $\boldsymbol{i} = (i_1, \ i_2)$, $\boldsymbol{c} = (c_1, c_2)$, and $\boldsymbol{i}_0$, $\boldsymbol{c}_0$ are fixed value vectors. We use an algorithm by the policy iteration method for optimal design [11].

6.1.4.2 Numerical Considerations

In this section, the structure of the problem of the cooperative type is numerically considered. We set up the parameters as follows:

Arrival rate $\lambda = 4.0$,
Holding cost rate $h = 0.05$,
Processing cost rate $r_1 = 0.5, \ r_2 = 1.75$,
Switching cost $K = 3.0$,
Processing rate $\mu_1 = 1.0$, $\mu_2 = 2.0$,
Idle cost rate $r_0 = 0.1$,
Price rate $\alpha \equiv \alpha(0) = 1.0$

Tables 6.1.1 and 6.1.2 are the results of the optimal design when we changed λ and K, respectively. From Tables 6.1.1 and 6.1.2, the monotonicity that c_1 becomes larger than c_2 [3] does not hold, when λ or K is large, and the reverse phenomenon occurs.

Figures 6.1.4–6.1.5 show the behavior of the selection criteria c_1^*, c_2^*, in the case when $K = 0.0$, 2.0, and 6.0. Under $K = 0$, it is seen from Fig. 6.1.4 that the selection criteria c_1^*, c_2^* are a monotonic increasing function of λ, and that the monotonicity ($c_1^* \leq c_2^*$) holds. In contrast, under $K \neq 0$, it is seen from Fig. 6.1.5

Table 6.1.1 Optimal design: $\lambda = 1.0\ (1.0)\ 6.0$

λ	f_1^*	F_1	F_2	F
1.0	$(0.6,\ 1.3;\ 19.7)_1$	0.9160	0.4675	0.4485
2.0	$(1.0,\ 1.4;\ 14,\ 4)_1$	1.5332	0.6727	0.8605
3.0	$(1.3,\ 1.4;\ 13,\ 3)_1$	1.9506	0.8139	1.1367
4.0	$(1.5,\ 1.3;\ 11,\ 1)_1$	2.3279	0.9837	1.3442
5.0	$(1.5,\ 1.3;\ 9,\ 0)_1$	2.9484	1.4186	0.5298
6.0	$(1.5,\ 1.4;\ 8,\ 0)_1$	3.4897	1.7623	1.7275

f_1^*: Optimal in cooperative.

Table 6.1.2 Optimal design: $K = 0.0\ (1.0)\ 5.0$

K	f_1^*	F_1	F_2	F
0.0	$(1.1,\ 1.3;\ 2,\ 2)_1$	2.7316	1.2431	1.4885
1.0	$(1.3,\ 1.3;\ 7,\ 2)_1$	2.5546	1.1582	1.3964
2.0	$(1.4,\ 1.3;\ 9,\ 1)_1$	2.4489	1.0869	1.3620
3.0	$(1.5,\ 1.3;\ 11,\ 1)_1$	2.3279	0.9837	1.3442
4.0	$(1.5,\ 1.3;\ 12,\ 1)_1$	2.3227	0.9893	1.3334
5.0	$(1.6,\ 1.4;\ 14,\ 2)_1$	2.2013	0.8768	1.3246

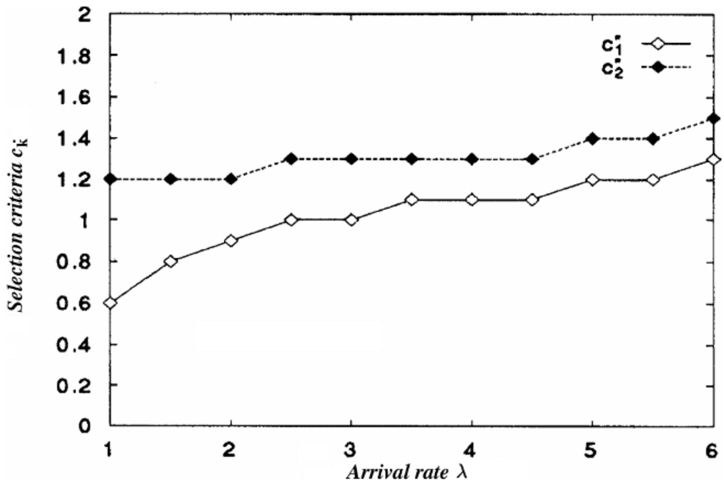


Fig. 6.1.4 Behavior of selection criteria $c_1,\ c_2:\ K = 0.0$

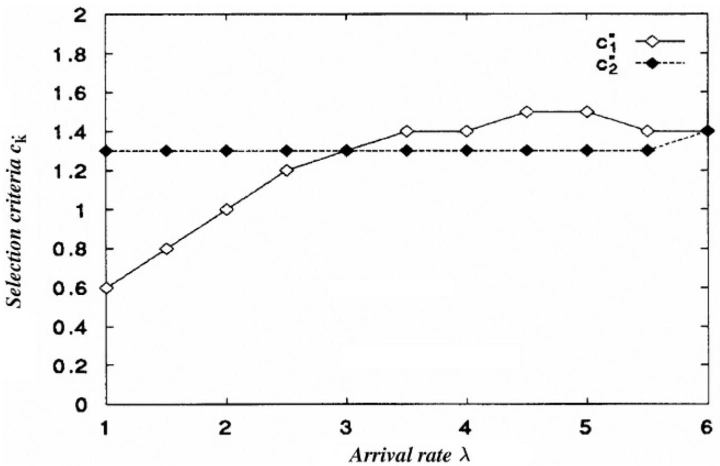


Fig. 6.1.5 Behavior of selection criteria $c_1,\ c_2:\ K = 2.0$

that the selection criteria $c_1^*,\ c_2^*$ are not monotonic increasing functions, and that a reverse or zigzag phenomenon occurs.

The reason for this is as follows: When the arrival rate increases, the holding cost of the backlog becomes large. So the selection criterion c_1^* is set high in order not to accept the orders with low price. However, under $K \neq 0$, the selection criteria c_2^* must be set low in order to continue the Type 2 without frequent switch-over.

6.1.5 Cooperative versus Non-Cooperative Type

6.1.5.1 Two-Level Formulation

In this section, we formulate the problem of a non-cooperative type and try to consider the cooperative versus non-cooperative type comparatively. We consider the functions $F_1,\ F_2$ by Eq. (6.1.11) for this problem. The mean accepted price F_1 is the adjustable function in the sale center, and the sales center tries to maximize this. In contrast, the mean operating cost F_2 is the adjustable function of the production center, and the production center tries to minimize this. This problem is a non-cooperative type and does not necessarily maximize the net reward rate F. We call it Problem 2.

Problem 2 is introduced to consider the loss that occurs for non-cooperation between centers, and is formulated as follows:

$$\begin{aligned}
&\operatorname*{Max}_{c} F_1(\boldsymbol{c};\hat{\boldsymbol{i}}(\boldsymbol{c})),\\
&\quad s.t.\ 0 \le \boldsymbol{c} \le \boldsymbol{c}_0\\
&\qquad\qquad F_2(\boldsymbol{c};\hat{\boldsymbol{i}}(\boldsymbol{c})) = \operatorname*{Max}_{i} F_2(\boldsymbol{c};\boldsymbol{i}),\\
&\qquad\qquad s.t.\ 0 \le i \le i_0, i_2 - i_1 \le 0,
\end{aligned} \tag{6.1.13}$$

Where $i = (i_1,\ i_2),\ c = (c_1,\ c_2)$, and $i_0,\ c_0$ are fixed value vectors. For the solution, we use the dual-matrix method for the optimal design of the noncooperative type [6]. The dual matrix is the matrix in which the element is $(F_1(c;i), -F_2(c;i))$.

6.1.5.2 Numerical Considerations

In this section, a cooperative versus non-cooperative comparison is numerically considered. Table 6.1.3 shows the result of the optimal design for the case when λ is changed. From Table 6.1.3, it is seen that the non-cooperative type is not controllable under $\lambda(c_2) < \mu_1$.

Table 6.1.3 Optimal design: $\lambda = 1.0\ (1.0)\ 6.0$

λ	f_2^*	F_1	F_2	F
1.0	$(0.0,\ 0.0;\ 10,\ 1)_2$	1.0000	8.8904	0.1096
2.0	$(0.0,\ 0.1;\ 4,\ 0)_2$	1.9920	2.3304	−0.3385
3.0	$(0.1,\ 0.5;\ 4,\ 0)_2$	2.7520	2.4978	0.2542
4.0	$(0.2,\ 0.7;\ 1,\ 0)_2$	3.3798	9.2645	−5.8848
5.0	$(0.4,\ 1.0;\ 3,\ 0)_2$	3.7391	2.6730	1.0661
6.0	$(0.4,\ 1.1;\ 1,\ 0)_2$	4.1954	38.0872	−33.8918

f_2^*: Optimal in noncooperative.

Thus, let us compare the cooperative type with the noncooperative type under $\lambda(c_2) < \mu_1$. The loss brought by the noncooperation is defined by the difference of the two net reward rates, and is denoted by δ.

Tables 6.1.4–6.1.6 show the comparative results in the case when λ, K, and h are changed, respectively, under $c_1 \neq c_2$. From Tables 6.1.4–6.1.6, it is ascertained that the cooperative type has a better net reward rate, and that the loss, δ, is relatively large. Generally, the loss becomes large in the case when the arrival rate is low, the operating cost is high, and so, the net reward rate is lower.

Figure 6.1.6 shows the behavior of selection criteria c_1^*, c_2^* in the case of the non-cooperative type under $K = 3.0$. From Fig. 6.1.6, it is seen that the selection criteria c_1^*, c_2^* are monotonic increasing functions of λ, and that the monotonicity $(c_1^* \leq c_2^*)$ holds.

Now, let us compare Tables 6.1.4–6.1.6 ($c_1 \neq c_2$) with the case ($c_1 = c_2$). For the non-cooperative type, it is noted that the case for one criterion ($c_1 = c_2$) is better than the case for two criteria.

By numerical considerations, we can say that the noncooperative type is more unstable than the cooperative type when $\lambda(c_2) < \mu_2$. The holding cost increases with a rapid increase of the backlog, so that the net reward rate sometimes becomes minus. Hence, we added the severe condition: $\lambda(c_2) < \mu_2$, so that backlog does not

Table 6.1.4 Cooperative versus non-cooperative: $c_1, \neq c_2,\ \lambda = 1.0\ (1.0)\ 6.0$

λ	f_1^* (cooperative)	F	f_2^* (noncooperative)	F	δ
1.0	$(0.6,\ 1.3;\ 19,\ 7)_1$	0.4485	$(0.0,\ 0.1;\ 10,\ 1)_2$	0.1235	0.3250 (72.5%)
2.0	$(1.0,\ 1.4;\ 14,\ 4)_1$	0.8605	$(0.2,\ 0.7;\ 9,\ 0)_2$	0.2880	0.5725 (66.5%)
3.0	$(1.3,\ 1.4;\ 13,\ 3)_1$	1.1367	$(0.4,\ 1.1;\ 9,\ 0)_2$	0.6366	0.5001 (44.0%)
4.0	$(1.5,\ 1.4;\ 11,\ 2)_1$	1.3439	$(0.5,\ 1.4;\ 10,\ 0)_2$	0.8949	0.4490 (33.4%)
5.0	$(1.6,\ 1.7;\ 11,\ 1)_1$	1.5126	$(0.7,\ 1.7;\ 10,\ 0)_2$	1.1572	0.3555 (23.5%)
6.0	$(1.6,\ 1.8;\ 10,\ 1)_1$	1.6680	$(0.8,\ 1.8;\ 10,\ 0)_2$	1.3961	0.2720 (16.3%)

Table 6.1.5 Cooperative versus non-cooperative: $c1, \neq c2$, $K = 0.0\ (1.0)\ 5.0$

K	f_1^* (cooperative)	F	f_2^* (noncooperative)	F	δ
0.0	$(1.1,\ 1.4;\ 2,\ 2)_1$	1.4856	$(0.6,\ 1.4;\ 1,\ 1)_2$	1.3598	0.1259 (8.5%)
1.0	$(1.3,\ 1.4;\ 7,\ 2)_1$	1.3948	$(0.5,\ 1.4;\ 5,\ 0)_2$	1.1114	0.2834 (20.3%)
2.0	$(1.4,\ 1.4;\ 9,\ 2)_1$	1.3607	$(0.5,\ 1.4;\ 8,\ 0)_2$	0.9930	0.3677 (27.0%)
3.0	$(1.5,\ 1.4;\ 11,\ 2)_1$	1.3439	$(0.5,\ 1.4;\ 10,\ 0)_2$	0.8949	0.4490 (33.4%)
4.0	$(1.5,\ 1.4;\ 12,\ 1)_1$	1.3331	$(0.5,\ 1.4;\ 11,\ 0)_2$	0.8085	0.5246 (39.3%)
5.0	$(1.6,\ 1.4;\ 14,\ 2)_1$	1.3246	$(0.5,\ 1.4;\ 13,\ 0)_2$	0.7331	0.5914 (44.7%)

Table 6.1.6 Cooperative versus non-cooperative: $c_1, \neq c_2,\ h = 0.05\ (0.05)\ 0.20$

h	f_1^* (cooperative)	F	f_2^* (non-cooperative)	F	δ
0.05	$(1.5,\ 1.4;\ 11,\ 2)_1$	1.3439	$(0.5,\ 1.4;\ 10,\ 0)_2$	0.8949	0.4490 (33.4%)
0.10	$(1.6,\ 1.4;\ 8,\ 1)_1$	1.0105	$(0.5,\ 1.4;\ 6,\ 0)_2$	0.4816	0.5289 (52.3%)
0.15	$(1.7,\ 1.4;\ 7,\ 0)_1$	0.7159	$(0.5,\ 1.4;\ 5,\ 0)_2$	0.1240	0.5920 (82.7%)
0.20	$(1.7,\ 1.5;\ 6,\ 0)_1$	0.4413	$(0.5,\ 1.4;\ 4,\ 0)_2$	−0.2094	0.6507 (147.4%)

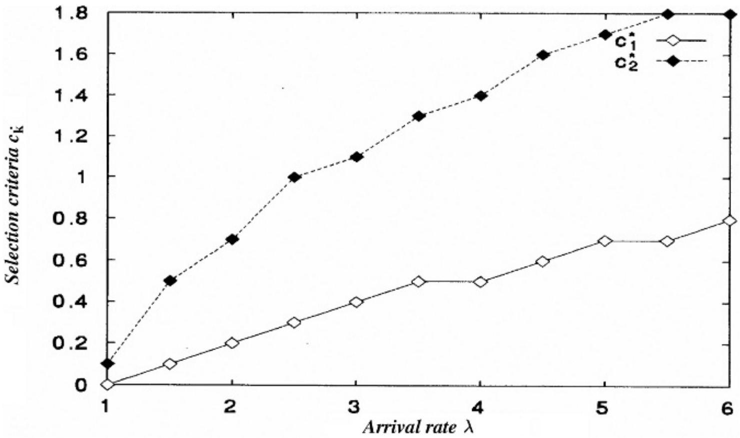


Fig. 6.1.6 Behavior of the selection criteria, c_1^*, c_2^*: Non-cooperative type, $K = 3.0$

increase so quickly and we are able to consider the cooperative versus noncooperative type.

In this case, it is known from the past studies of the cooperative type that it is beneficial to introduce plural order-selection criteria, but the result is obtained for only one of the case showing that the non-cooperative type for one criterion is better than that for two criteria. There are some cases when the monotonicity of c_1 and c_2 does not exist in the cooperative type with switch-over cost, but the monotonicity always exists in the non-cooperative type.

The difference of the net reward rate of cooperative and non-cooperative types (the loss, δ, brought by the non-cooperation of the two centers) enlarges when the arrival rate becomes smaller and the switch-over and holding costs become larger. That is, we can say that when the arrival of job orders is less, the operating cost is high, and so the net reward rate is lower, and the loss brought by the non-cooperative type is large.

References

1. Fujiwara, H. and Matsui, M., Order-Selection and Switch-Over Policies for Controlling the Backlog, *Journal of Japan Industrial Management Association*, 40(4), 218–224, 1989 (in Japanese)
2. Matsui, M., Job-shop Model: A M/(G,G)/1(N) Production System with Order Selection, *International Journal of Production Research*, 20(2), 201–210, 1982
3. Matsui, M., Optimal Order-Selection Policies for a Job Shop Production System, *International Journal of Production Research*, 23(1), 21–31, 1985
4. Matsui, M., On a Joint Policy of Order-Selection and Switch-Over, *Journal of Japan Industrial Management Association*, 39(2), 83–87, 1988 (in Japanese)
5. Matsui, M., Yang, G. and Miya, T., Optimal Control of a Job-Shop Production System with Order-Selection and Switch-Over, *International Journal of Production Research*, 37(1), 73–90, 1999

6. Morris, P., *Introduction to Game Theory*, Springer, Berlin, 1991
7. Muramatsu, R., *New Principles of Production Management*, Kunimoto shobo, Tokyo, Japan, 267–277, 1979 (in Japanese)
8. ten Kate, H.A., Towards a Better Understanding of Order Acceptance, *International Journal of Production Economics*, 37, 139–152, 1994
9. Tijms, H.C., On the Optimality of a Switch-Over Policy for Controlling the Queue Size in a M/G/1 Queue with Variable Service Rates: Optimization Techniques, In: G. Goos and J. Hartmanis (eds.), *Optimization Techniques*, Springer, Berlin, 736–741, 1976
10. Tijms, H.C., On a Switch-Over Policy for Controlling the Workload in a System with Two Constant Service Rates and Fixed Switch-Over Costs, *Zeitschrift für Operations Research*, 21, 19–32, 1977
11. Tijms, H.C., An Algorithm for Average Costs Denumerable State Semi-Markov Decision Problems with Application to Controlled Production and Queueing System, In: R. Hartly and D.L. White (eds.), *Recent Developments in Markov Decision Processes*, Academic, London, 143–179, 1980
12. Tijms, H.C., *Stochastic Modelling and Analysis: A Computational Approach*, Wiley, Chichester, 1986
13. Ross, S.M., *Applied Probability Models with Optimization Applications*, Holden-Day, San Francisco, 1970

6.2 Dynamic Type Strategy

6.2.1 Introduction

A macro-level (or economic) problem for job-shop production is considered under a periodic type versus a semi-dynamic type [4]. Job orders have variable estimated prices and arrive frequently at irregular or random intervals. Then, the problem of selecting/processing the orders according to the periodic, dynamic, and semi-dynamic types is discussed under the changeable production capacity.

This chapter also considers the control problem of maximizing the marginal profit (= accepted price-operating cost) of a job-shop production system with order-selection and switch-over. First, a generalized stochastic model with fixed switching costs under a semidynamic type is proposed in order to derive the two sub-objective functions: mean accepted price and mean operating cost.

Next, a cooperative versus non-cooperative problem of sales and production centers is discussed numerically, and the non-monotonicity of optimal selection criteria is again found. Finally, a numerical comparison of the alternative periodic, dynamic, and semi-dynamic types is given, and the optimal structure is found.

6.2.2 Stochastic Model

Generally, job-shop production systems consist of the sales center with order-selection and the production center with scheduling. For this study, we introduce a stochastic model of the job-shop production system consisting of the sales center with order-selection and the production centre with switch-over (see Fig. 6.1.1).

Corresponding to the two main order-selection policies [2], there are two periodic-type and dynamic-type models of a job shop. The former is treated in Chapter 6.1, and the latter is discussed in [1]. These two models are outlined here, and a semi-dynamic type model for a comparison of alternative types is proposed.

The dynamic-type model is different from the periodic-type model in the following ways: An arriving order is accepted or rejected on its arrival at the sales center by selection criteria. If the backlog size, i, is equal to, $i_1 + 1$, or, if it is more than,

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_11,

i_1, the decision $u = 2$ is made and the sales center will only accept job orders larger than, $\bar{c}_2$. If i is less than, i_1, the decision, $u = 1$, is made and the sales center will only accept job orders larger than c_1.

If the backlog size, i, is zero after completion of an order, the decision $k = 1$ is made and the system will wait (idling) for the arrival of an order larger than c_1. If the backlog size is, i, it is zero after completion of an order, the processing Type 1 is made and the system will wait (idling) for the arrival of an order larger than c_1. In the same way, as the processing of Type 1, if the backlog size i is equal to, $i_1 + 1$, or, if it is more than, i_1, processing Type 2 is made (this switch also incurs a cost of, K). After acceptance or completion with processing Type 2, if the backlog size, i, is equal to i_2, the processing Type 1 is made (this switch also incurs a cost of K). The *quoting time* is assumed to be zero.

Also, the dynamic-type model may be modified as shown in Fig. 6.2.1, and this alternative type is called the semi-dynamic type model. This type model is changed such that the selection criterion c_2 is not altered to the criterion c_1 when the backlog size i $(> i_1)$ crosses the size i_1.

6.2.3 Objective Functions

6.2.3.1 Embedded Approach

In this section, we present the two sub-objective functions: mean accepted price and mean operating cost. Here we use the embedded approach by Tijms [8] (see Fig. 6.2.1).

This semi-dynamic type model can be formularized by semi-Markov decision processes in which the decision epochs are given by the service completion or arrival epochs (see Fig. 6.2.2). The state of decision epochs can be represented by (*i, k*), in which i and k respectively mean the backlog size and the action type in the system.

At any decision epoch, the system can be classified into a state space $I = \{(i;\ k) \mid I = 0, 1, 2, \ldots;\ k = 1, 2\}$. Then, the embedded set of decision epochs can be denoted by $E = \{(i_1 + 1,\ 1), (i_2, 2)\}$, and one cycle is the time from the state $(i_2, 2)$ to $(i_2, 2)$ via $(i_1 + 1,\ 1)$.

Now, let us introduce the birth and death processes [7] with state space in non-negative integer 0, 1, 2, . . ., and denote the birth and death rates at state, i, by $\lambda(c_k)$ and μ_k, regardless of the backlog size, i. The processes start from the state, i, at the time zero, and the following notations are defined here.

- $v_k(i)$: Mean sojourn time until the next decision epoch $(i, k) \in E$.
- $g_k(i)$: Mean accepted price until the next decision epoch $(i, k) \in E$, when the reward $\lambda(c_k)\alpha^{-1}(c_k)$ per unit time occur.
- $u_k(i)$: Mean operating cost till the next decision epoch $(i, k) \in E$, when the holding cost h and processing cost r_k per unit time occur.

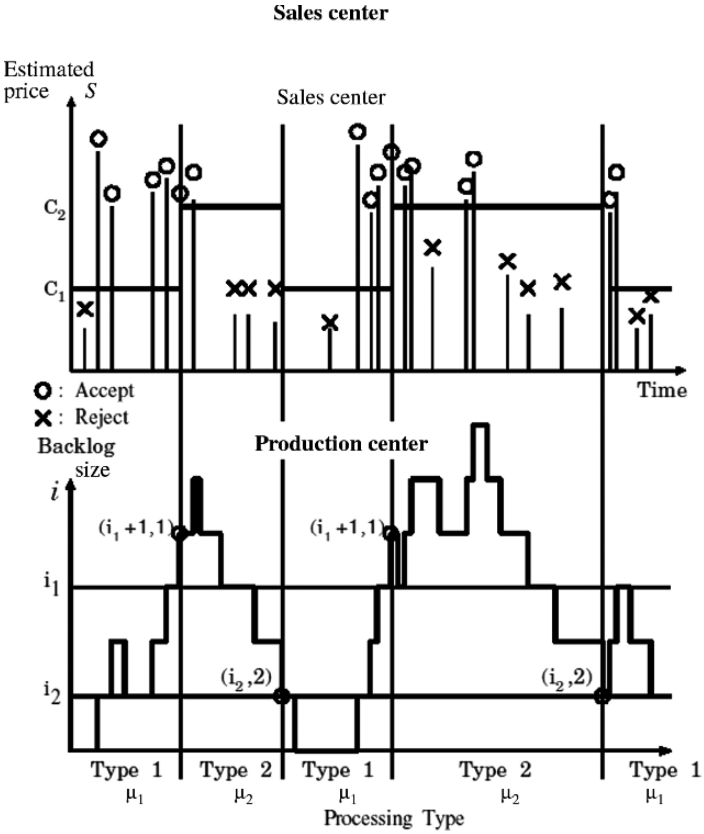


Fig. 6.2.1 Time processes of semi-dynamic type

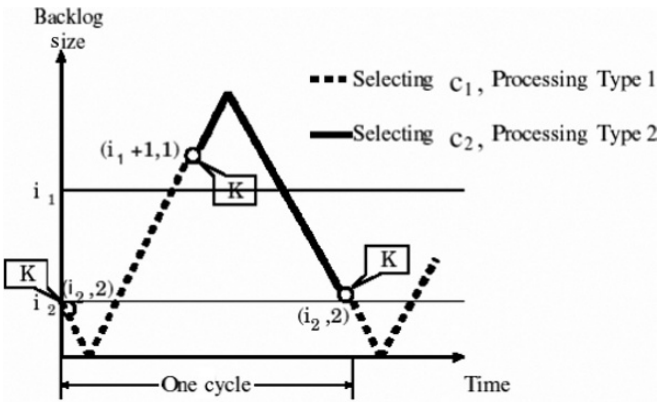


Fig. 6.2.2 Stochastic model of semi-dynamic type

These recurrence formulas are seen in Tijms [8], and are as follows:

$$v_k(i) = \frac{1}{\lambda(c_k)+\mu_k} + \frac{\lambda(c_k)}{\lambda(c_k)+\mu_k}v_k(i+1) + \frac{\mu_k}{\lambda(c_k)+\mu_k}v_k(i-1). \tag{6.2.1}$$

$$g_k(i) = \frac{\lambda(c_k)\alpha^{-1}(c_k)}{\lambda(c_k)+\mu_k} + \frac{\lambda(c_k)}{\lambda(c_k)+\mu_k}g_k(i+1) + \frac{\mu_k}{\lambda(c_k)+\mu_k}g_k(i-1). \tag{6.2.2}$$

$$u_k(i) = \frac{hi+r_k}{\lambda(c_k)+\mu_k} + \frac{\lambda(c_k)}{\lambda(c_k)+\mu_k}u_k(i+1) + \frac{\mu_k}{\lambda(c_k)+\mu_k}u_k(i-1). \tag{6.2.3}$$

6.2.3.2 Accepted Price and Operating Cost

The mean accepted price and mean operating cost per unit time are obtained here. Now, let one cycle be divided into a subcycle from $(i_2, 2)$ to $(i_1+1, 1)$ and the subcycle from $(i_1+1; 1)$ to $(i_2, 2)$. And, let the mean sojourn time, accepted price, and operating cost in the former subcycle be denoted by $\tau(i_2, i_1+1),\ m(i_2,\ i_1+1)$ and $c(i_2, i_1+1)$, and the latter by $\tau(i_1+1,\ i_2),\ m(i_1+1,\ i_2)$ and $c(i_1+1,\ i_2)$.

First, we consider $\tau(i_2, i_1+1)$. In Type 1 ($k=1$), the mean sojourn time from the backlog size $i (1 \le i < i_1)$ to i_1+1 can be obtained, provided the border condition is

$$v_1(0) = \frac{1}{\lambda(c_1)} + v_1(1), v_1(i_1+1) = 0, \tag{6.2.4}$$

because the backlog size does not become negative. From Eqs. (6.2.1) and (6.2.4), $v_k(i)$, is derived recursively as follows:

$$v_1(i)\frac{1}{(\lambda(c_1)-\mu_1)^2}\left[(\lambda(c_1)-\mu_1)(i_1+1-i)+\mu_1\left\{\left(\frac{\mu_1}{\lambda(c_1)}\right)^{i_1+1}-\left(\frac{\mu_1}{\lambda(c_1)}\right)^{i}\right\}\right]. \tag{6.2.5}$$

Then, if, i, in Eq. (6.2.5) is replaced by $i_2,\ \tau(i_2,\ i_1+1)$ is

$$\begin{aligned}\tau(i_2, i_1+1) = &\frac{1}{(\lambda(c_1)-\mu_1)^2}\left[(\lambda(c_1)-\mu_1)(i_1+1-i_2)\right.\\ &\left.+\mu_1\left\{\left(\frac{\mu_1}{\lambda(c_1)}\right)^{i_1+1}-\left(\frac{\mu_1}{\lambda(c_1)}\right)^{i_2}\right\}\right].\end{aligned} \tag{6.2.6}$$

Second, we consider $\tau(i_1+1,\ i_2)$. In Type 2 ($k=2$), the mean sojourn time from the backlog size i ($i_2 \le i < i_1+1$) to i_2 can be obtained under the condition, provided by $\mu_2 > \lambda(c_2)$:

$$v_2(1) = \frac{1}{\mu_2-\lambda(c_2)}, \quad v_2(i_2) = 0. \tag{6.2.7}$$

From Eqs. (6.2.1) and (6.2.7), $v_k(i)$ is derived recursively, and $\tau(i_2,\ i_1+1)$ is given as follows:

$$\tau(i_1+1, i_2) = \frac{i_1+1-i_2}{\mu_2-\lambda(c_2)}, \tag{6.2.8}$$

if i in $v_k(i)$ is replaced by i_1+1-i_2.

Corresponding to the mean sojourn time Eq. (6.2.6), we obtain $m\ (i_2,\ i_1+1)$ in the case of

$$g_1(0) = \alpha^{-1}(c_1) + g_1(1), \quad g_1(i_1+1) = 0. \tag{6.2.9}$$

From Eqs. (6.2.2) and (6.2.9), $g_k(i)$ is derived recursively, and $m\ (i_2,\ i_1+1)$ is given as follows:

$$\begin{aligned} m(i_2, i_1+1) =& \frac{1}{(\lambda(c_1)-\mu_1)^2}\Big[(\lambda(c_1)-\mu_1)(i_1+1-i_2)\lambda(c_1)\alpha^{-1}(c_1) \\ & +\lambda(c_1)\mu_1\alpha^{-1}(c_1)\left\{\left(\frac{\mu_1}{\lambda(c_1)}\right)^{i_1+1} - \left(\frac{\mu_1}{\lambda(c_1)}\right)^{i_2}\right\}\Big], \end{aligned} \tag{6.2.10}$$

if, i, in $g_k(i)$ is replaced by i_2.

Similar to Eq. (6.2.10), we consider $m\ (i_1+1,\ i_2)$. In Type 2 ($k=2$), the mean accepted price from the backlog size $i(i_2 \le i < i_1+1)$ to i_2 can be obtained under the condition, provided by $\mu_2 > \lambda(c_2)$:

$$m_2(1) = \frac{\lambda(c_2)\alpha^{-1}(c_2)}{\mu_2-\lambda(c_2)}. \qquad m_2(i_2) = 0. \tag{6.2.11}$$

From Eqs. (6.2.2) and (6.2.9), $g_k(i)$ is derived recursively, and $m\ (i_1+1,\ i_2)$ is given as follows:

$$m(i_1+1, i_2) = \frac{i_1+1-i_2}{\mu_2-\lambda(c_2)}\lambda(c_2)\alpha^{-1}(c_2), \tag{6.2.12}$$

if, i, in $g_k(i)$ is replaced by i_1+1-i_2.

Next, we consider the mean operating cost. The operating cost corresponding to transitions between states is assumed to consist of the fixed switch-over cost and some variable costs. That is,

$$\text{Operatingcost} = \text{Fixedswitch-overcost} + \text{Variablecost},$$

where the variable cost is the sum of the holding, processing, and idle costs.

Corresponding to the mean sojourn time given by Eq. (6.2.8) we obtain $c(i_2, i_1 + 1)$ in the case of

$$\begin{aligned} u_1(0) &= \frac{r_0}{\lambda(c_1)} + u_1(1), \\ u_1(i_1 + 1) &= 0. \end{aligned} \tag{6.2.13}$$

From Eqs. (6.2.3) and (6.2.11), $u_k(i)$ is derived recursively, and is $c(i_2, i_1 + 1)$ given as follows:

$$\begin{aligned} c(i_2, i_1 + 1) = & \frac{1}{(\lambda(c_1) - \mu_1)^3} \left[\frac{h}{2} (\lambda(c_1) - \mu_1)^2 \left\{ (i_1 + 1)^2 - i_2^2 \right\} \right. \\ & + \left\{ r_1 (\lambda(c_1) - \mu_1)^2 - \frac{h(\lambda(c_1) + \mu_1)(\lambda(c_1) - \mu_1)}{2} \right\} (i_1 + 1 - i_2) \\ & + \left\{ r_1 \lambda(c_1)(\lambda(c_1) - \mu_1) - r_0 (\lambda(c_1) - \mu_1)^2 - h\lambda(c_1)\mu_1 \right\} \\ & \left. \times \left\{ \left(\frac{\mu_1}{\lambda(c_1)} \right)^{i_1 + 1} - \left(\frac{\mu_1}{\lambda(c_1)} \right)^{i_2} \right\} \right] + K, \end{aligned} \tag{6.2.14}$$

if, i, in $u_k(i)$ is replaced by i_2.

Similar to Eq. (6.2.12), we consider $c(i_2, i_1 + 1)$. In Type 2 ($k = 2$), the mean operating cost from the backlog size $i(i_2 \le i < i_1 + 1)$ to i_2 can be obtained under the condition, provided $\mu_2 > \lambda(c_2)$:

$$u_2(1) = \frac{r_2}{\mu_2 - \lambda(c_2)} + \frac{h\lambda(c_2)}{(\mu_2 - \lambda(c_2))^2}, \; u_2(i_2) = 0. \tag{6.2.15}$$

From Eqs. (6.2.3) and (6.2.13), $u_k(i)$ is derived recursively, and $c(i_1 + 1, i_2)$ is given as follows:

$$c(i_1 + 1, i_2) = \frac{i_1 + 1 - i_2}{\mu_2 - \lambda(c_2)} \left\{ \frac{h}{2}(i_1 + i_2 + 2) + \frac{h\lambda(c_2)}{\mu_2 - \lambda(c_2)} + r_2 \right\} + K. \tag{6.2.16}$$

if, i, in, $u_k(i)$, is replaced by, $i_1 + 1 - i_2$.

Then, the mean accepted price per unit time, $F_1(c_1, c_2; i_1, i_2)$, is given in [7] by

$$F_1(c_1, c_2; i_1, i_2) = \frac{m(i_2, i_1 + 1) + m(i_1 + 1, i_2)}{\tau(i_2, i_1 + 1) + \tau(i_1 + 1, i_2)}, \tag{6.2.17}$$

and the mean operating cost per unit time, $F_2(c_1, c_2; i_1, i_2)$, is also given by

$$F_2(c_1, c_2 : i_1, i_2) = \frac{c(i_2, i_1 + 1) + c(i_1 + 1, i_2)}{\tau(i_2, i_1 + 1) + \tau(i_1 + 1, i_2)}. \tag{6.2.18}$$

6.2.4 Optimal Control

6.2.4.1 Cooperative versus Non-Cooperative

A cooperative versus non-cooperative problem of sales and production centers is defined in [3], and is developed for the periodic type in Chapter 6.1 [5]. This problem under a distributed environment is considered here for the semi-dynamic type.

The sales center pursues the maximization of the mean accepted price F_1 by Eq. (6.2.17), while the production center pursues the minimization of the mean operating cost F_2 by Eq. (6.2.18). The problem is to maximize the difference $F\ (= F_1 - F_2)$:

$$\begin{aligned}&(\text{Net reward rate } F) = (\text{Mean accepted price} F_1) - \\ &(\text{Mean operating cost } \mathrm{F}_2)\end{aligned} \tag{6.2.19}$$

under the distributed environment. These functions are computed numerically.

The problem of the cooperative type is called Problem 1, and the net reward rate is as follows:

$$Nr(Coo) = \max_{c_1 c_2} \max_{i_1 i_2} (F_1 - F_2). \tag{6.2.20}$$

Also, the problem of the noncooperative type is called Problem 2, and the net reward rate is as follows:

$$Nr(Non) = \max_{c_1 c_2} (F_1 - \min_{i_1, i_2} F_2) \tag{6.2.21}$$

A cooperative (Coo) versus noncooperative (Non) problem is considered here numerically under arrival rate, $\lambda = 3.0$, in Section 6.2.4.

Table 6.2.1 shows the result of optimal control and its net reward under $\lambda(c_2) < \mu_2$. From Table 6.2.1, it is seen that the cooperative type is better than the non-type, but some net reward of the nontype is negative. Thus, it is said that the non-type is not controllable and stable under $\lambda(c_2) < \mu_2$.

Table 6.2.1 Cooperative versus non-cooperative type: $\lambda\ (c_2) < \mu_2$

λ	$f^*(Coo)$	Nr	$f^*(Non)$	Nr
1.0	(0.6, 1.4; 19, 6)	0.4978	(0.1, 0.0; 13, 2)	0.2440
2.0	(1.0, 1.4; 15, 4)	0.9414	(0.0, 0.1; 6, 0)	−0.3127
3.0	(1.3, 1.4; 13, 3)	1.2566	(0.1, 0.5; 6, 0)	0.3218
4.0	(1.5, 1.4; 12, 2)	1.5063	(0.2, 0.7; 1, 0)	−5.7155
5.0	(1.6, 1.4; 11, 1)	1.7268	(0.4, 1.0; 5, 0)	1.2071
6.0	(1.6, 1.4; 9, 0)	1.9405	(0.4, 1.1; 1, 0)	−33.6145

In Table 6.2.1, the nonmonotonic structure of the optimal control problem is again found at the cooperative type. This structure means that the optimal selection criterion, c_2^*, is not necessarily larger than the optimal selection criterion, c_1^*. This phenomenon is first discussed in Matsui et al. [5] or Yang and Matsui [9].

The monotonicity ($c_1^* \leq c_2^*$) holds when $K = 0$, but does not hold when $K > 0$.

6.2.4.2 Model Comparison

A numerical comparison of periodic, dynamic, and semi-dynamic type models is given, and the optimal structure of a job-shop model is discussed. First, the three main models are compared with the view of net reward.

Now, we search all the combinations to obtain the optimal solution for each parameter. Tables 6.2.2–6.2.4 show a model comparison of the net reward in the case of variable λ, K, and h, respectively. The loss, δ, is the difference of the two net rewards and is occasioned by the noncooperative type.

From Tables 6.2.2–6.2.4, it is seen that the dynamic- and semi-dynamic-type models are superior to the periodic-type model and are alternative. The superiority becomes large according to the increase of arrival rate λ, and, the cooperative type becomes superior to the non-cooperative type.

The behaviors of the loss, δ, in terms of, λ and K, show that the semi-dynamic type model is less superior to the periodic-type model, but the three main models have respective cross-points.

Table 6.2.2 Model comparison of net reward: $\lambda = 1.0\ (1.0)\ 6.0,\ \ K = 3.0,\ \ h = 0.50$

λ		Semidynamic	Dynamic	Periodic
1.0	*Coo.*	(0.6, 1.4; 19, 6) 0.4978	(0.6, 1.6; 20, 7) 0.4978	(0.7, 2.0; 21, 8) 0.4287
	Non	(0.1, 0.1; 12, 2) 0.2524	(0.1, 0.1; 12, 2) 0.2524	(0.0, 0.1; 10, 1) 0.0846
	δ	0.2454 (49.30%)	0.2454 (49.30%)	0.3441 (80.27%)
2.0	*Coo.*	(1.0, 1.4; 15, 4) 0.9414	(1.0, 1.6; 15, 4) 0.9412	(1.0, 2.0; 14, 4) 0.8094
	Non	(0.1, 0.7; 11, 0) 0.2295	(0.1, 0.7; 7, 0) 0.1054	(0.2, 0.7; 9, 0) 0.2108
	δ	0.7119 (75.62%)	0.8358 (88.80%)	0.5986 (73.96%)
3.0	*Coo.*	(1.3, 1.4; 13, 3) 1.2566	(1.3, 1.6; 13, 3) 1.2566	(1.3, 1.7; 13, 3) 1.0560
	Non	(0.3, 1.1; 11, 0) 0.6384	(0.3, 1.1; 6, 0) 0.6110	(0.4, 1.1; 9, 0) 0.5328
	δ	0.6182 (49.20%)	0.6456 (51.38%)	0.5233 (49.55%)
4.0	*Coo.*	(1.5, 1.4; 12, 2) 1.5063	(1.5, 1.6; 12, 2) 1.5062	(1.5, 1.5; 11, 1) 1.2337
	Non	(0.5, 1.4; 11, 0) 1.0108	(0.5, 1.4; 6, 0) 1.0841	(0.5, 1.4; 10, 0) 0.7653
	δ	0.4955 (32.90%)	0.4221 (28.02%)	0.4684 (37.97%)
5.0	*Coo.*	(1.6, 1.4; 11, 1) 1.7268	(1.6, 1.7; 11, 1) 1.7229	(1.6, 1.7; 10, 1) 1.3781
	Non	(0.7, 1.7; 12, 0) 1.3170	(0.8, 1.7; 6, 0) 1.5061	(0.7, 1.7; 10, 0) 1.0113
	δ	0.4098 (23.73%)	0.2168 (12.58%)	0.3668 (26.62%)
6.0	*Coo.*	(1.6, 1.4; 9, 0) 1.9405	(1.5, 1.8; 10, 0) 1.9311	(1.6, 1.8; 10, 1) 1.5089
	Non	(0.7, 1.8; 12, 0) 1.5250	(0.8, 1.8; 5, 0) 1.773	(0.8, 1.8; 10, 0) 1.2273
	δ	0.4155 (21.41%)	0.1538 (7.96%)	0.2816 (18.66%)

Table 6.2.3 Model comparison of net reward: $K = 1.0\ (1.0)\ 6.0,\ \lambda = 3.0,\ h = 0.50$

K		Semi-dynamic	Dynamic	Periodic
1.0	*Coo.*	(1.2, 1.3; 9, 2) 1.2777	(1.2, 1.5; 9, 2) 1.2775	(1.2, 1.4; 8, 2) 1.0737
	Non	(0.3, 1.1; 6, 0) 0.8638	(0.3, 1.1; 3, 0) 0.7741	(0.3, 1.1; 5, 0) 0.6713
	δ	0.4139 (32.39%)	0.5034 (39.41%)	0.4023 (37.47%)
2.0	*Coo.*	(1.3, 1.4; 12, 3) 1.2620	(1.3, 1.6; 12, 3) 1.2620	(1.3, 1.6; 11, 3) 1.0623
	Non	(0.3, 1.1; 9, 0) 0.7389	(0.3, 1.1; 5, 0) 0.6829	(0.3, 1.1; 7, 0) 0.5501
	δ	0.5231 (41.45%)	0.5791 (45.89%)	0.5122 (48.22%)
3.0	*Coo.*	(1.3, 1.4; 13, 3) 1.2566	(1.3, 1.6; 13, 3) 1.2566	(1.3, 1.7; 13, 3) 1.0560
	Non	(0.3, 1.1; 11, 0) 0.6384	(0.3, 1.1; 6, 0) 0.6110	(0.4, 1.1; 9, 0) 0.5328
	δ	0.6182 (49.20%)	0.6456 (51.38%)	0.5233 (49.55%)
4.0	*Coo.*	(1.3, 1.5; 15, 3) 1.2528	(1.3, 1.7; 15, 2) 1.2527	(1.3, 1.8; 14, 3) 1.0516
	Non	(0.3, 1.1; 13, 0) 0.5528	(0.3, 1.1; 7, 0) 0.5571	(0.4, 1.1; 11, 0) 0.4544
	δ	0.7000 (55.87%)	0.6956 (55.53%)	0.5972 (56.79%)
5.0	*Coo.*	(1.3, 1.5; 16, 2) 1.2498	(1.3, 1.7; 16, 2) 1.2497	(1.4, 2.0; 17, 4) 1.0500
	Non	(0.3, 1.1; 14, 0) 0.4760	(0.4, 1.1; 8, 0) 0.5702	(0.3, 1.1; 13, 0) 0.2953
	δ	0.7738 (61.91%)	0.6795 (54.37%)	0.7546 (71.88%)
6.0	*Coo.*	(1.3, 1.5; 17, 2) 1.2473	(1.3, 1.7; 17, 2) 1.2473	(1.4, 2.0; 18, 4) 1.0494
	Non	(0.3, 1.1; 16, 0) 0.4073	(0.4, 1.1; 9, 0) 0.5289	(0.4, 1.1; 14, 0) 0.3192
	δ	0.8400 (67.35%)	0.1784 (57.60%)	0.7302 (69.58%)

Table 6.2.4 Model comparison of net reward: $h = 1.0\ (1.0)\ 6.0,\ \lambda = 3.0,\ K = 0.50$

h	Semi-dynamic	Dynamic	Periodic	
0.05	*Coo.*	(1.3, 1.4; 13, 3) 1.2566	(1.3, 1.6; 13, 3) 1.2566	(1.3, 1.7; 13, 3) 1.0560
	Non	(0.3, 1.1; 11, 0) 0.6384	(0.3, 1.1; 6, 0) 0.6110	(0.4, 1.1; 9, 0) 0.5328
	δ	0.6182 (49.20%)	0.6456 (51.38%)	0.5232 (49.55%)
0.10	*Coo.*	(1.4, 1.6; 10, 2) 1.1203	(1.4, 1.8; 10, 1) 1.1204	(1.5, 2.0; 10, 2) 0.7225
	Non	(0.3, 1.1; 8, 0) 0.3561	(0.3, 1.1; 5, 0) 0.3534	(0.3, 1.1; 6, 0) −0.0107
	δ	0.7642 (68.21%)	0.7670 (68.46%)	0.7332 (101.48%)
0.15	*Coo.*	(1.5, 1.7; 9, 1) 1.0196	(1.5, 2.0; 9, 1) 1.0196	(1.6, 2.0; 8, 1) 0.4273
	Non	(0.3, 1.1; 6.0) 0.1282	(0.3, 1.1; 4, 0) 0.1298	(0.4, 1.1; 5, 0) −0.3222
	δ	0.8915 (87.44%)	0.8898 (87.27%)	0.7495 (175.40%)
0.20	*Coo.*	(1.5, 1.8; 7, 1) 0.9371	(1.5, 2.0; 7, 1) 0.9371	(1.7, 2.0; 7, 0) 0.1507
	Non	(0.3, 1.1; 5, 0) −0.0719	(0.4, 1.1; 4, 0) 0.0210	(0.3, 1.1; 4, 0) −0.8062
	δ	1.0090 (107.67%)	0.9161 (97.76%)	0.9569 (634.97%)

Also, the dynamic and semi-dynamic type models are superior to the periodic-type model and are alternative, but only the dynamic-type model holds the monotonicity ($c_1^* \le c_2^*$).

Thus, it is concluded that the dynamic-selection strategy in the sales center is better, but it should cooperate with the switching or scheduling strategy in the production center. In addition, it is noted that the fixed switching cost gives the nonmonotonicity of the selection strategy.

References

1. Kanbara, K., Tamaki, K. and Matsui, M., Queueing Analysis and Optimal Control of a Job-Shop Production System of Dynamic Type, *Journal of Japan Industrial Management Association*, 49(5), 327–337, 1998 (in Japanese)
2. Matsui, M., Optimal Order-Selection Policies for a Job-Shop Production System, *International Journal of Production Research*, 23(1), 21–31, 1985
3. Matsui, M., On a Joint Policy of Order-Selection and Switch-Over, *Journal of Japan Industrial Management Association*, 39(2), 83–87, 1988 (in Japanese)
4. Matsui, M., Kaneda, K. and Kanbara, K., Optimal Control of a Job-Shop Production System: Periodic versus Dynamic Type, *International Journal of Production Research*, 38(13), 2951–2966, 2000
5. Matsui, M., Yang, G. and Miya, T., Optimal Control of a Job-Shop Production System with Order-Selection and Switch-Over, *International Journal of Production Research*, 37, 73–90, 1999
6. Ross, S.M., *Applied Probability Models with Optimization Applications*, Holden-Day, San Francisco, 1970
7. Taylor, H.M. and Karlin, S., *An Introduction to Stochastic Modeling*, Academic Press, London, 243–253, 1984
8. Tijms, H.C., *Stochastic Modelling and Analysis: A Computational Approach*, Wiley, Chichester, 239–244, 1986
9. Yang, G. and Matsui, M., A Job-Shop Control Policy Under Fixed Switching-Costs: Periodic Type, *Journal of the Japan Industrial Management Association*, 45(4), 360–371, 1994 (in Japanese)

Part IV
Flexible Risk Processes

Chapter 7
Flexible Cell System

7.1 Flexible Assembly System (FAS)

7.1.1 Introduction

The flexible assembly system (FAS) in this chapter is similar to a *M/M/n* queueing system with ordered-entry. Ordered-entry means an item (customer) that seeks service from channels in a prescribed order, and the decision regarding the entrance of the item to a channel available to the item.

A multi-channel queueing system with ordered entry, but with homogeneous servers, was first discussed by Disney [1]. The system with heterogeneous servers, but without ordered entry, was analyzed by Gumbel [5]. An interesting consideration on heterogeneous versus homogeneous servers systems was given later in [4, 10].

In the following sections [6], an overflow probability is obtained explicitly by the steady-state analysis of the system with two or three servers. The best arrangement of servers is obtained by interchanging their order so as to minimize the overflow probability and thereby minimize the number of items processed per unit time. In addition, a FAS with Generalized CSPSs [3, 7] in Chapter 7.2 is considered under finite buffers, and some contradictory results are pointed out.

The model considered here is traditionally applicable, for example, to the production systems with a closed-loop conveyor [2, 8, 9]. In this case, it is noted that the "prescribed order" of service channels means the order of production-stations arranged along the running direction of a conveyor, and the distances between each pair of stations are neglected.

7.1.2 A FAS Model

7.1.2.1 Assumptions and Notation

A flexible assembly system (FAS) in this chapter is modeled in Fig. 7.1.1. This model is formulated as a M/M/n queueing system with ordered-entry and heterogeneous servers.

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_12, © Springer Science+Business Media, LLC 2009

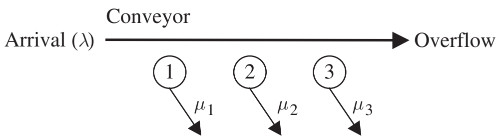


Fig. 7.1.1 A FAS model

Several symbols used later are:

n = Number of service-channels in the system.
λ = Poisson arrival rate.
μ_i, $(i = 1, 2, \ldots, n)$ = Negative exponential service rate for the server of ith channel in the prescribed order $m_i = \mu_i / \lambda$.
P_0 = steady-state probability that the system is idle.
$P_{i_1, i_2 \ldots i_k}$, $(k \le n)$ = Steady-state probability that the i_1th, i_2th, …, and i_kth channels are busy and the others are idle.
$P(m_1, m_2, \ldots, m_n) \equiv P_{1,2\ldots n}$ = Overflow probability, that is, the steady-state probability that the system is busy.

7.1.2.2 Preliminary Cases

This case is considered to facilitate the analysis of the case where $n = 3$. For $n = 1$, the overflow probability is easily obtained as:

$$P(m_1) = 1 / (1 + m_1). \tag{7.1.1}$$

In the case, where $n = 2$, a family of equations for the steady-state probabilities, P_0, P_1, P_2, and P_{12} is given by

$$\left.\begin{aligned} P_0 &= m_1 P_1 + m_2 P_2, \\ (1 + m_1) P_1 &= P_0 + m_2 P_{12}, \\ (1 + m_2) P_2 &= m_1 P_{12}. \end{aligned}\right\}. \tag{7.1.2}$$

Using Eq. (7.1.2) and the normalization condition: $P_0 + P_1 + P_2 + P_{12} = 1$, we obtain

$$P_{12} = \frac{1 + m_2}{(1 + m_1)\left\{(1 + m_2)^2 + m_1 m_2\right\}}. \tag{7.1.3}$$

Note that the Equation

$$P_1 + P_{12} = P(m_1), \tag{7.1.4}$$

where $P(m_1)$. is given in Eq. (7.1.1), may be used instead of the normalization condition.

Now let us consider the arrangement problem of better servers. To do this, the overflow probability in the case where two servers are interchanged is denoted by $P(m_2, m_1)$. Then the following result is easily obtained using Eq. (7.1.3):

Theorem 1.

$$m_1 \gtreqqless m_2 => P(m_1, m_2) \lesseqqgtr P(m_2, m_1). \tag{7.1.5}$$

This means that the faster server in service should be assigned to the first channel to decrease the overflow probability, that is, to increase the number of units serviced per unit time.

7.1.3 Three Station Case

7.1.3.1 Overflow Probability

The system with three servers can be treated through a method similar to that for the system with two servers. The set of equations describing the system in the steady-state is as follows:

$$P_0 = m_1 P_1 + m_2 P_2 + m_3 P_3. \tag{7.1.6a}$$

$$\left.\begin{aligned} (1+m_1) P_1 &= P_0 + m_2 P_{12} + m_3 P_{13}, \\ (1+m_2) P_2 &= m_1 P_{12} + m_3 P_{23}, \\ (1+m_3) P_3 &= m_1 P_{13} + m_2 P_{23}. \end{aligned}\right\} \tag{7.1.6b}$$

$$\left.\begin{aligned} (1+m_1+m_2) P_{12} &= P_1 + P_2 + m_3 P_{123}, \\ (1+m_1+m_3) P_{13} &= P_3 + m_2 P_{123}, \\ (1+m_2+m_3) P_{23} &= m_1 P_{123}. \end{aligned}\right\} \tag{7.1.6c}$$

Let $Q_1 = [P_1,\ P_2,\ P_3]^T$ and $Q_2 = [P_{12},\ P_{13},\ P_{23}]^T$, and Eq. (7.1.6) may be rewritten by the matrix notations:

$$[m_1, m_2, m_3]\, Q_1 = P_0, \tag{7.1.7a}$$

$$\begin{bmatrix} 1+m_1 & 0 & 0 \\ 0 & 1+m_2 & 0 \\ 0 & 0 & 1+m_3 \end{bmatrix} Q_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} P_0 + \begin{bmatrix} m_2 & m_3 & 0 \\ m_1 & 0 & m_3 \\ 0 & m_1 & m_2 \end{bmatrix} Q_2, \tag{7.1.7b}$$

$$\begin{bmatrix} 1+m_1+m_2 & 0 & 0 \\ 0 & 1+m_1+m_3 & 0 \\ 0 & 0 & 1+m_2+m_3 \end{bmatrix} Q_2 = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} Q_1 + \begin{bmatrix} m_3 \\ m_2 \\ m_1 \end{bmatrix} P_{123}. \tag{7.1.7c}$$

The vector Q_2 can be expressed using P_{123} in the following fashion: Substituting Eq. (7.1.7a) into Eq. (7.1.7b), the vector Q_1 may be expressed using the vector Q_2.

Next substitute Q_1, thus, obtained into Eq. (7.1.7c), and Q_2 may be expressed using P_{123} as

$$Q_2 = \begin{bmatrix} 1 & \frac{m_3(1+m_1+m_3)}{(1+m_3)^2+m_3m_1} & \frac{m_3}{1+m_3}\left[1+\frac{m_2(1+m_1+m_3)}{(1+m_2+m_3)\left\{(1+m_3)^2+m_3m_1\right\}}\right] \\ 0 & \frac{1+m_3}{(1+m_3)^2+m_3m_1} & \frac{m_2(1+m_3)}{(1+m_2+m_3)\left\{(1+m_3)^2+m_3m_1\right\}} \\ 0 & 0 & \frac{1}{1+m_2+m_3} \end{bmatrix} \begin{bmatrix} m_3 \\ m_2 \\ m_1 \end{bmatrix} P_{123}. \quad (7.1.8)$$

Instead of the normalization condition, the following equation similar to Eq. (7.1.4) is used to obtain the overflow probability $P\,(m_1,\ m_2,\ m_3) \equiv P_{123}$:

$$P_{12} + P_{123} = P\,(m_1, m_2)\,. \quad (7.1.9)$$

Substituting Eq. (7.1.4) and P_{12} contained in Eq. (7.1.8) into Eq. (7.1.9), we have

$$\begin{aligned} P^{-1}\,(m_1, m_2, m_3) = \frac{(1+m_1)\left\{(1+m_2)^2 + m_2m_1\right\}}{1+m_2} \cdot \\ \left[\frac{N\,(m_1, m_2, m_3)}{(1+m_3)\,(1+m_2+m_3)\left\{(1+m_3)^2 + m_1m_3\right\}}\right], \end{aligned} \quad (7.1.10)$$

where

$$\begin{aligned} N\,(m_1, m_2, m_3) &= (1+m_2+m_3)\left\{(1+m_3)^2 + m_3m_1\right\}^2 \\ &+ m_2m_3\,(1+m_1+m_3)\,\{(1+m_3)\,(1+m_2+m_3) + m_1\}\,. \end{aligned} \quad (7.1.11)$$

7.1.3.2 Arrangement of the Server

The following theorems are first established using Eq. (7.1.10), and these proofs are directed and omitted.

Theorem 2. *For the interchange of two adjacent servers,*

$$m_1 \gtreqless m_2 => P\,(m_1, m_2, m_3) \lesseqgtr P\,(m_2, m_1, m_3)\,, \quad (7.1.12a)$$

and

$$m_2 \gtreqless m_3 => P\,(m_1, m_2, m_3) \lesseqgtr P\,(m_1, m_3, m_2)\,, \quad (7.1.12b)$$

where $P\,(m_2,\ m_1,\ m_3)$ denotes the overflow probability in the case, where two servers in the first and second channels are interchanged in their channels and the server in the third channel is unchanged, and so forth.

Theorem 3. *For the interchange of two nonadjacent servers,*

$$m_1 \gtreqless m_3 \geq P(m_1, m_2, m_3) \lesseqgtr P(m_3, m_2, m_1), \tag{7.1.13}$$

if, $m_2 < \max(m_1, m_3)$.

(N.B.) When $m_2 > \max(m_1, m_3)$, the Expression (7.1.13) does not necessarily hold. For example,

$$P(m_1, m_2, m_3) < P(m_3, m_2, m_1), \text{ for } m_1 = 0.2, m_2 = 0.5 \text{ and } m_3 = 0.1,$$

but

$$P(m_1, m_2, m_3) > P(m_3, m_2, m_1), \text{ for } m_1 = 0.2, m_2 = 0.6 \text{ and } m_3 = 0.1.$$

Applying Eq. (7.1.12a) and Eq. (7.1.12b), we have:

Lemma $m_1 \geq m_2 \geq m_3 \geq$

$$m_1 \geq m_2 \geq m_3 \geq$$

$$P(m_1, m_2, m_3) \begin{matrix} \leq P(m_2, m_1, m_3) \leq P(m_2, m_3, m_1) \\ / \\ \leq P(m_1, m_3, m_2) \leq P(m_3, m_1, m_2) \end{matrix} \leq P(m_3, m_2, m_1) \tag{7.1.14}$$

Table 7.1.1 Probabilities for each arrangement of the three servers: $\mu_1 = 1.2, \ \mu_2 = 1.0, \ \mu_3 = 0.8$ and $\lambda = 0.5, \ 1.0, \ 2.0$

λ	m_1	m_2	m_3	Probabilities $\overline{P}(m_1)^*$	$\overline{P}(m_2)$	$\overline{P}(m_3)$	$P(m_1, m_2, m_3)$
0.5	2.4,	2.0,	1.6	0.2941	0.1151	0.0032	0.0109
	2.0,	2.4,	1.6	0.3333	0.1100	0.0359	0.0118
	2.4,	1.6,	2.0	0.2941	0.1387	0.0301	0.0119
	1.6,	2.4,	2.0	0.3846	0.1249	0.0354	0.0140
	2.0,	1.6,	2.4	0.3333	0.1539	0.0304	0.0140
	1.6,	2.0,	2.4	0.3846	0.1450	0.0331	0.0152
1.0	1.2,	1.0,	0.8	0.4545	0.2797	0.1467	0.0575
	1.0,	1.2,	0.8	0.5000	0.2649	0.1526	0.0600
	1.2,	0.8,	1.0	0.4545	0.3247	0.1339	0.0609
	0.8,	1.2,	1.0	0.5556	0.2874	0.1446	0.0661
	1.0,	0.8,	1.2	0.5000	0.3465	0.1299	0.0669
	0.8,	1.0,	1.2	0.5556	0.3241	0.1349	0.0696
2.0	0.6,	0.5,	0.4	0.6250	0.5147	0.4069	0.2049
	0.5,	0.6,	0.4	0.6667	0.4895	0.4120	0.2082
	0.6,	0.4,	0.5	0.6250	0.5682	0.3767	0.2094
	0.4,	0.6,	0.5	0.7143	0.5102	0.3857	0.2153
	0.5,	0.4,	0.6	0.6667	0.5864	0.3585	0.2170
	0.4,	0.5,	0.6	0.7143	0.5539	0.3626	0.2198

$^*\overline{P}(m_i)$ = Probability that the i*th* server is busy.

From this Lemma, a result similar to the case where, $n = 2$, is also given for the case where, $n = 3$. The best arrangement is one in which the first channel server is the fastest, the second channel server is the second fastest, and the third channel server is the slowest. The worst arrangement has the inverse order of the best arrangement.

A numerical example to illustrate the above Lemma is given in Table 7.1.1, accompanied with the probabilities that the respective servers are busy. It is difficult to apply the same treatment as in the case, where, $n < 3$, to the case, where $n > 4$, but similar results may be correct for these cases.

7.1.4 Concluding Remarks

In addition, a flexible assembly system with Generalized CSPSs is considered here under finite buffers. In the Generalized CSPSs, there are two buffer variables: reserve capacity, N_i, and time-range, $c_i,\ i = 1,\ 2,\ \ldots,\ n$.

Table 7.1.2 shows a simulation result for arrangements in the three station case. From Table 7.1.2, it is seen under buffers allocation that not the faster order but the slower order is better from the viewpoint of processed units. This shows some contradictory results for the Section 7.1.3.

Table 7.1.2 Three station case with generalized CSPSs: 10,000 units (runs), Poisson arrival, Erlang service with Phase 4

Arrangement	Average $\mu_i = 1.0,\ i = 1,\ 2,\ 3$	Slower order $\mu_1 = 0.8,\ \mu_2 = 1.0,\ \mu_3 = 1.2$	Faster order $\mu_1 = 1.2,\ \mu_2 = 1.0,\ \mu_3 = 0.8$
Processed units	7488	9096	5537
Optimal design $\left(d = {}^{1}/_{\lambda}\right)$	$d = 0.44$	$d = 0.44$	$d = 0.40$
	$N_1 = 3,\ c_1 = 0.100$ $N_2 = 4,\ c_2 = 0.205$ $N_3 = 10,\ c_3 = 1.472$	$N_1 = 3,\ c_1 = 0.100$ $N_2 = 4,\ c_2 = 0.350$ $N_3 = 10,\ c_3 = 0.744$	$N_1 = 4,\ c_1 = 0.100$ $N_2 = 4,\ c_2 = 0.290$ $N_3 = 9,\ c_3 = 1.144$
Utilization	0.818, 0.751, 0.609	0.859, 0.761, 0.576	0.823, 0.760, 0.688

References

1. Disney, R.L., Some Multichannel Queueing Problems with Ordered Entry, *The Journal of Industrial Engineering*, 13(1), 46–48, 1962
2. Disney, R.L., Some Multichannel Queueing Problems with Ordered Entry — An Application to Conveyor Theory, *The Journal of Industrial Engineering*, 14(2), 105–108, 1963
3. Feyzbakhsh, S.A. and Matsui, M., Optimal Design of a Generalized Conveyor-Serviced Production Station: Fixed and Removal Item Cases, *International Journal of Production Economics*, 55, 177–189, 1998

4. Fukuta, J. and Matsui, M., A Queueing Analysis of Conveyor System, *Preliminary Report of Operations Research Society of Japan*, Autumn, 9–10, 1969 (in Japanese)
5. Gumbel, H., Waiting Lines with Heterogeneous Servers, *Operations Research*, 8(4), 504–511, 1960
6. Matsui, M. and Fukuta, J., On a Multichannel Queueing System with Ordered Entry and Heterogeneous Servers, *American Institute of Industrial Engineers Transactions*, 9(2), 209–214, 1977
7. Matsui, M., A Generalized Model of Conveyor-Serviced Production Station (CSPS), *Journal of Japan Industrial Management Association*, 44(1), 25–32, 1993 (in Japanese)
8. Phillips, D.T. and Skeith, R.W., Ordered Entry Queueing Networks with Multiple Servers and Multiple Queues, *American Institute of Industrial Engineers Transactions*, 1(4), 333–342, 1969
9. Pritsker, A.A.B., Application of Multichannel Queueing Results to the Analysis of Conveyor Systems, *Journal of Industrial Engineering*, 17(7), 14–21, 1966
10. Singh, V.P., Markovian Queues with Three Heterogeneous Servers, *American Institute of Industrial Engineers Transactions*, 3(1), 45–48, 1971

7.2 FAS with Generalized CSPSs

7.2.1 Introduction

An ordered-entry array of the multiple-production stations connected by conveyors [13] is focused on management views [16], and is here called the flexible assembly system (FAS), meaning that it is flexible in processing and routing. The system-centered approach is an ordered-entry type queue [1, 6, 10, etc.] and the station-centered approach involves unit-stations coordination [2–4, 11].

The FAS manager faces stochastic variations such as arrival/service times, which causes stochastic system balancing problems for absorbing the variations. However, there is no effective design method for FAS from past studies, except the simple design method in [3, 4], and the lead time in reliability is ignored.

We apply a two-stage design method [9, 17] to stochastic system balancing problems through the station-centered approach. The FAS is then regarded as a coordination/balancing problem between the unit stations of Generalized CSPSs [5, 8], and is called the simple FAS [3, 4, 14]. This chapter presents a useful management design approach for the simple FAS in view of the cost and lead time views [14].

First, the simple FAS is briefly outlined. Next, the two-stage design procedure is presented for both types of the existing and installation problems of production facility. Third, an optimal design example is shown and discussed numerically. Finally, the production matrix tables of both types are given, and a strategic relation of economic traffic (d, K) and lead time is discussed.

7.2.2 Simple FAS Model

7.2.2.1 Definitions and Notation

The simple FAS consists of multiple unit stations (Generalized CSPSs) of an unloading type [12, 13], and their coordination/balancing problem is considered as the two-level structure (Fig. 7.2.1). There are buffer-design problems of each station at

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_13, © Springer Science+Business Media, LLC 2009

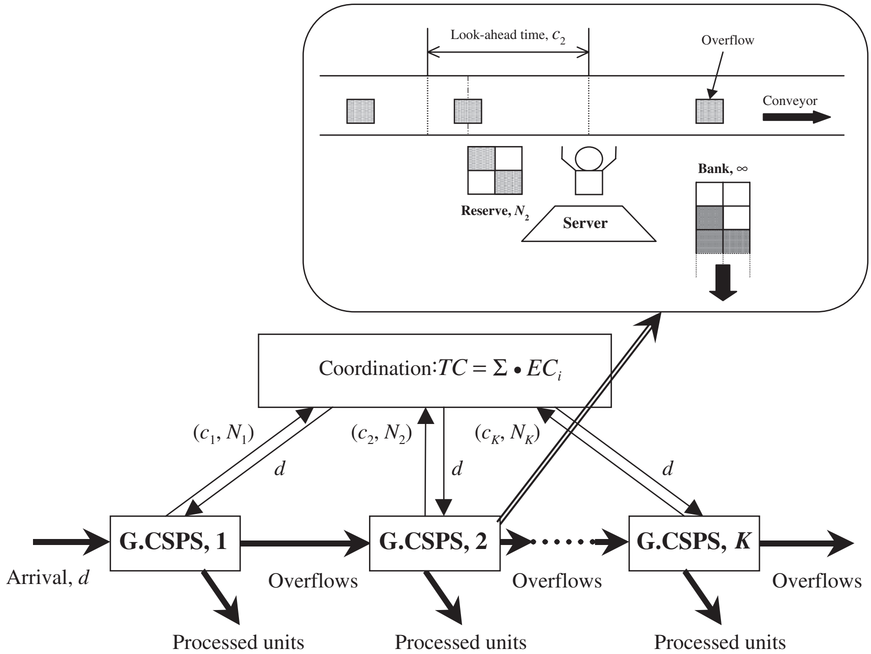


Fig. 7.2.1 2-level structure of simple FAS

the lower level, and the coordination problem of buffers by the mean of the interarrival time (cycle time), d, in the upper level.

Under the cycle time of d, the buffers, the capacity of the reserve at station i,N_i and the look-ahead time at station i,c_i, are decided under the cycle time, d, and the number of Generalized CSPSs, K, according to the respective minimization of the total expected operating cost at station i,EC_i in the lower level. The respective information (N_i, c_i) in EC_i is communicated to the upper level. By iterations, the cycle time, d, and the buffers (N_i, c_i) are decided in order to minimize the total expected cost of system $TC = \Sigma\ EC_i$ in the upper level.

Then, it is assumed that the usables flow according to Poisson arrival at the mean interarrival time, d. The service time in each station is supposed to follow the Erlang distribution. Under these assumptions, each station individually decides the two buffer variables, capacity of reserve (N_i), and look-ahead time (c_i) in order to minimize the total expected operating cost, EC_i

The usables are removed in to reserve and wait to be processed. If the operator is busy, the usables become overflows without removing. The stored useables in the reserve at each station are processed, removed to the bank, and become finished products. The overflowed useables at the i-th station become inputs into the $(i+1)$-th station. The look-ahead time, c_i, at the i-th station is the control variable in the optimal operating policy called RdSRP [8, 12].

7.2.2.2 Two-Stage Design Method

For the design of simple FAS, both types of the existing and installation problems of production facility exist. In the former problem, the cycle time, which is the demand speed of the market, is chosen under the given number of stations in the existing production facility (leader in game theory [15]). On the other hand, the number of stations, which is the production speed in the production facility, is designed or installed under the given cycle time (leader).

In Fig. 7.2.2, the simple FAS is regarded as the two-level structure, and is considered as the decision-making problem of the economic traffic (cycle time, d, and number of stations, K) in the upper level, and the buffer-design problem of each station in the lower level. The two-stage design method is further developed and is seen in Fig. 7.2.2.

At Stage 1, the economic traffic (d^*, K^*) is first determined, and, at Stage 2, each station individually decides the buffer $\left(N_i^*, c_i^*\right)$ in order to minimize the sum of the minimum total expected operating cost, EC_i^*, at station i, TC. Here, the economic lead time, LT^*, is also determined and added at the 2nd Stage.

Here, the total expected operating cost in the production-planning period T_0, EC_i, is introduced as an objective function at each station. EC_i is the sum of in-process inventory cost, $\alpha_i L_i$, and delay-and-overflow cost, Y_i, and is given by

$$EC_i = \alpha_i L_i + Y_i, \qquad i = 1, 2, \ldots, K \tag{7.2.1}$$

where Y_i is from Eq. (5.1.2) as follows:

$$Y_i = (\beta_{1i} D_i + \beta_{2i} \eta_i) \cdot \frac{T_0}{\overline{x_i} + D_i}. \tag{7.2.2}$$

For any array of traffic (d, K), the simultaneous table of operating cost at system, UC, and economic lead time, LT, is introduced, here and is called the production matrix table [17]. Based on this table, a strategic relation of economic traffic (d, K), and lead time, LT, is numerically considered later.

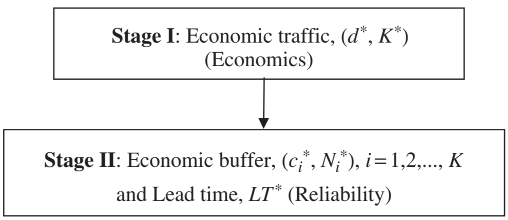


Fig. 7.2.2 Two-stage design method

7.2.3 Two-Stage Design Procedures

7.2.3.1 Installation Case of New Facility

The two-stage design procedure for a simple FAS is developed here on the basis of the two-stage method shown in Fig. 7.2.2. The first stage is to decide the economic cycle time and number of stations, and the second stage is to decide the economic buffers, which minimize the expected operating costs under the economic cycle time and number of stations at the first stage. In addition, the first and second stages are repeated by feedback loop.

Generally, there are two cases: the new production facility installed under the given demand of the market (market, first), and the demand of the market chosen under the existing production facility (production, first). In the former, the number of stations (follower), which minimize the operating cost is chosen under the given cycle time, market speed (leader). In the latter, a cycle time (follower), which minimizes the operating cost is chosen under the number of stations given, which decides the production speed (leader).

First, the details of the steps in the case of market first are as follows:

Step 1 (Preliminary stage): Parameters setting

This step is similar to the so called line-balancing procedure in the assembly line.

(i) Maximal cycle time

From the production-planning quantity N_0 and production-planning period T_0, the maximum cycle time is initially set by the following equation:

$$CT = \frac{T_0}{N_0}. \tag{7.2.3}$$

(ii) Condition on the number of stations

Under the cycle time, CT, in Eq. (7.2.3) and the mean of total assembly time, S_0, given, the number of stations K must be restricted to $K_{\max} \geq K_0$. Here, K_0 is the minimal number of stations:

$$K_0 = \left\lceil \frac{S_0}{CT_0} \right\rceil, \tag{7.2.4}$$

in which $\lceil A \rceil$ is the minimal value of integers, which is equal to or no smaller than A. (If this is not possible, the management design is infeasible.)

In the following steps, the two-stage design method in Fig. 7.2.2 is used.

Step 2 (Stage 1): Economic traffic

At this stage, the economic number of stations minimizing the expected operating cost is decided. Also, the number of stations, K, is viable from the initial value, K_0, because attempts are made to improve K.

Step 3 (Stage 2): Economic buffers

Under the economic traffic, K^*, at the Stage 1, the buffers $(N_i,\ c_i)$ minimizing the operating cost are decided in each station.

(i) **Decision of buffers, $\boldsymbol{c_i}$ and $\boldsymbol{N_i}$**

Under the design factor, ε_i, given in the preliminary stage, the optimal buffers, c_i and N_i, which minimizes the total cost at each station, $EC_i\left(d, c_i\left(d\right), N_i\left(d\right)\right)$, are decided by using the simulation optimization (e.g., complex method [7]).

(ii) **Calculation of cost**

The total cost, $TC\left(d, c_i\left(d\right), N_i\left(d\right)\right)$, of the system is the sum of the minimal total cost, $EC_i^*\left(d, c_i\left(d\right), N_i\left(d\right)\right)$, required at each station. And, the cost UC per unit produced is given below:

$$UC(\overset{\vee}{d}; c_1(\overset{\vee}{d}), \cdots, c_K(\overset{\vee}{d}); N_1(\overset{\vee}{d}), \cdots, N_K(\overset{\vee}{d})) = \frac{TC}{NP}. \qquad (7.2.5)$$

Then, the economic lead time, LT^*, is set at the economic traffic.

(iii) **Termination condition**

If the change of K is finished, it ends. If not, K is changed from K to $K+1$, then it returns to Step 2 again, and the minimum of UC is searched for.

7.2.3.2 Existing Case of Production Facility

Next, the details of the steps in the case of production first are as follows:

Step 1 (Preliminary stage): Parameters setting

This step is similar to the so called line-balancing procedure in the assembly line, as well as the installation case of a new facility.

(i) **Maximal cycle time**

From the production-planning quantity, N_0, and production-planning period, T_0, the maximal cycle time is initially set by the following equation:

$$CT = \frac{T_0}{N_0}. \qquad (7.2.6)$$

(ii) Condition on the number of stations

Under the cycle time, CT, in Eq. (7.2.6) and the mean of total assembly time, S_0, given, the number of stations, K, must be restricted to, $K \geq K_0$. Here, K_0 is the minimal number of stations as follows:

$$K_0 = \left\lceil \frac{S_0}{CT} \right\rceil, \tag{7.2.7}$$

(If this is not possible, the management design is infeasible.)

In the following steps, the two-stage design method in Fig. 7.2.2 is used.

Step 2 (Stage I): Economic traffic

At this stage, the economic cycle time minimizing the expected operating cost is decided. Also, an attempt is made to improve the interarrival time, d, from the initial value, $S_0 \big/ K$, because, d, is viable.

Step 3 (Stage 2): Economic buffers

Under the economic traffic, d^*, at stage 1, the buffers in each station minimizing the cost are decided.

(i) Decision of buffers c_i and N_i

Under the design factor, ε_i, given in the preliminary stage, the optimum buffers, c_i and N_i, which minimizes the total cost in each station, $EC_i\left(d, c_i\left(d\right), N_i\left(d\right)\right)$, are decided by using the simulation optimization (e.g., complex method).

(ii) Calculation of cost

The total cost, $TC\left(d, c_i\left(d\right), N_i\left(d\right)\right)$, of the system is the sum of minimal total cost $EC_i^*\left(d, c_i\left(d\right), N_i\left(d\right)\right)$ required at each station. And, the cost UC per unit produced is given below:

$$UC(\overset{\vee}{d}; c_1(\overset{\vee}{d}), \cdots, c_K(\overset{\vee}{d}); N_1(\overset{\vee}{d}), \cdots, N_K(\overset{\vee}{d})) = \frac{TC}{NP}. \tag{7.2.8}$$

Then, the economic lead time, LT^*, is set at the economic traffic.

(iii) Termination condition

If the change of d is finished, it ends. If it is not finished, d is changed within $d \leq CT$, it returns to Step 2 again, and the minimum of UC is searched for.

7.2.4 Management Design Strategy

7.2.4.1 Production Matrix Table

The production matrix is introduced to integrate both the cases of market first and production first. A few examples of the production matrix table are shown in

Table 7.2.1 Production matrix table: $T_0 = 4,200$, $\beta_{1i} = 3.0$, $\beta_{2K} = 5.0$

d	K	1	2	3	4	5
	UC	4.6143	3.3944	2.7320	3.6838	14.4860
	LT	2.9457	2.9524	2.8046	2.7406	2.6959
	c_1, N_1	0.3626, 3	0.1000, 2	0.1000, 2	0.1000, 2	0.1000, 2
0.34	c_2, N_2	–	0.4261, 4	0.1000, 2	0.1000, 2	0.1000, 2
	c_3, N_3	–	–	0.7194, 5	0.2628, 4	0.5104, 3
	c_4, N_4	–	–	–	1.1736, 5	0.3807, 4
	c_5, N_5	–	–	–	–	0.5497, 5
	UC	4.2969	3.1910	2.6354	4.5604	22.6883
	LT	2.7987	2.9571	2.8525	2.7556	2.6916
	c_1, N_1	0.2921, 3	0.1000, 1	0.1000, 2	0.1000, 2	0.1000, 2
0.36	c_2, N_2	–	0.3031, 5	0.2697, 2	0.1121, 3	0.1000, 3
	c_3, N_3	–	–	0.7192, 4	0.3213, 4	0.8578, 3
	c_4, N_4	–	–	–	0.8520, 5	0.2622, 3
	c_5, N_5	–	–	–	–	1.4424, 3
	UC	4.0216	2.9034	**2.4662**	5.5043	30.6150
	LT	2.8201	2.9018	2.8138	2.8678	2.6024
	c_1, N_1	0.1748, 5	0.1106, 2	0.1000, 2	0.1000, 2	0.1000, 2
0.38	c_2, N_2	–	0.6240, 5	0.3266, 3	0.3646, 3	0.2708, 2
	c_3, N_3	–	–	0.6274, 5	0.3461, 4	0.3645, 3
	c_4, N_4	–	–	–	0.8487, 5	0.9954, 3
	c_5, N_5	–	–	–	–	1.0195, 3
	UC	3.7807	2.6649	2.4715	5.7338	46.1709
	LT	2.9535	2.6423	2.7839	2.7313	2.7648
	c_1, N_1	0.1000, 4	0.1000, 2	0.1000, 2	0.1938, 2	0.1890, 2
0.40	c_2, N_2	–	0.6093, 5	0.3275, 3	0.3492, 2	0.1747, 2
	c_3, N_3	–	–	0.9683, 5	0.7329, 3	0.1000, 3
	c_4, N_4	–	–	–	0.8851, 5	0.2618, 3
	c_5, N_5	–	–	–	–	0.1000, 5
	UC	3.5553	2.4856	2.6376	7.0628	99.3994
	LT	2.8180	2.9344	2.8661	2.5880	2.6145
	c_1, N_1	0.1000, 3	0.1000, 2	0.2269, 3	0.1471, 2	0.1000, 2
0.42	c_2, N_2	–	0.7378, 5	0.2247, 3	0.2366, 3	0.1000, 3
	c_3, N_3	–	–	1.1688, 5	0.4015, 3	0.8170, 4
	c_4, N_4	–	–	–	0.9374, 5	0.1000, 3
	c_5, N_5	–	–	–	–	0.1000, 1

Tables 7.2.1 and 7.2.2. Tables 7.2.1 and 7.2.2 are the case of the production-planning period, T_0, is $T_0 = 4,200$.

The parameter setting is as follows:

$$N_0 = 10,000,\ \varepsilon_i = 0.8,\ \alpha_i = 1,000,\ \bar{x}_i = 1.0\ (i = 1, 2, \ldots, K), \beta_{2j} = 0\ (j = 1, 2, \ldots K - 1)$$

In the tables, the values of the buffer (N_i, c_i) and lead time, LT, at the traffic (d, K) are indicated. Also, the gray element in the Tables shows the minimum point of the total expected cost per unit produced in the strategic map.

7.2.4.2 Management Strategy

On the basis of the production matrix, Tables 7.2.1 and 7.2.2, the management design strategy is discussed under $T_0 = 4,200$. From Tables 7.2.1 and 7.2.2, it is found that the optimal number of stations, K^*, exists. On the other hand, it is seen that the optimal cycle time increases according to the increase of the overflow cost coefficient, β_{2K}, from Tables 7.2.1 and 7.2.2.

Also, it is generally seen that the lead time decreases according to the increase of $K(\geq 2)$, except $K = 1$. Under practical situations, the manager often faces the reduction of lead time. For example, the economic lead time is $LT^* = 2.8138$ in

Table 7.2.2 Production matrix table: $T_0 = 4,200$, $\beta_{1i} = 3.0$, $\beta_{2K} = 7.0$

d	K	1	2	3	4	5
	UC	6.3392	4.4459	3.3035	3.8553	14.6695
	LT	3.2435	2.9245	2.7027	2.7147	2.6944
	c_1, N_1	0.1251, 5	0.1000, 2	0.1000, 2	0.1000, 2	0.1000, 2
0.34	c_2, N_2	–	0.5968, 5	0.1000, 2	0.1000, 2	0.1000, 2
	c_3, N_3	–	–	0.8089, 5	0.2628, 4	0.5104, 3
	c_4, N_4	–	–	–	1.2383, 5	0.3807, 4
	c_5, N_5	–	–	–	–	0.7508, 5
	UC	5.8935	4.1840	3.0886	4.5574	20.7365
	LT	2.9803	3.0629	2.7715	2.7763	2.6973
	c_1, N_1	0.1000, 3	0.1000, 1	0.1000, 2	0.1000, 2	0.1000, 2
0.36	c_2, N_2	–	0.1000, 5	0.2697, 2	0.1121, 3	0.1000, 3
	c_3, N_3	–	–	0.4891, 5	0.3213, 4	0.8578, 3
	c_4, N_4	–	–	–	0.8887, 5	0.2622, 3
	c_5, N_5	–	–	–	–	1.2464, 5
	UC	5.5217	3.7746	2.8660	5.5461	27.3255
	LT	2.9966	3.0541	2.8986	2.8594	2.6062
	c_1, N_1	0.6072, 5	0.1106, 2	0.1000, 2	0.1000, 2	0.1000, 2
0.38	c_2, N_2	–	0.2726, 5	0.3266, 3	0.3646, 3	0.2708, 2
	c_3, N_3	–	–	0.5583, 5	0.3461, 4	0.3545, 3
	c_4, N_4	–	–	–	1.4406, 5	0.9954, 3
	c_5, N_5	–	–	–	–	1.8530, 5
	UC	5.1538	3.4254	**2.8211**	5.8230	45.1438
	LT	3.1012	2.6671	2.7921	2.7358	2.7632
	c_1, N_1	0.5749, 4	0.1000, 2	0.1000, 2	0.1938, 2	0.1890, 2
0.40	c_2, N_2	–	1.1800, 5	0.3275, 3	0.3492, 2	0.1747, 2
	c_3, N_3	–	–	0.6579, 5	0.7329, 3	0.1000, 3
	c_4, N_4	–	–	–	1.2130, 5	0.2618, 3
	c_5, N_5	–	–	–	–	0.1000, 3
	UC	4.8995	3.1626	2.8907	7.1262	83.5860
	LT	3.0982	2.8744	2.9179	2.5977	2.6158
	c_1, N_1	0.6175, 5	0.1000, 2	0.2269, 3	0.1471, 2	0.1000, 2
0.42	c_2, N_2	–	0.6759, 5	0.2249, 3	0.2366, 3	0.1000, 3
	c_3, N_3	–	–	1.1449, 5	0.4015, 3	0.8170, 4
	c_4, N_4	–	–	–	2.0000, 5	0.1000, 3
	c_5, N_5	–	–	–	–	0.1000, 2

Table 7.2.3 Optimal design example: Installation case of new facility

$d = 0.40$	c_1, N_1	c_2, N_2	c_3, N_3	UC	LT
$K = 3$	0.1000, 2	0.3275, 3	0.9683, 5	2.4715	2.7839
$K^* = 2$	0.1000, 2	0.6093, 5	–	2.6649	2.6473

Table 7.2.4 Optimal design example: existing case of production facility

$K = 3$	c_1, N_1	c_2, N_2	c_3, N_3	UC	LT
$d = 0.40$	0.1000, 2	0.3275, 3	0.9683, 5	2.4715	2.7839

Table 7.2.1 for $d = 0.38$ and $K = 3$. If the demand lead time is below $LT = 2.7$, the positioning of management strategy would be changed to $d = 0.40$ and $K = 2$.

From Tables 7.2.1 and 7.2.3 shows an optimal design example for the installation case of a new facility. Also, from Tables 7.2.2 and 7.2.4 shows an optimal design example for the existing case of a new facility.

References

1. Buzacott, J.A., and Shanthikumar, J.G., *Stochastic Models of Manufacturing Systems*, Prentice Hall, New Jersey, 416–470, 1993
2. crisp, R.M. Jr., Skeith, R.W. and Wesley, J.B., A Simulated Study of Conveyor-Serviced Production Stations, *International Journal of Production Research*, 7(4), 301–309, 1969
3. Feyzbakhsh, S.A., Kimura, A. and Matsui, M., Performance Evaluation of a Simple Flexible Assembly System and Its 2-Stage Design, *Journal of Japan Industrial Management Association*, 49(6), 393–401, 1999 (in Japanese)
4. Feyzbakhsh, S.A. and Matsui, M., Adam-Eve like Genetic Algorithm: A Methodology for Optimal Design of a Simple Flexible Assembly System, *Computers and Industrial Engineering Journal*, 36, 233–258, 1999
5. Feyzbakhsh, S.A., Matsui, M. and Itai, K., Optimal Design of a Generalized Conveyor-Serviced Production: Fixed and Removal Item Cases, *International Journal of Production Economics*, 55(2), 177–189, 1998
6. Kasugai, H. and Kuroda, M., Monte Carlo Analysis of an Operation System for Processing Units Carried by Conveyor, *Journal of Japan Industrial Management Association*, 27, 20–23, 1963 (in Japanese)
7. Kowailk, K. and Osborne, M.R., *Methods for Unconstrained Optimization Problems*, Elsevier, NY, 1968
8. Matsui, M., A Generalized Model of Conveyor-Serviced Production Station (CSPS), *Journal of Japan Industrial Management Association*, 44(1), 25–32, 1993 (in Japanese)
9. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial management Association*, 53(1), 1–9, 2002
10. Matsui, M. and Fukuta, J., A Multichannel Queueing System with Ordered Entry and Heterogeneous Servers, *American Institute of Industrial Engineers Transactions*, 9(2), 209–214, 1977
11. Matsui, M., Shingu, T. and Makabe, H., Conveyor-Serviced Production System: An Analytic Framework for Station-Centered Approach by Some Queueing Formulas, *Preliminary Reports of the Operations Research Society of Japan*, Autumn, 104–107, 1977 (in Japanese)
12. Matsui, M., Shingu, T. and Makabe, H., A Comparative Consideration of Operating Policies for Conveyor-Serviced Production Station, *Journal of Japan Industrial Management Association*, 31(3), 342–348, 1980 (in Japanese)

13. Muth, E.J. and White, J.A., Conveyor Theory: A Survey, *American Institute of Industrial Engineers Transactions*, 11(4), 270–277, 1979
14. Nakase, N., Yamada, T. and Matsui, M., A Management Design Approach to a Simple Flexible Assembly System, *International Journal of Production Economics*, 76, 281–291, 2002
15. Suzuki, M., *An Introduction to Game Theory*, Kyoritsu Syuppan, Tokyo, Japan, 1981 (in Japanese)
16. Tuggle, G., Job Enlargement: An Assault on Assembly Line Inefficiencies, *Industrial Engineering*, February, 26–31, 1969
17. Yamada, T. and Matsui, M., A Management Design Approach to Assembly Line Systems, *International Journal of production Economics*, 84, 193–204, 2003

Chapter 8
Job/Customers Routing

8.1 Flexible Machining System (FMS)

8.1.1 Introduction

Flexible manufacturing systems (FMSs) are networks of production systems that are linked by material handling systems (MHSs) that are controlled by a computer. The performance evaluation of FMSs with infinite local buffers was first presented by Solberg [7]. He formulated a model of an FMS by using the theory of closed queueing networks [3] and compared it with a real system. The FMSs with finite local buffers were treated, and the three models of fixed routing, fixed loading, and dynamic routing were presented in [13].

The throughput of a closed queueing network with finite buffers was given by using the probability of blocking [1]. This introduced four kinds of blocking and discussed the relationships between them. Several stochastic models of FMSs were formulated in [2]. The performance evaluation of an FMS with finite local buffers is seen in [5, 6, 8, etc.], but it was not sufficiently discussed in these works.

Also, the design problems of FMSs were addressed in [9, 12, etc.]. A design problem for a system configuration that minimizes the facility costs is first formulated under the desired system throughput. Several design problems are also discussed in [9].

On the basis of Uehara and Matsui [10, 11], this chapter evaluates the performance of FMSs with finite local buffers and a fixed- or dynamic-routing rule, and discusses the optimal design or system configuration problem of maximizing the system throughput [4].

First, the system throughputs and their behaviors are considered under both queueing network analysis and simulation, and it is shown for a fixed-routing model that the system throughput in the case of finite local buffers is greater than the system throughput in the case of infinite local buffers. For a fixed versus dynamic-routing rule, it is also found that throughput in the former case can be close to the one in the latter case by changing the setting parameters.

Next, the design problems of maximizing the system throughput are considered numerically for fixed- and dynamic-routing cases. Then, it is seen that the better combination/configuration of design variables is a class of the monotonicity in local buffers, service rates, and routing probabilities.

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_14,

8.1.2 The Model: Fixed and Dynamic

In this chapter, we consider the model introduced by Solberg [7], but we assume that the local buffers are finite. We introduce two models of fixed- and dynamic-routing types. The model of a fixed type is explained first, and the model of a dynamic type is discussed later.

8.1.2.1 Assumptions and Notation

FMSs are networks of production systems that are linked by material handling systems (MHSs) that are controlled by a computer. They consist of M's machine groups of various sizes and a transporter. The machine groups have finite local buffers.

The local buffers reflect a storage that holds parts of different types, when one of the next machines are busy. When the finite local buffers are full, a new part carried by a transporter remains on the transporter. The transporter has sufficient capacity over the total number of parts in the system. This event is called blocking.

The system of fixed routing is conceptualized in Fig. 8.1.1. The assumptions of the model for the proposed analysis are as follows:

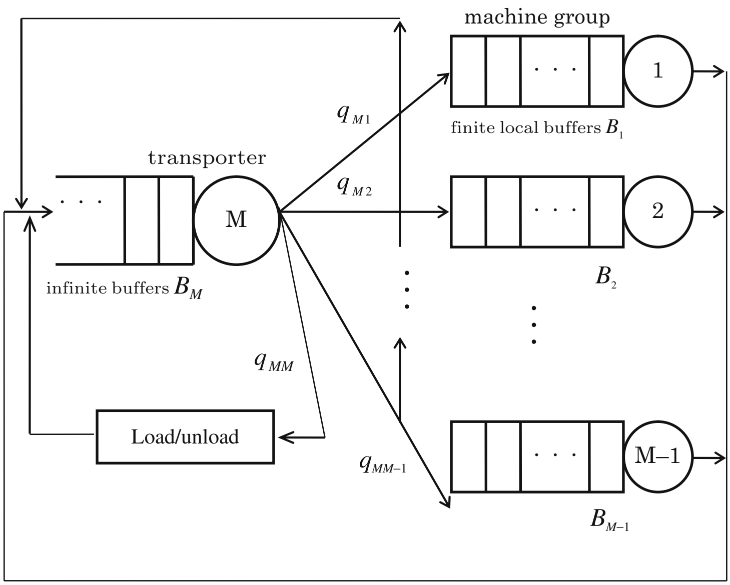


Fig. 8.1.1 The model: fixed routing

The system is stationary.
Machines are mutually independent.
Service times of each of the machines are exponentially distributed.
The total number of parts (of a single type) in the system is a constant, N.
A part blocked is returned to the end of the queue in the transporter.
The travel time of each part is zero.

The notation in Fig. 8.1.1 is defined as follows:

N: Total number of parts (of a single type) in the system
q_{ij}: Routing probability
μ_i: Service rate of a machine in a machine group, i
B_i: Finite local buffer at machine group, i
c_i: Number of the machines in machine group, i

where $i, j = 1, 2, \ldots, M$.

8.1.2.2 Fixed versus Dynamic Routing

An outline of a fixed-routing model is as follows: Parts are carried by the transporter to machine group, i, with routing probability, q_{Mi} $(i = 1, \ldots, M - 1)$. Machine group, i, has $c_i(i = 1, \ldots, M)$ machines, which are all the same. Their service rates are μ_i $(i = 1, \ldots, M)$, and the service rule is FCFS (first come, first served).

Parts that have completed their processing are returned to the transporter by their routing probability from machine group, i, to the transporter, $q_{iM}(= 1)$. Also, parts are sent to the load/unload station at the rate of routing probability, q_{MM} and exchanged for new incoming parts. So the total number of parts in the system is a constant, N.

Machine group, i, has finite local buffers, $B_i(\geqq c_i,\ i = 1, \ldots, M-1)$. When the machines are busy, the new parts that are carried by the transporter are stored at the finite local buffers. When the finite local buffers are full, the new part that is carried from the transporter is blocked and returned to the end of the transporter's queue. The blocked and returned part is sent to machine group, i, by routing probability, q_{Mi}, again. This kind of blocking is called repetitive service blocking by Balsamo and Nitto-Persone [1].

In the case of the dynamic-routing model (Fig. 8.1.2), the destinations of the parts that are carried from the transporter to the machine groups are decided under the conditions of the machine groups. The condition is the number of parts in each machine group. That is, when a destination is chosen, this choice will have a higher system performance profit than the others.

Then a basis of judgment for transportation must be decided. One of the simple ones is to carry a part to a machine group that has the shortest queue length. When

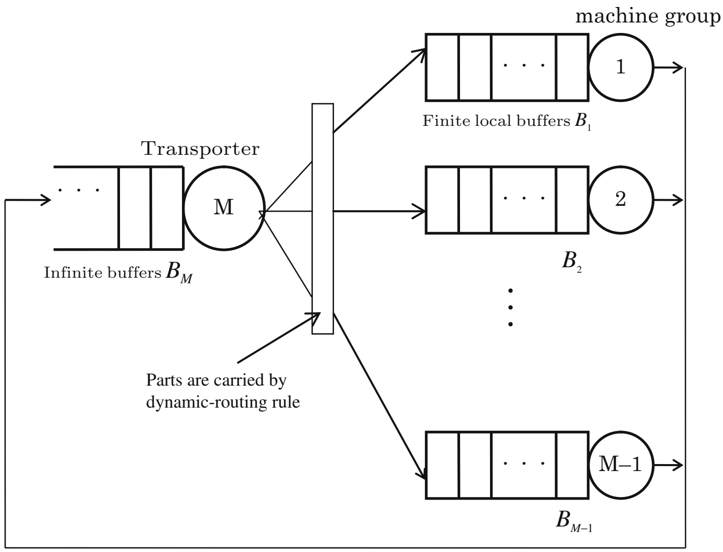


Fig. 8.1.2 The model: Dynamic routing

the finite local buffers in all of the machine groups are the same, the machine group, which has the shortest queue length has the largest space in the finite local buffers, too. Thus, the above basis has intuitive appeal.

But, when all of the finite local buffers are not the same, the machine group that has the shortest queue lengths does not always have the largest space. So the above basis often shows a wrong judgment in this case. That is, a blocking may happen at a small finite local buffer, even if other larger buffers have some spaces.

8.1.3 Performance Evaluation

In this section, we give the throughput of machine group i for a fixed-routing model. First, the steady-state equation of the system is formulated. The blocking probability and marginal probability are then derived by using the solution of the equation. Next, the throughput of machine group, i, is derived by using the probability and marginal probability and is simplified by the definition of the utilization of machine group, i.

8.1.3.1 Steady-State Probabilities and Throughputs

The steady-state equation of the system is given from [9] as follows:

$$
\begin{aligned}
&\left\{\sum_{i=1}^{M} \varepsilon\left(n_i\right) \alpha_i\left(n_i\right) \mu_i\right\} \pi\left(n_1, \cdots, n_M\right) \\
&= \sum_{i=1}^{M-1} b\left(n_i\right) \alpha_M\left(n_M+1\right) \mu_M q_{Mi} \pi\left(n_1, \cdots, n_i-1, \cdots, n_M+1\right) \\
&+\varepsilon\left(n_M\right) \alpha_M\left(n_M\right) \mu_M q_{MM} \pi\left(n_1, \cdots, n_M\right) \\
&+\sum_{i=1}^{M-1} \varepsilon\left(n_M\right) \alpha_i\left(n_i+1\right) b_i\left(n_i\right) \mu_i q_{iM} \pi\left(n_1, \cdots, n_i+1, \cdots, n_M-1\right) \\
&+\sum_{i=1}^{M-1} \varepsilon\left(n_M\right) \alpha_M\left(n_M\right)\left\{1-b_i\left(n_i\right)\right\} \mu_M q_{Mi} \pi\left(n_1, \cdots, n_M\right)
\end{aligned}
$$

where

$$
\begin{aligned}
\varepsilon\left(n_i\right) &= 1,\ if\ n_i \neq 0; \\
&= 0,\ if\ n_i = 0; \\
\alpha\left(n_i\right) &= n_i,\ if\ n_i \leq c_i; \\
&= c_i,\ if\ n_i > c_i; \\
b_i\left(n_i\right) &= 1,\ if\ n_i < B_i; \\
&= 0,\ if\ n_i \geq B_i; \\
\varepsilon\left(n_i\right)\alpha\left(n_i\right) &= \alpha\left(n_i\right).
\end{aligned} \tag{8.1.1}
$$

Thus, the solution of these equations is as follows:

$$
\pi(s) = G_M^{-1}(N) \prod_{i=1}^{M} f_i\left(n_i\right) b_i\left(n_i\right) \text{ for all } s \in S \tag{8.1.2}
$$

where

$$
\begin{aligned}
f_i\left(n_i\right) &= X_i^{ni} \beta_i^{-1}\left(n_i\right),\ n_i = 0, 1, 2, \cdots, N \\
\beta_i\left(n_i\right) &= n_i!, \qquad \text{if} \quad n_i \leq c_i \\
&= c_i! c_i^{(ni-ci)}, \qquad \text{if} \quad n_i > c_i \\
Xi &= \mu_M q_{Mi} x_M \big/ \mu_i,\ i = 1, \cdots, M-1.
\end{aligned}
$$

And the notation in Eq. (8.1.2), S, is a state space:

$$
S = \left\{\left(n_1, \cdots, n_i, \cdots, n_M\right) \middle| \sum_{i=1}^{M} n_i = N, n_i \geq 0, i = 1, \cdots, M\right\}.
$$

There is a relation between $\beta_i\left(n_i+1\right)$ and $\beta_i\left(n_i\right)$:

$$\beta_i(n_i+1) = \beta_i(n_i)\,\alpha_i(n_i+1)$$

and $G_M(N)$ is a normalizing constant. This can be defined as follows:

$$G_M(N) = \sum_{s\in S}\prod_{i=1}^{M} f_i(n_i)\,b_i(n_i).$$

The blocking probability $BL_i(k)$ can be derived by using the steady-state probability $\pi(S)$ from (1) (Balsamo and Nitto-Persone [1]):

$$BL_i(k) = \sum_{j\neq i}\sum\nolimits_{\{s|s\in S, n_i=k, n_j=B_j\}} \pi(s) q_{ij}.$$

Then the throughput of machine group, i, can be derived as follows:

$$Th_i = \mu_i\sum_{k=1}^{B_i}\{p_i(k) - BL_i(k)\},$$

where $p_i(k)$, the marginal probability distribution of machine group, i, is given by

$$p_i(k) = \sum\nolimits_{\{s|s\in S, n_i=k\}} \pi(s).$$

Now, we define the utilization of the machine group i, V_i, as follows:

$$V_i = 1 - p_i(0) - TBL_i, \tag{8.1.3}$$

where TBL_i is the total blocking rate given by

$$TBL_i = \sum_{k=1}^{N} BL_i(k).$$

Because the capacity of the transporter is infinite, Eq. (8.1.3) can be separated as follows:

$$\begin{aligned} V_i &= 1 - p_i(0),\ i = 1,\cdots,M-1; \\ V_M &= 1 - p_M(0) - TBL_M. \end{aligned}$$

Finally, the throughput can be shown from Eq. (8.1.3) as follows:

$$Th_i = \mu_i V_i.$$

8.1.3.2 Behavior of System Throughput

We observed the behavior of system throughput by using a numerical example. First, we observed the behavior of the system throughput when the finite local buffers are changeable. The way of changing the finite local buffers is as follows: All finite local buffers of machine group, B_i, are the same, $B_i = B(i = 1, 2, \cdots, M-1, 1 \leq B \leq N)$, and these buffers increased from $B = 1$ to $B = N$.

There are two ways to define the system throughput: $TH = Th_M$ or $TH = \sum_{i=1}^{M-1} Th_i$. We label each case as follows:

Evaluation Form I: $TH = Th_M$
Evaluation Form II: $TH = \sum_{i=1}^{M-1} Th_i$.

It is noted that Evaluation Form I is given by the throughput at the central server.

The numerical example is calculated when $M = 4$ and $N = 10$. Table 8.1.1 gives the input parameters. Figure 8.1.3 shows the behavior of the system throughput with both finite local buffers and infinite local buffers. Figure 8.1.3 reveals that the throughput in the case of finite local buffers is greater; it is maximum for some buffers.

The cause of the former is clear: The parts that are transported to a local buffer cannot leave there without processing. If all local buffers are infinite, the parts stay a long time at these buffers. Because the number of parts in the system is finite, the

Table 8.1.1 Input parameters: $M = 4$, $N = 20$

Machine Group i	1	2	3	4
q_{Mi}	0.25	0.25	0.25	0.25
μ_i	10	30	50	100
c_i	1	1	1	1
B_i	$B_1 = B_2 = B_3 = B$, $B = 1, 2, \cdots, 20$			20

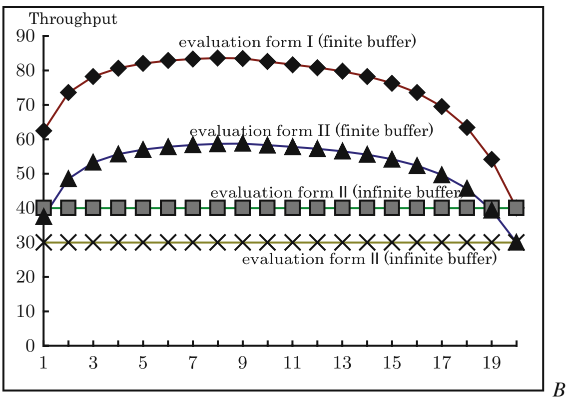


Fig. 8.1.3 Behaviors of the system throughput

other machine groups can process only the remaining parts. If some machine groups process parts faster, these groups may often be idle. Thus, the system throughput in the case of infinite local buffers is less.

When the local buffers are smaller than their optimal size, the system throughput decreases because machine groups are blocked. But when the local buffers are larger than their optimal size, parts stay idle in the buffers longer. Because the number of parts in the system is a constant N, this may lead to a reduction of the system's throughput.

For example, under $N = 10$ and the five machine groups as five, if machine group 1 has 5 parts and machine group 2 has 3 parts, the other machine groups have only 2 parts to work with, so at least one is idle. Cases similar to these often arise with long production schedules.

8.1.4 Fixed versus Dynamic Routing

In this section, we compare the fixed-routing rule with a dynamic-routing rule. A similar approach to the dynamic-routing rule is adopted, and the characteristics of the fixed-routing rule are pointed out.

8.1.4.1 Throughput of Dynamic Routing

Dynamic routing means that parts in the transporter are carried to machine groups, depending on the queue length in the finite local buffers. The dynamic-routing rule is more efficient than the fixed-routing rule and is adopted in many companies. But in the physical and economical situation that a manager must consider, an adoption of a fixed-routing rule often happens. That is, dynamic routing necessitates information about queus, and thus it requires a higher cost to observe.

The configuration of the system for a dynamic-routing rule is the same as that of the fixed-routing rule except for the rule of parts flow. A destination of parts that are carried from transporter to machine groups is decided, depending on the shortest queus of parts in machine groups. The assumptions of the model are the same as those of the fixed-routing model. An analysis for the dynamic-routing rule is obtained as follows:

In analysis, it is difficult to formulate the model of a dynamic-routing rule as it is, so we use the equation of the fixed-routing rule, approximately. Then, the steady-state probability of a dynamic-routing model is formulated as follows:

$$\pi(s) = G_M^{-1}(N) \prod_{(i=1)\cap S}^{M} f_i(n_i) b_i(n_i)$$

where $G_M(N)$ is a normalizing constant and

$$f_i(n_i) = X_i^{ni}\beta_i^{-1}(n_i),\ n_i = 0, 1, 2, \cdots, N \tag{8.1.4}$$
$$X_i = \frac{\mu_M}{\mu_i}\hat{q}_{Mi}X_M.$$

The notation $\hat{q}_{Mi}$ in Eq. (8.1.4) indicates a quasi-routing probability that is defined by

$$\hat{q}_{Mi} = \frac{(B_i - n_i)\big/B_i}{\sum_{i=1}^{M-1}(B_i - n_i)\big/B_i}. \tag{8.1.5}$$

Note that $\hat{q}_{Mi}$ is now a function of the system state $n = (n_1, n_2, \cdots, n_M)$, that is, $\hat{q}_{Mi}$(n).

The quasi-routing probabilities are given by Yao and Buzacott [13], and this method is called the probabilistic shortest queue method. Equation (8.1.5) means that $\hat{q}_{Mi}$ is more closer to 1 when

$$\frac{\text{(space of the finite local buffer)}}{\text{(capacity of the finite local buffers)}}$$

is close to 1. The probability that parts are carried to machine group, i, increases when, $\hat{q}_{Mi}$, is more closer to 1 than when using this basis, blocking only occurs when all of the finite local buffers are full. It is changed under the condition of the machine groups, and, $\hat{q}_{Mi}$, is different from the routing probability of fixed routing model, q_{Mi}.

8.1.4.2 Throughput Comparison

We here compare the fixed-routing rule with the dynamic-routing rule from the point of view of system throughput. Table 8.1.2 is a result of this comparison. In the case of the fixed-routing rule, the routing probabilities of machine groups are the same, and the service rates of each rule are $\mu_1 = 10$, $\mu_2 = 30$, $\mu_3 = 50$, $\mu_4 = 100$.

Table 8.1.2 shows clearly that the dynamic-routing rule has a higher performance than the fixed-routing rule. However, some interesting examples are shown in Table 8.1.3. The parameters of Table 8.1.3 are different from that of Table 8.1.2 in service rates (they are changed to $\mu_1 = \mu_2 = \mu_3 = 30$ in Table 8.1.3).

This example shows that the performance of the fixed-routing rule is close to that of the dynamic-routing rule. The unification of the each parameter means that the system has a good load balance, and the total blocking rate decreases. The utilization of the machine groups also shows that the system in the Table 8.1.3 has a better load balance than the system that of Table 8.1.2.

As a result, the fixed-routing rule has some possibilities of the performance being close to that of the dynamic-routing rule. From these results, it is necessary

Table 8.1.2 Comparison of the fixed-routing rule with dynamic-routing rule: Case of bad balance $M = 4,\ N = 20,\ \mu_1 = 10,\ \mu_2 = 30,\ \mu_3 = 50$

Machine group i		Input parameter q_{ij}	μ_i	B_i	c_i	Result Utilization	System throughput
Fixed-routing rule	1	1/3	10	5	1	0.998	
	2	1/3	30	5	1	0.889	69.4
	3	1/3	50	5	1	0.655	
	4	—	100	20	1	0.992	
Dynamic-routing rule	1	0.125	10	5	1	0.993	
	2	0.125	30	5	1	0.939	82.0
	3	0.75	50	5	1	0.878	
	4	0.0	100	20	1	1.0	

Table 8.1.3 Comparison of the fixed-routing rule with dynamic-routing rule: Case of good balance $M = 4,\ N = 20,\ \mu_i = 30\ (i = 1, 2, 3)$

Machine group i		Input parameter q_{ij}	μ_i	B_i	c_i	Result Utilization	TH2
Fixed-routing rule	1	1/3	30	10	1	0.928	
	2	1/3	30	10	1	0.911	81.96
	3	1/3	30	10	1	0.893	
	4	—	100	20	1	0.857	
Dynamic-routing rule	1	0.077	30	10	1	0.952	
	2	0.077	30	10	1	0.952	85.65
	3	0.846	30	10	1	0.952	
	4	0.0	100	20	1	0.935	

to observe the utilization of the machine groups in order for the system to have a good load balance. That is, the system throughput has good performance when the workload for each machine group is balanced.

Remarks

For the fixed type, we can support the intuition that the local buffers at the faster machines should be larger than that at the slower machines. However, the example for a dynamic type shows a contradictory result that this intuition may hold under Evaluation Form II, but it gives the inverse result under Evaluation Form I. This finding is very interesting to managers because of incompatible assignment.

References

1. Balsamo, S. and Nitto-Persone, V.D., Closed Queueing Networks with Finite Capacities: Blocking Types, Product-form Solution and Performance Indices, *Performance Evaluation*, 12, 85–102, 1991
2. Buzacott, J.A. and Shanthikumar, J.G., *Stochastic Models of Manufacturing Systems*, Prentice Hall, NY, 1996
3. Gordon, W.J. and Newell, G.F., Closed Queueing Systems with Exponential Servers, *Operations Research*, 15, 254–265, 1967
4. Matsui, M., Uehara, S. and Ma, J., Performance Evaluation of Flexible Manufacturing System with Finite Local Buffers: Fixed and Dynamic Routings, *The International Journal of Flexible Manufacturing Systems*, 13, 405–424, 2001
5. Seidmann, A., Optimal Dynamic Routing in Flexible Manufacturing Systems with Limited Buffers, *Annals of Operations Research*, 15, 291–311, 1986
6. Seidmann, A. and Tenenbaum, A., Throughput Maximization of Flexible Manufacturing Systems, *IIE Transactions*, 26(1), 90–100, 1994
7. Solberg, J.J., A Mathematical Model of Computerized Manufacturing Systems, *4th International Conference on Production Research*, (*ICPR*), Tokyo, Japan, 22–30, 1997
8. Tenenbaum, A. and Seidmann, A., Dynamic Load Policies for a Flexible Manufacturing System with Stochastic Processing Rates, *International Journal of Flexible Manufacturing Systems*, 2(2), 93–120, 1989
9. Tetzlaff, U.A.W., *Optimal Design of Flexible Manufacturing Systems*, Physica-Verlag, Heidelberg, 1990
10. Uehara, S. and Matsui, M., The Performance Evaluation of Flexible Manufacturing Systems with Finite Local Buffers and Its Design Problem, *Journal of Japan Industrial Management Association*, 45(5), 464–471, 1994 (in Japanese)
11. Uehara, S. and Matsui, M., The Performance Evaluation of Flexible Manufacturing Systems with Dynamic Routing and Its Optimal System Configurations, *Journal of Japan Industrial Management Association*, 47(2), 126–134, 1996 (in Japanese)
12. Vinod, B. and Solberg, J.J., The Optimal Design of Flexible Manufacturing Systems, *International Journal of Production Research*, 23(6), 1141–1151, 1985
13. Yao, D.D. and Buzacott, J.A., Models of Flexible Manufacturing Systems with Limited Local Buffers, *International Journal of Production Research*, 24(1), 107–118, 1986

8.2 FMS/FAS and Optimal Routing

8.2.1 Introduction

Because of a variety of modern demands, several flexible manufacturing systems (FMS) have been recently developed. Several kinds of research on FMS of central server types were begun by Solberg [6]. Such as research on finite local buffers as discussed in Chapter 8.1 which focuses on cases of a fixed or dynamic routing rule.

Let us consider flexible manufacturing systems with an ordered-entry rule. The ordered-entry (OE) rule is well known as a class of the flexible assembly system of open queueing network types [1, 2, 3, 5].

This system is similar to the flexible assembly system of central-server types. Thus, we call this class the flexible machining/assembly system (FMS/FAS) of central-server types. This chapter gives the performance evaluation of FMS/FAS and a comparative consideration of fixed, dynamic versus ordered-entry routing rules for routing development [4].

First, the steady-state equations are given, and the system throughput is obtained. Next, the system configurations of FMS/FAS are numerically discussed on the basis of the system throughput. Finally, the superiority of an ordered-entry routing rule that is numerically found is discussed for the development of routing theory.

8.2.2 Explanation of the Model

8.2.2.1 Assumptions and Notation

A flexible-machining system with an ordered-entry routing rule (OE rule) is seen in Fig. 8.2.1. Also, a flexible assembly system of a central-server type is seen in Fig. 8.2.2 [1]. The common model with an ordered entry that contains a common part of Figs. 8.2.1 and 8.2.2 is generally included in Fig. 8.2.1 and is called the FMS/FAS of the central-server type.

The OE means that the central server will transport a part to stations according to the routing probability, q, and will seek service from stations in a prescribed order.

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_15,

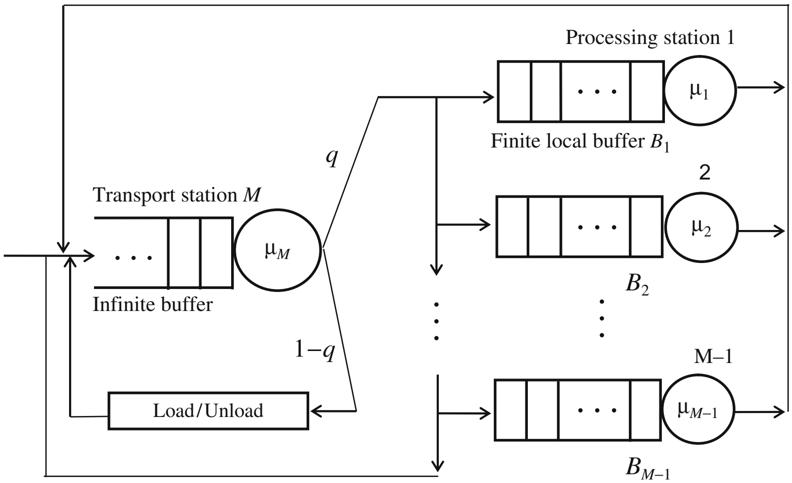


Fig. 8.2.1 Flexible Machining System (FMS) with ordered-entry rule

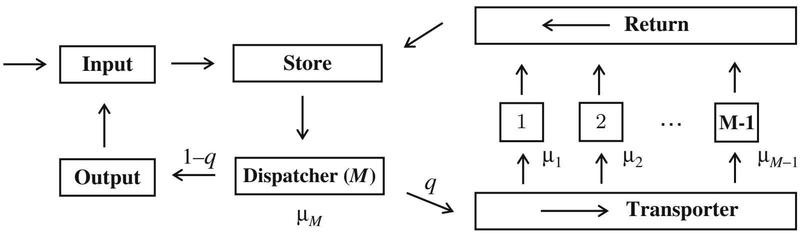


Fig. 8.2.2 Flexible Assembly System (FAS) of central-server type

The decision regarding the entrance of the part to a station is determined strictly on the basis of the first available station acceptable to the part.

Each processing station has single or multiple machines. The respective processing stations except the transport station, M, has a finite local buffer for storing the unprocessed parts. The part is sent to the processing stations from the transport station according to the OE routing rule.

If all the local capacities are full, the part will be returned to the transport station with an infinite capacity. This phenomenon is called the blocking. The processed parts go back to the transport station after they are finished, and they are exchanged for the unprocessed parts in the load/unload station. Therefore, the number of parts in the system is always fixed.

The assumptions of the model are as follows:

(i) The system is stationary.
(ii) Machines operate mutually independently.
(iii) The service time of each of the machines is exponentially distributed.
(iv) The total number of parts in the system is a constant, N.

(v) The part blocked will be returned to the end of the queue in the transport station.
(vi) The travel time of each part is zero.

8.2.2.2 Routing Rules

The flexible-machining/assembly model is regarded as the FMS model with the OE routing rule (Fig. 8.2.1). In this OE routing model, the routing probability, q, means there is a probability that the routing of the part will be done in the first processing station, while the probability, $(1-q)$, is the probability that turns to the load/unload station.

By the OE rule, the routing of the part is to the Station 1 from the transport station. The part receives the service immediately. If Station 1 is in service, it waits at the local buffer. The part then goes to Station 2 if the local buffer of Station 1 is full.

The part goes to Station 3, if the local buffer of Station 2 is full. Then, the part is kept until the process station with a vacancy in the local buffer is found. The part is then returned to the end of the infinite buffer of the transport station without receiving the service, if all local buffers are full. In short, the blocking is generated.

The OE rule in the flexible-machining/assembly model has not been compared with routing rules in the literature until now. The outline of the fixed or dynamic model is seen in Matsui's, Chapter 8.1, and is summarized as follows:

In the fixed-routing rule, the routing probability, q_{Mi}, gives the proportion of the part that is sent to the processing station, i, from the transport station. This fixed proportion causes the phenomenon that generates the blocking in sending the part even if the local buffer is full.

In the dynamic-routing rule, the transport of the part is decided by the condition of each processing station. The condition here indicates the vacancy rate, RS_i $(= (B_i - n_i)/B_i)$, of the local buffer of each processing station. n_i is the number of parts that exist in station, i. In short, this routing is the rule that transports the part to the station in which the vacancy rate, RS_i, is nearest to 1.

Then, the blocking is not generated, as long as all local buffers do not become full. Also, the transport station stops to transport the part, when the blocking is generated, and it waits until the vacancy is possible for any of the local buffer.

8.2.3 Throughputs for the System

8.2.3.1 System Throughput

Now, let us denote the steady-state probabilities that the n_i parts are at each station of the system by $\pi(n_1, n_2, \cdots, n_M)$, in which $\sum_{i=1}^{M} n_i = N,\ 0 \leq n_i \leq B_i$. Then, the steady-state equations of the system are as follows:

$$
\begin{aligned}
&d\pi(n_1, n_2, \cdots, n_M)\big/dt \\
&= -\left\{\sum_{i=1}^{M} \varepsilon(n_i)\mu_i\right\} \pi(n_1, n_2, \cdots, n_M) \\
&\quad + \sum_{i=1}^{M-1} \varepsilon'(n_i)\varepsilon(n_M)\mu_i\, \pi(n_1, \cdots, n_i + 1, n_{i+1}, \cdots, n_{M-1}, n_M - 1) \\
&\quad + q\varepsilon(n_1)\mu_M \pi(n_1 - 1, n_2, \cdots, n_{M-1}, n_M + 1) \\
&\quad + \sum_{i=1}^{M-2} \{1 - \varepsilon'(n_1)\}\{1 - \varepsilon'(n_2)\} \cdots \{1 - \varepsilon'(n_i)\} q\mu_M \\
&\qquad \times \pi(n_1, n_2, \cdots, n_i, n_{i+1} - 1, n_{i+2}, \cdots, n_{M-1}, n_M + 1) \\
&\quad + (1 - q)\varepsilon(n_M)\mu_M \pi(n_1, n_2, \cdots, n_M),
\end{aligned} \tag{8.2.1}
$$

where $\varepsilon(n_i)$ and $\varepsilon'(n_i)$ are defined, respectively, by

$$
\begin{aligned}
\varepsilon(n_i) &= 0, \quad \text{if } n_i = 0 \qquad & \varepsilon'(n_i) &= 0, \quad \text{if } n_i = B_i \\
&= 1, \quad \text{if } n_i \neq 0, & &= 1, \quad \text{if } n_i \neq B_i.
\end{aligned}
$$

The steady-state probabilities are obtained from Eq. (8.2.1) and any initial condition, and the busy probability, V_i, of station, i, is given by

$$
V_i = \sum_{n_i \neq 0} \pi(n_1, \cdots, n_i, \cdots n_M), \qquad i = 1, 2, \cdots, M \tag{8.2.2}
$$

Then, the throughput, Th_i, of station, i, is obtained from the following equation:

$$
Th_i = \mu_i V_i, \qquad i = 1, 2, \cdots, M \tag{8.2.3}
$$

From Eq. (8.2.3), the system throughput is considered as the performance function in the model, and is defined in the following equation:

$$
TH = \sum_{i=1}^{M-1} Th_i \tag{8.2.4}
$$

This is the sum of the throughputs in each station except in the transport station. Still, there is the case that the throughput of the transport station is considered as the performance function of the system from the viewpoint of the bottleneck.

8.2.3.2 Numerical Considerations

In this section, the system configurations of FMS/FAS are numerically discussed on the basis of the system throughput. For numerical evaluations, the parameters are set as shown in Table 8.2.1.

The steady-state probabilities, $\pi(n_1,\ n_2,\ n_3,\ n_4)$, are obtained by solving the equation, $d\pi/dt = 0$. For example, the matrix form of the equation is represented as shown in Fig. 8.2.3. Then, the simultaneous equations are solved under the initial condition: $\pi(0,\ 0,\ 0,\ 3) = 1$, and the steady-state probabilities are obtained.

The performance by $q,\ \mu_i$'s and B_i's is numerically considered as follows:

(1) Effect of $q_{M1} \equiv q$

First, the effect of routing probability, q, is examined. Figure 8.2.4 shows the behavior of the system throughput under $B = 1$ and $\mu_1 = \mu_2 = \mu_3 = \mu,\ \mu = 10, 20, \cdots,\ 100$. From Fig. 8.2.4, it is seen that the system throughput increases with the larger probability, q, and the service rate, μ.

(2) Server arrangement

From the OE model of open networks, it is guessed that the system throughput is better in a faster order than in slower service rates [3, 5]. This arrangement problem of heterogeneous servers is considered for a class of closed queueing networks.

Figure 8.2.5 shows the effect of homogenous versus. heterogeneous servers on system throughput. From Fig. 8.2.5, it can be seen that the system throughput is best

Table 8.2.1 Parameters setting: $M = 4,\ N = 10$

Service rate Station i	1	2	3	4(= M)
Faster order	50	30	10	100
Slower order	10	30	50	100
Average	30	30	30	100
Number of servers, c_i	1	1	1	1
Routing probabilities	$q = 0.9$			$1 - q = 0.1$
Local buffers, B_i	$B_1 = B_2 = B_3 = B,\quad B = 1,\ 2, \cdots,\ 10$			10(= N)

000	001	010	011	100	101	110	111		
$-q\mu_4$	μ_3	μ_2		μ_1				000	3
	$-\mu_3 - q\mu_4$		μ_2		μ_1			001	2
		$-\mu_2 - q\mu_4$	μ_3			μ_1		010	2
			$-\mu_2 - \mu_3 - q\mu_4$				μ_1	011	1
$q\mu_4$				$-\mu_1 - q\mu_4$	μ_3	μ_2		100	2
	$q\mu_4$				$-\mu_1 - \mu_3 - q\mu_4$		μ_2	101	1
		$q\mu_4$		$q\mu_4$		$-\mu_1 - \mu_2 - q\mu_4$	μ_3	110	1
			$q\mu_4$		$q\mu_4$	$q\mu_4$	$-\mu_1 - \mu_2 - \mu_3$	111	0

Fig. 8.2.3 Matrix form of $d\pi / dt = 0:\ M = 4,\ N = 3,\ B_1 = B_2 = B_3 = 1$

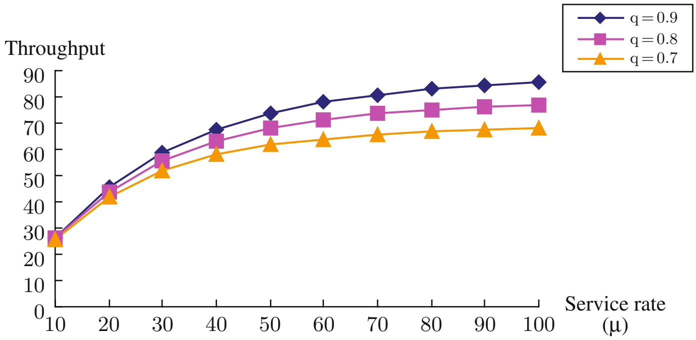


Fig. 8.2.4 Behavior of the throughput: $q = 0.7$, 0.8 and 0.9

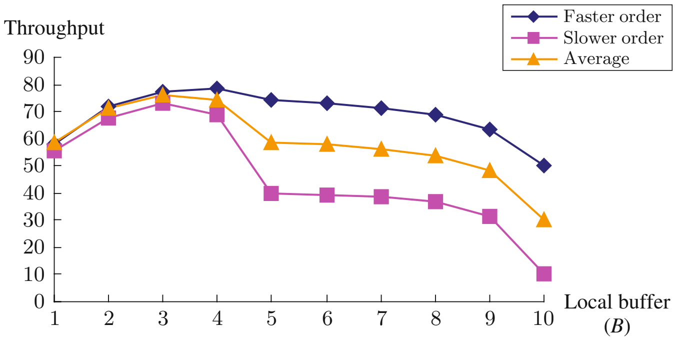


Fig. 8.2.5 Behavior of the throughput for heterogeneous servers

in cases of faster order, and is worst in cases of slower orders adversely. In addition, the system throughput is in the middle-average range of the processing rate.

Also, it is seen that the system throughput increases according to the increase of the local buffer, B, and has the maximum at $B = 4$ or 5. This is because the total of the local buffers in each processing station is 9, 12, and 15 for $B = 3,\ 4$, and 5, respectively, under the total number of parts, $N = 10$.

No job is sent to the following stations, even if the local buffer is further increased. This is similar to the effect of the finite local buffer in the fixed routing [5].

(3) Buffer allocation

Finally, the allocation problem of the local buffers in each processing station is considered. The setting of input parameters is $M = 4,\ N = 10$, and $\mu_1 = 50,\ \mu_2 = 30,\ \mu_3 = 10,\ \mu_4 = 100$. The local buffer in each processing station is near 4, and the allocation of the local buffers is shown as $(B_1,\ B_2,\ B_3)$.

Figure 8.2.6 shows the effect of system throughput for some of the allocation patterns. From Fig. 8.2.6, it is seen that the system throughput is largest for $B_1 = 3,\ B_2 = 4,\ B_3 = 3$, and the value is 78.621. Thus, it is assumed that the average allocation is better.

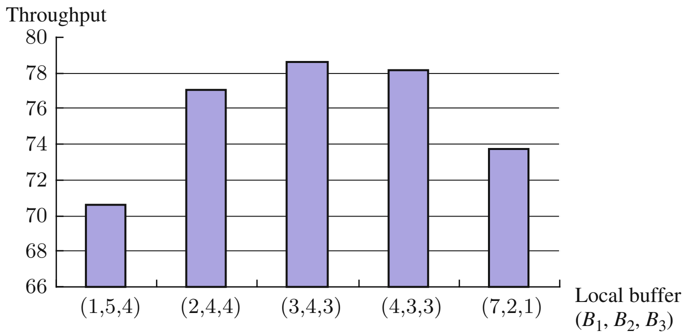


Fig. 8.2.6 Behavior of the throughput under allocation $(B_1,\ B_2,\ B_3)$, where $\sum B_i = 10$

8.2.4 Comparative Rules

8.2.4.1 Local Buffer: B $= 1$

For the local buffer of $B_1 = B_2 = \cdots = B_{M-1} = B = 1$, the OE routing rule is compared here with the fixed or dynamic-routing rule. The parameters are set as shown in Table 8.2.2.

In the fixed and OE routings, it is noted that the routing to the unload-and-loading activity is routed at the probability $0.1 (= 1 - q)$, while there is no unload-and-loading activity at the load/unload station in the dynamic model.

A comparison result of the system throughput of each model is shown in Table 8.2.3. From Table 8.2.3, when the service rate of each processing station is different, the system throughput in the OE model is the largest under $B = 1$.

For homogeneous servers ($m = 1\big/\mu_i$ for all i), we introduce the throughput matrix (N, m) under the optimal choice of those belonging to q, q_i, and B_i. For $M = 4$, $B_i = 1 (i = 1 \sim 3)$, it is seen that the OE routing is superior to that of other models, and the fixed model (FR) is better than that of the dynamic model (DR)

Table 8.2.2 Input parameters: $M = 4,\ N = 10$

Model	Ordered-entry (OE)	Fixed routing	Dynamic routing
Routing probabilities	$q = 0.9$	$q_1 = q_2 = q_3 = 1/3$	(RS_i)
		$[q = q_1 + q_2 + q_3 = 0.9]$	$[(RS_1) + (RS_2) + (RS_3) = 1]$
Limited local buffers		$B_1 = B_2 = B_3 = 1,\ B_4 = N (= 10)$	
Number of servers		$c_1 = c_2 = c_3 = c_4 = 1$	

Table 8.2.3 Routing comparison: Heterogeneous servers and $B = 1,\ M = 4,\ N = 10$

Models / Service rates	Ordered entry (OE)	Fixed routing (FR)	Dynamic routing (DR)
$\mu_1 = 50, \mu_2 = 30, \mu_3 = 10, \mu_4 = 100$	58.069	43.480	46.072
$\mu_1 = 30, \mu_2 = 30, \mu_3 = 30, \mu_4 = 100$	58.846	47.366	47.785
$\mu_1 = 100, \mu_2 = 100, \mu_3 = 100, \mu_4 = 100$	85.494	74.994	59.528

except in the case of $N > 2$ and $m > 0.0125$. The latter result would suggest that the DR in Chapter 8.1 uses an approximate routing rule and the approximation is not appropriate for a lower N and m.

8.2.4.2 Local Buffer: $B \neq 1$

Next, let us set the service rates $\mu_1 = 50$, $\mu_2 = 30$, $\mu_3 = 10$, $\mu_4 = 100$, and the local buffers $B_1 = B_2 = B_3 = B$ $(B = 1, 2, \cdots, 10)$. The numerical result is shown in Fig. 8.2.7. From Fig. 8.2.7, it is seen that the OE model is better until $B = 4$. After $B = 5$, the dynamic routing model is better.

Also, the largest throughput for the total of local buffers is considered under the three-routing models. Then, for the ordered entry, the probability, q, is, $q = 0.9$, and for the fixed routing, the probabilities are $q_1 = 0.6$, $q_2 = 0.3$, $q_3 = 0.1$. The service rates are fixed at $\mu_1 = 50$, $\mu_2 = 30$, $\mu_3 = 10$ for each model.

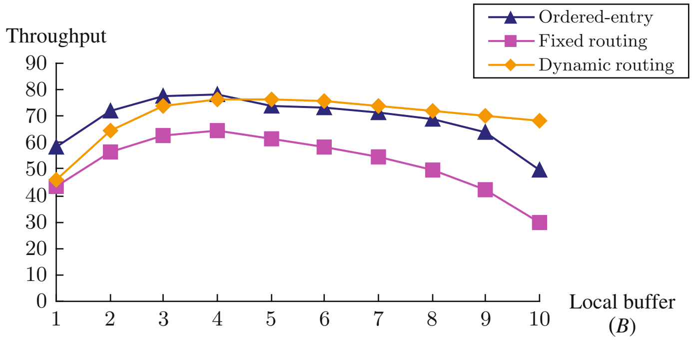


Fig. 8.2.7 Routing comparison: $B = 1, \cdots, 10$ $(= N)$ and faster order

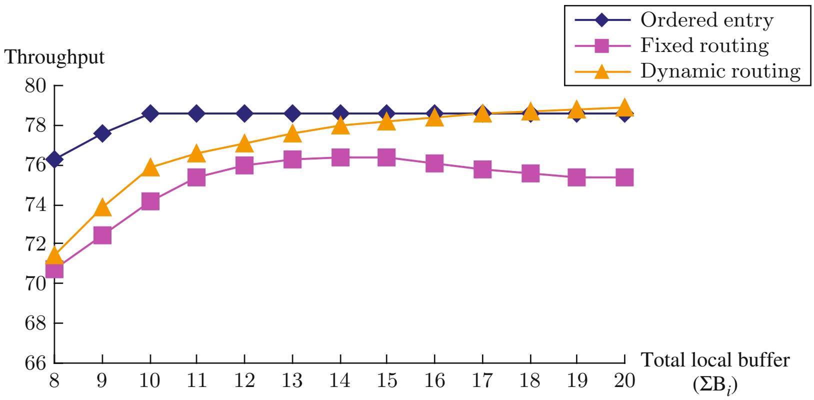


Fig. 8.2.8 Routing comparison under all combinations

Figure 8.2.8 shows the behavior of the largest throughput of all the configurations. From Fig. 8.2.8, it is seen that the OE model is considerably better than the fixed- or dynamic-routing model, especially when the total of the local buffers are 8–18.

References

1. Buzacott, J.A. and Shanthikumar, J.G., *Stochastic Models of Manufacturing Systems*, Prentice-Hall, New Jersey, 1993
2. Disney, R.L., Some Multichannel Queueing Problems with Ordered Entry-An Application to Conveyor Theory, *Journal of Industrial Engineering*, 14, 105–108, 1963
3. Gregory, G. and Litton, C.D., A Conveyor Model with Exponential Service Times, *International Journal of Production Research*, 13, 1–7, 1975
4. Ma, J. and Matsui, M., Performance Evaluation of a Flexible Manufacturing/Assembly System and Routing Comparisons, *International Journal of Production Research*, 40(7), 1713–1724, 2002
5. Matsui, M. and Fukuta, J., On a Multichannel Queueing System with Ordered Entry and Heterogeneous Servers, *American Institute of Industrial Engineers Transactions*, 9, 209–214, 1977
6. Solberg, J.J., A Mathematical Model of Computerized Manufacturing Systems, *4th International Conference on Production Research (ICPR)*, Tokyo, Japan, 22–30, 1977

Part V
Ellipse Management with Risks

Chapter 9
Assembly Enterprise

9.1 Efficient Assembly and Reconfiguration

9.1.1 Introduction

Recently, manufacturing and assembly environments are changing extensively such as small lot sizes, shifting from domestic production to overseas production, temporary workers and workers' motivations [7]. Conventionally, their environments include Assembly Line Systems (ALS) [15, 16], which are traditional production systems, and they often consist of serial production stations connected by conveyors. Moreover, various new assembly systems have emerged that have a dissimilar and flexible configuration, such as Cell Production System (CPS) [5, 14]. In practice, a design issue still remains for assembly systems that are inefficient in different assembly environments [4, 12].

The ALS is superior in its efficiency for flow of materials/units because the work stations are connected by material handlings, such as conveyors. However, the balance losses occur from line-balancing and different abilities of the operators, so it is inferior in terms of its efficiency for processing of units. On the other hand, CPS is superior in its efficiency for processing of units, because it has self-completion stations called Cells and no balance losses. However, it is inferior in its efficiency for flow of units, because the stations are not connected by material handlings. Therefore, we propose the Flexible Cell System (FCS), which enables both efficient flow and processing of units [2, 11] in which the self-completion stations in an ordered-entry array are connected by conveyors.

In typical designs for assembly systems, first, the necessary number of work stations is calculated and determined to meet the demand quantity (production-planning quantity) based on the demand forecasting. Next, some alternative plans with different system configurations are modeled by designing cycle times and buffers, and so on. Finally, their system performances are compared with mathematical analysis and/or simulation, and the best plan is selected and implemented.

Several comparative studies of efficient assembly systems [13] have been conducted between assembly lines and cell-production systems in view of the utilizations and the mean-flow times. However, the studies examined only limited cases for the demand quantity and the number of stations. In addition, the comparisons are not based on the most economic system design, though the efficiency of the

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_16,

systems significantly depends on the system design, including the cycle times and buffers.

This chapter focuses on the assembly environment with viable demands, introduces the pair-matrix tables (a strategic map) in Chapter 4.1 by the demand quantity and the number of stations, strategically compares assembly lines and cell production systems, and discusses efficient assembly systems quantitatively from the view of profit and lead times [17].

9.1.2 Efficient Assembly Problem

9.1.2.1 Explanation of Three Assembly Models

This chapter deals with three assembly models with different system configurations as shown in Fig. 9.1.1: ALS with stoppers [15] as a line type, ACS as cell types and FCS [2, 11] as flexible cell type.

In a cell type, each station has self-completion work, but is isolated among the stations because it is not connected by material handlings, such as conveyors, and it does not have the pace of work by the material handlings. Thus, we call it the ACS (Autonomous Cell System) and distinguish it from the FCS. The FCS enables both the efficient flow and processing of items, and it has the self-completion stations as well as the ACS, but all the stations are connected and have the pace of work by conveyors as well as the ALS.

It is assumed that items arrive at the system at the cycle time, d, and the arrivals in the respective three assembly models are set to each system's advantage. The ALS has the regular arrival to decrease the waiting time at each station, and the FCS has the Poisson arrival to balance the utilizations among the stations [2]. The service time at each station in the ALS and FCS is supposed to follow the Erlang distribution with phase, k.

In the case of ACS, it is assumed that the busy or idle periods occur depending on traffic at each station. The operators themselves obtain the units during the idle period, and the service time at each station is the mean of total assembly time without the waiting time and follows any distribution in service.

9.1.2.2 Station Models and Objectives

(a) ALS

The $D/E_k/1$ queueing model is used as a unit station. While a station is busy, unprocessed and arriving items stop and wait in buffers in front of the station. After that, they are processed and sent to the next station. Since the division of labor is carried out at each station, items receive different services at all the stations from the first to the last station and become finished products.

The expected operating cost at station i, EC_i, is the sum of buffer, busy, and idle costs [15], and is given by (5.2.1). The lead time at system, *LT*, in the ALS

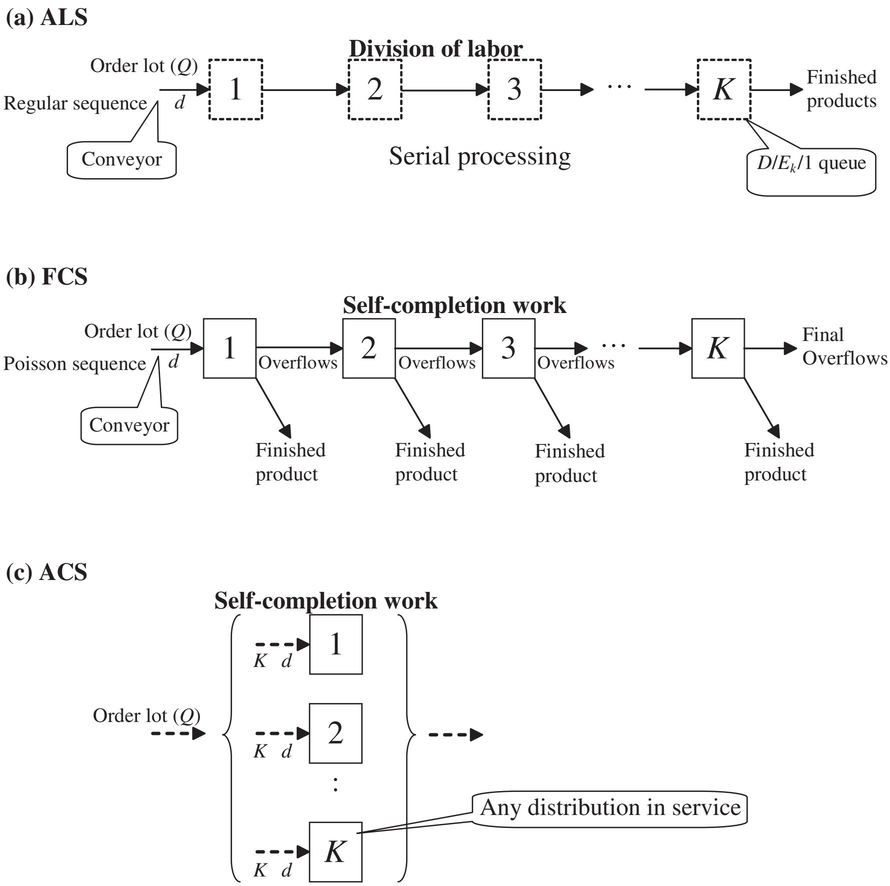


Fig. 9.1.1 Efficient assembly models

is the sum of the lead time at each station, which consists of the waiting and service times at each station.

(b) FCS

The generalized conveyor-serviced production station (Generalized CSPS) [1] is regarded as a unit station. Unprocessed and arriving items on the conveyors are removed into the inprocess inventory called the reserve at each station, and they wait in buffers. After that they process all the tasks in the station itself and become finished products.

Unprocessed items that arrive while a station is busy become overflows, bypass the station, and move on to the next station. The overflowed items at the last station become final overflows, and they are received by the relief operators such as supervisors and operators near the station in consideration of the final overflow cost.

The expected operating cost at system, EC_i, is the sum of the mean number of inprocess inventory at each station, and delay-and-overflow costs [11], and is given by Eq. (7.2.1 and 7.2.2). The lead time at system, *LT*, is the mean of the sum of the removal, waiting, and service times at all stations and is calculated by a simulation [11].

(c) ACS

It is assumed that the mean of service time at a unit station is the mean of total assembly time, S_0, and is also equal to the lead time, *LT*. Arrival items are processed for all tasks in the station only and becomes finished products. Busy or idle periods occur depending on the traffic at each station.

The expected operating cost at station i, EC_i, is the sum of busy and idle costs, and is given by

$$EC_i = \alpha_{2i}\ \rho_i + \alpha_{3i}(1 - \rho_i) \tag{9.1.1}$$

where $\rho_i = S_0/(K \times d)$, and $\alpha_{2i},\ \alpha_{3i}$: Cost coefficients of busy and idle at station i, respectively.

The efficiencies of the systems represent the expected net reward, *EN*, and the lead time, *LT* [6]. Furthermore, *ROW* (Return on Wait) ($= EN/LT$) [9], which means the ratio of the expected net reward, *EN*, to the lead time, *LT*, is also used to consider the balance between them.

9.1.3 Strategic Map

9.1.3.1 An Assembly Problem

For comparison of the three models, an example of the assembly problem is set. It is assumed that a product with the mean of total assembly time, S_0, [min] and the price of product per unit produced, P, [US$] is treated, and the number of products produced meets the quantity of the demand (lot size), Q, [pieces] during the production planning period, T_0 [min].

The precedence relations among element tasks shown in Fig. 5.1.6 [3] are expanded and applied to this assembly problem. In the case of ALS and FCS, the mean of the service time at each station is obtained as the sum of the task times of the element task assigned to the station, and it has the stochastic variations by following the Erlang distribution with phase, k.

Here, the assembly problem is set as follows:

$S_0 = 4.6$ [min.] (The number of the element tasks: 11),
$T_0 = 8,400$ [min.],
$p = 120$ [US$]
Erlang service (phase $k = 3$),

ALS parameter: $\alpha_{1i} = \alpha_{2i} = 1, \alpha_{3i} = 5$
FCS parameter: $\alpha_i = 1,000,\ \beta_{1i} = 1.8,\ \beta_{2i} = 0,\ \beta_{2K} = 3$

Design factor at station, i, in the Generalized CSPS [11] $\varepsilon_i = 0.5$, where the design factor is the removal/moving speed coefficient, which is proper to station, i. Operating policy in the Generalized CSPS: SRP (Sequential Range Policy) [8]

ACS parameter: $\alpha_{2i} = 1,\ \alpha_{3i} = 5$.

9.1.3.2 Pair-Matrix Tables

The pair-matrix table [6, 10] is a strategic map showing profit (expected net reward), *EN*, and the lead time, *LT*, at the same time in the different demand(arrival) /supply (production) speeds. It is helpful for managers to easily consider the before-after examination in terms of the positioning management policies, because the profit and lead time can be seen at a glance for changes of the demand and supply.

In this chapter, the demand and supply speeds mean the quantity of demand (lot size), Q, and the number of the work stations, K, respectively. Next, the simulators for the respective production models are constructed, and the production simulations are conducted. Finally, the pair-matrix tables with the profit and lead time are drawn and shown for the comparison of the systems.

Then, the two-stage design method [6] is applied to the cases of the ALS and FCS, [11, 15, 16] respectively. In this case, the net reward and the buffers/lead-times are determined at the same time under the demand and supply traffic (*Q, K*). The expected sales reward, *ER*, for each demand, Q, is obtained by its definition and $CT = T_0/Q$ as follows:

$$ER = p/CT = Qp/T_0 \tag{9.1.2}$$

In addition, the cycle time, d^*, and the buffers in each (*Q, K*) are decided to minimize the expected operating cost, *EC*, by the simulation optimization, and the minimal cost, EC^*, is obtained. Under the calculations, the expected net reward, $EN(= ER - EC^*)$, and the lead time, *LT*, in each (*Q, K*) are obtained uniformly.

Tables 9.1.1 to 9.1.3 are examples of pair-matrix tables for the ALS, FCS, and ACS, respectively. Here, 77 points are being investigated where there are 7 demand quantities, Q, from 1,800 to 16,800 and the number of work stations, K, is 11 from 1 to 11.

With ALS, the line-balancing is carried out to assign the element tasks to the work stations, so that the cycle time cannot be set to less than the longest element task time. Therefore, while the demand quantity range of up to $Q = 16,800$ can be feasible with the other two systems, the feasible range for ALS is smaller at up to $Q = 10,500$.

The expected sales reward, *ER*, is the same for the three models. It increases as the demand quantity, Q, increases, but it is not changed by the number of stations, K. With ACS, the lead time, *LT*, always equals the total assembly time, $S_0 = 4.6$, because neither balance loss nor the waiting time is assumed.

As was the case with the ellipse theory in past studies [6, 9, 10], the ellipse shapes are seen in Tables 9.1.1 to 9.1.3, where the profit (net reward) maximization

Table 9.1.1 An example of pair-matrix table: Assembly line systems (ALS)

Q	K	1	2	3	4	5	6	7	8	9	10	11
1,800	*d*	4.60	4.10	4.10	4.10	4.10	4.10	4.10	4.10	4.10	4.10	4.10
	ER	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71
	EC	30.45	6.71	11.64	16.63	21.63	26.63	31.63	36.63	41.63	46.63	51.63
	EN	–4.73	19.00	14.07	9.08	4.08	–0.92	–5.92	–10.92	–15.92	–20.92	–25.92
	LT	135.43	4.92	4.63	4.60	4.59	4.60	4.60	4.60	4.60	4.61	4.58
	ROW	–0.03	3.86	3.04	1.97	0.89	–0.20	–1.29	–2.37	–3.46	–4.54	–5.65
2,100	*d*		3.00	2.10	2.10	2.10	2.10	2.10	2.10	2.10	2.10	2.10
	ER		30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00
	EC		5.95	9.00	13.55	18.47	23.44	28.44	33.43	38.43	43.43	48.43
	EN		24.05	21.00	16.45	11.53	6.56	1.56	–3.43	–8.43	–13.43	–18.43
	LT		6.24	5.77	4.86	4.68	4.62	4.64	4.60	4.60	4.61	4.60
	ROW		3.85	3.64	3.38	2.46	1.42	0.34	–0.74	–1.83	–2.91	–4.01
4,200	*d*			2.00	1.50	1.30	1.10	1.10	1.10	1.10	1.10	1.10
	ER			60.00	60.00	60.00	60.00	60.00	60.00	60.00	60.00	60.00
	EC			8.97	11.96	15.35	18.62	23.16	27.72	32.62	37.62	42.62
	EN			51.03	48.04	44.65	41.38	36.84	32.28	27.38	22.38	17.38
	LT			6.34	6.34	5.84	5.86	5.39	4.88	4.77	4.78	4.79
	ROW			8.05	7.58	7.65	7.06	6.84	6.61	5.74	4.69	3.63
8,400	*d*						1.00	1.00	0.90	0.90	0.90	0.90
	ER						120.00	120.00	120.00	120.00	120.00	120.00
	EC						18.76	22.88	25.64	30.35	35.25	40.30
	EN						101.24	97.12	94.36	89.65	84.75	79.70
	LT						7.15	6.28	5.46	5.24	5.13	5.16
	ROW						14.17	15.47	17.29	17.12	16.53	15.44
10,500	*d*								0.80	0.80	0.80	0.80
	ER								150.00	150.00	150.00	150.00
	EC								25.38	29.34	34.41	39.26
	EN								124.62	120.66	115.59	110.74
	LT								6.70	5.86	5.93	5.80
	ROW								18.61	20.60	19.48	19.08
12,600	*d*											
	ER											
	EC											
	EN											
	LT											
	ROW											
16,800	*d*											
	ER											
	EC											
	EN											
	LT											
	ROW											

Min *LT*

Max *LT*

Note: ( ) Means an exceptional case

usually lies between the sales maximization and cost minimization poles in the gray elements on the pair-matrix tables.

9.1.4 Strategic Consideration

9.1.4.1 Strategic Comparison

(1) Behavior of expected operating cost, *EC*, and net reward, *EN*

With FCS, the expected operating cost, *EC*, is smaller than that of any other systems at any (*Q, K*), therefore, FCS gives the highest net reward, *EN*, of the three assembly systems. Even if there are changes for (*Q, K*), there is no negative range for *EN* between 17.16 and 236.29, which means it is stable.

With ALS and ACS, when the demand is low at $Q = 1,800$ or 2,100 and the number of stations is larger, the idle cost increases and the operating cost, *EC*, also increases. Therefore, the ranges where the net reward, *EN*, becomes negative are 10 and 11 points in ALS and ACS, respectively, shown underlined in Tables 9.1.1 and 9.1.3.

Table 9.1.2 An example of pair matrix table: Flexible cell system (FCS)

Q	K	1	2	3	4	5	6	7	8	9	10	11
1,800	*d*	4.20	4.10	4.10	4.10	4.30	4.10	4.20	4.30	4.20	4.30	4.20
	ER	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71
	EC	0.96	1.93	3.53	5.29	6.80	8.16	7.85	8.25	8.56	7.51	8.21
	EN	24.76	23.79	22.19	20.42	18.92	17.55	17.86	17.47	17.16	18.20	17.51
	LT	9.19	8.28	8.28	8.16	8.28	8.17	8.07	8.17	7.98	8.33	8.63
	ROW	2.70	2.87	2.68	2.50	2.29	2.15	2.21	2.14	2.15	2.18	2.03
2,100	*d*		2.10	2.10	2.10	2.10	2.10	3.60	2.80	2.70	3.50	4.00
	ER		30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00
	EC		1.40	2.18	3.64	5.35	7.14	8.26	7.24	7.85	7.44	7.76
	EN		28.60	27.82	26.36	24.65	22.86	21.74	22.76	22.15	22.56	22.24
	LT		10.09	9.50	9.48	9.39	9.33	8.74	9.84	8.70	9.33	8.27
	ROW		2.83	2.93	2.78	2.63	2.45	2.49	2.31	2.55	2.42	2.69
4,200	*d*			1.40	1.10	1.10	1.10	1.10	1.10	1.10	1.70	2.00
	ER			60.00	60.00	60.00	60.00	60.00	60.00	60.00	60.00	60.00
	EC			1.77	2.09	2.51	4.02	5.57	7.46	9.19	9.57	9.86
	EN			58.23	57.91	57.49	55.98	54.43	52.54	50.81	50.43	50.14
	LT			9.69	9.11	(7.33)	8.29	8.95	8.98	8.23	9.61	9.37
	ROW			6.01	6.36	7.84	6.75	6.08	5.85	6.17	5.25	5.35
8,400	*d*					0.90	0.90	0.90	0.90	0.90	0.90	1.00
	ER					120.00	120.00	120.00	120.00	120.00	120.00	120.00
	EC					2.37	3.03	4.28	5.89	7.68	9.41	10.59
	EN					117.63	116.97	115.72	114.11	112.32	110.59	109.41
	LT					9.36	9.28	8.62	8.94	9.07	9.13	8.22
	ROW					12.57	12.60	13.43	12.76	12.39	12.11	13.30
10,500	*d*						0.70	0.70	0.70	0.70	0.70	0.70
	ER						150.00	150.00	150.00	150.00	150.00	150.00
	EC						2.64	2.98	3.85	5.24	6.88	8.75
	EN						147.36	147.02	146.15	144.76	143.12	141.25
	LT						8.27	8.50	8.31	8.39	8.06	8.44
	ROW						17.83	17.30	17.58	17.25	17.76	16.74
12,600	*d*							0.60	0.60	0.60	0.60	0.60
	ER							180.00	180.00	180.00	180.00	180.00
	EC							2.85	3.15	3.96	5.27	6.94
	EN							177.15	176.85	176.04	174.73	173.06
	LT							7.94	8.53	8.83	8.87	8.07
	ROW							22.31	20.74	19.95	19.70	21.44
16,800	*d*										0.50	0.50
	ER										240.00	240.00
	EC										3.71	4.63
	EN										236.29	235.37
	LT										7.89	7.94
	ROW										29.96	29.65

Max *LT*

Min *LT*

Note: ( ) Means an exceptional case

(2) Behavior of lead time, *LT*

The shortest *LT* is equal to the total assembly time, $S_0 = 4.6$, and is obtained at the 12 points with ALS (shown in bold) in Table 9.1.1 when the demand is very low, such as $Q = 1,800$ or 2,100, because the waiting time decreases at each station. With ACS, *LT* is also obtained at any feasible points in Table 9.1.3.

With FCS, the range of the lead time, *LT*, shown in Table 9.1.2 is from 7.89 to 10.09 and is only slightly affected by changes in (*Q, K*). Unlike the serial division of labor of ALS, the production in FCS is conducted in parallel through the self-completion work at each station. Therefore, changes in (*Q, K*) do not easily impact the waiting time, and the lead time, *LT*, for each product is stable.

Table 9.1.3 An example of pair matrix table: Autonomous cell system (ACS)

Q	K	1	2	3	4	5	6	7	8	9	10	11
1,800	*d*	4.67	4.67	4.67	4.67	4.67	4.67	4.67	4.67	4.67	4.67	4.67
	ER	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71	25.71
	EC	1.06	6.06	11.06	16.06	21.06	26.06	31.06	36.06	41.06	46.06	51.06
	EN	24.66	19.66	14.66	9.66	4.66	-0.34	-5.34	-10.34	-15.34	-20.34	-25.34
	LT	4.60	4.60	4.60	4.60	4.60	4.60	4.60	4.60	4.60	4.60	4.60
	ROW	5.36	4.27	3.19	2.10	1.01	-0.07	-1.16	-2.25	-3.34	-4.42	-5.51
2,100	*d*		4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
	ER		30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00
	EC		5.40	10.40	15.40	20.40	25.40	30.40	35.40	40.40	45.40	50.40
	EN		24.60	19.60	14.60	9.60	4.60	-0.40	-5.40	-10.40	-15.40	-20.40
	LT		4.60	4.60	4.60	4.60	4.60	4.60	4.60	4.60	4.60	4.60
	ROW		5.35	4.26	3.17	2.09	1.00	-0.09	-1.17	-2.26	-3.35	-4.43
4,200	*d*			2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
	ER			60.00	60.00	60.00	60.00	60.00	60.00	60.00	60.00	60.00
	EC			5.80	10.80	15.80	20.80	25.80	30.80	35.80	40.80	45.80
	EN			54.20	49.20	44.20	39.20	34.20	29.20	24.20	19.20	14.20
	LT			4.60	4.60	4.60	4.60	4.60	4.60	4.60	4.60	4.60
	ROW			11.78	10.70	9.61	8.52	7.43	6.35	5.26	4.17	3.09
8,400	*d*					1.00	1.00	1.00	1.00	1.00	1.00	1.00
	ER					120.00	120.00	120.00	120.00	120.00	120.00	120.00
	EC					6.60	11.60	16.60	21.60	26.60	31.60	36.60
	EN					113.40	108.40	103.40	98.40	93.40	88.40	83.40
	LT					4.60	4.60	4.60	4.60	4.60	4.60	4.60
	ROW					24.65	23.57	22.48	21.39	20.30	19.22	18.13
10,500	*d*						0.80	0.80	0.80	0.80	0.80	0.80
	ER						150.00	150.00	150.00	150.00	150.00	150.00
	EC						7.00	12.00	17.00	22.00	27.00	32.00
	EN						143.00	138.00	133.00	128.00	123.00	118.00
	LT						4.60	4.60	4.60	4.60	4.60	4.60
	ROW						31.09	30.00	28.91	27.83	26.74	25.65
12,600	*d*							0.67	0.67	0.67	0.67	0.67
	ER							180.00	180.00	180.00	180.00	180.00
	EC							7.40	12.40	17.40	22.40	27.40
	EN							172.60	167.60	162.60	157.60	152.60
	LT							4.60	4.60	4.60	4.60	4.60
	ROW							37.52	36.43	35.35	34.26	33.17
16,800	*d*										0.50	0.50
	ER										240.00	240.00
	EC										13.20	18.20
	EN										226.80	221.80
	LT										4.60	4.60
	ROW										49.30	48.22

(3) Behavior of return on wait, *ROW*

With ACS, it is assumed that the lead time, *LT*, is equal to the total assembly time, S_0, and the return on wait, *ROW*, is higher than that of any other systems with the smaller number of stations, K.

With FCS, the changes in lead time, *LT*, are small for (*Q, K*), so that the value of the return on wait, *ROW*, is also stable, and there is no negative range as is the case with the other systems.

9.1.4.2 Effect of the Cell Implementation Coefficient

In the discussion up to now, the return on wait, *ROW*, which takes into consideration both the expected net reward, *EN*, and the lead time, *LT*, is most advantageous using ACS regardless of the demand quantity. However, ACS is assumed to be at its most ideal point, and thus, it does not incur the losses for process and material handling. In an actual assembly environment, it is difficult to obtain the necessary number of multi-skilled operators for a large number of self-completion stations.

Therefore, the operators with single skills should be trained to acquire multiple skills when transforming from the line into cell production. Further, there is the possibility that the work efficiency may decrease without the pace by conveyors, such as with ALS and FCS. Therefore, during the initial implementation period, the total assembly time in ACS would be longer than that of the standard one.

A TV program [12] shows an example of work that is performed in 3 min 27 sec (207 sec) by 6 operators using line production, which initially takes 5 min 35 sec (335 sec) for 1 operator using cell production. Here, the percent of the total assembly time of the extension during the transformation to cell production in relation to the standard total assembly time is found, which is called the cell implementation coefficient, δ.

Table 9.1.4 shows a summary of the strategic selection in assembly systems for demand quantity, Q, when the cell implementation coefficient, $\delta = 1.4$. This is obtained from the another pair-matrix table with ACS using $S_0 = 6.44$, which is 1.4 times the initial and standard total assembly time, S_0. By increasing the total assembly time, the demand quantity, $Q = 16,800$, m addition addition becomes infeasible.

Unlike the cell implementation coefficient, $\delta = 1.0$, ACS is not selected for *EN* in medium *Q, LT* in small and large Q, and total in large Q (see Table 9.1.4).

Table 9.1.4 A summary of strategic selection in assembly systems for demand quantity, Q: cell implementation coefficient, $\delta = 1.4$

Demand quantity (lot size), Q	Net reward *EN*	Lead time *LT*	Return on wait *ROW*	Total
Small	FCS ACS with smaller K	ALS	ACS with smaller K FCS with larger K	ACS
Medium	FCS	ALS ACS with smaller K	ACS with smaller K FCS with larger K	FCS
Large	FCS	ALS	ACS ALS	ALS
Viable	FCS	ACS FCS	FCS	FCS

Note: k means the number of stations

References

1. Feyzbakhsh, S.A., Matsui, M. and Itai, K., Optimal Design of a Generalized Conveyor-Serviced Production Station: Fixed and Removal Item Cases, *International Journal of Production Economics*, 55, 177–189, 1998
2. Feyzbakhsk, S.A., Kimura, A. and Matsui, M., Performance Evaluation of a Simple Flexible Assembly System and Its 2-Stage Design, *Journal of Japan Industrial Management Association*, 49(6), 393–401, 1999 (in Japanese)
3. Ignall, E.J., A Review of Assembly Line Balancing, *The Journal of Industrial Engineering*, 16(4), 244–254, 1965

4. Ikoma, M., Problem in Comparison between Cell Production and Line Production, *Communications of Japan Industrial Management Association*, 12(2), 81–85, 2002 (in Japanese)
5. Iwamuro, H., *Cell Production System*, Nikkankogyo Shinbunsya, Tokyo, 2002 (in Japanese)
6. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
7. Matsui, M., Environmental Changes and Efficient Systems in Assembly Works, *Communications of Japan Industrial Management Association*, 12(2), 86–88, 2002 (in Japanese)
8. Matsui, M., CSPS Model: Look-Ahead Controls and Physics, *International Journal of Production Research*, 43(10), 2001–2025, 2005
9. Matsui, M., Management Game Theory: Manufacturing vs. Service Enterprise Type, *International Journal of Productivity and Quality Management*, 1(1/2), 103–115, 2006
10. Matsui, M. and Nakada, Y., Strategic Management/Design Approach to a Job-shop Production System, *International Journal of Production Research*, 41(14), 3257–3271, 2003
11. Nakase, N., Yamada, T. and Matsui, M., A Management Design Approach to a Simple Flexible Assembly System, *International Journal of Production Economics*, 75(3), 281–292, 2002
12. NHK Special, Break the Common Sense – Factory Innovation from Mass Production, *A TV Program by Japan Broadcasting Corporation*, May 12, 2001
13. Sengupta, K. and Jacobs, F.R., Impact of Work Teams: A Comparison Study of Assembly Cells and Assembly Line for a Variety of Operating Environments, *International Journal of Production Research*, 42(19), 4173–4193, 2004
14. Shinohara, T., Shocking News of the Removal of Conveyor System, *Nikkei Mechanical*, 459, 20–38, 1995 (in Japanese)
15. Yamada, T. and Matsui, M., 2-Stage Design Method for Assembly Line Systems with Stoppers, *Journal of Japan Industrial Management Association*, 51(6), 594–602, 2001
16. Yamada, T. and Matsui, M., A Management Design Approach to Assembly Line Systems, *International Journal of Production Economics*, 84(1), 99–110, 2002
17. Yamada, T., Kakefuda, S. and Matsui, M., Strategic Selection of Assembly Systems under Viable Demands, *Assembly Automaton*, 26(4), 335–342, 2006

9.2 Mixed Line Design with Look-Ahead

9.2.1 Introduction

Recently, the demand for products has changed from single products and large quantities to a variety of products and small quantities. As a result, manufacturers often use mixed model assembly lines in which several models of the same general product are assembled and processed on a common line [3, 4].

Under the Build to Order (BTO) environment, the final assembly of products often begins to be processed after the customer orders arrive at the production system [1]. Since the design changes are dynamically adapted to follow demand fluctuations, it is also necessary that the setting time for the line design should be shorter in order to apply design changes quickly.

Therefore, design methods require not only consideration of many control factors, such as, sequence, cycle time, buffers, and working constraints such as line length (lead time), but also these methods have to solve problems within a reasonable computational time. Hence, Genetic Algorithms (GAs) [7, 11] can be effective for searching for the solution of space in consideration of the control factors and constraints within a given and reasonable computational time.

Moreover, Adam-Eve GA [6] is expected in terms of computational time. This is the case because it starts with small populations such as two individuals to maintain smaller combinations at the early step of the searching process, and it has the "death" operator to carry out a local search at the final step.

This chapter [2] develops a stochastic line model for a single model [1] to consider the sequencing, and proposes a two-phase method for a stochastic mixed line based on the pair-matrix design [9, 10] and simulation optimization with GAs [6, 12].

9.2.2 Design Problem

9.2.2.1 Mixed-Line Model

Based on [1], a stochastic mixed line is treated in consideration of the sequence and line length. The line consists of K unit stations connected by conveyors (Fig. 9.2.1), where the Generalized CSPS with the working zone is used as a unit station [5].

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_17,

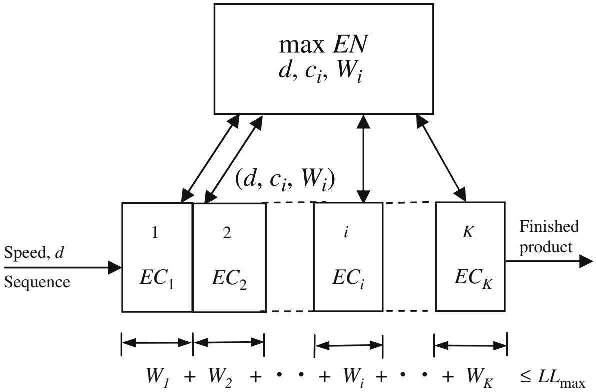


Fig. 9.2.1 A stochastic mixed-line model

It is assumed that similar items of the product model are launched onto the conveyor, and product items flow according to a sequence and the regular arrival at cycle time, d. Service times are different for each unit of the model at each station, and follow the Erlang distribution with phase, k.

After being serviced at every station from the first to the last, input items at the system become finished products.

9.2.2.2 Two-Phase Design

The optimal design in this study is defined as the maximization of the net reward, EN, by coordinating cycle time, d, at the system, look-ahead time, c_i, and working zone, W_i, at each station.

The formulation for a single model is set from [1] as follows:

$$EN(d, c_i, W_i) = ER(d) - EC(d, c_i, W_i) \rightarrow \max \tag{9.2.1}$$

s.t.

$$\min \bar{x}_{im} \le d \le CT \qquad \text{(Cycle-time constraint)} \tag{9.2.2}$$

$$\sum_{i=1}^{K} W_i \le LL_{\max} \qquad \text{(Line-length constraint)} \tag{9.2.3}$$

$$p_i \le SO_i \qquad \text{(Overflow and semi-process constraint)} \tag{9.2.4}$$

$$0 \le c_i \le W_i \qquad \text{(Look-ahead time constraint)} \tag{9.2.5}$$

$$\bar{x}_i \le W_i \le W_{a\max i} + \bar{x}_i \qquad \text{(Working-zone constraint)} \tag{9.2.6}$$

$$\text{Assembly work} \qquad \text{(Precedence constraint)} \tag{9.2.7}$$

In considering the application for mixed lines [3, 4] from stochastic assembly lines for a single model [1], design methods should also determine a sequence of the input items. In the traditional GA and Adam-Eve GA designs, an optimal design is obtained by simulation optimization with the GAs.

The net reward, EN, is derived from the simulation result at each station. Then, the penalty cost is imposed if the overflow and semi-process constraints are not satisfied. The fitness value is calculated from the net reward and penalty cost, and new offsprings are produced according to this value. The above procedure is repeated a predetermined number of times and also used for the GA designs.

Adam-Eve GA [6] is based on (traditional) GA and named after its characteristics with a very small initial population, which are two or a fewer individuals such as Adam and Eve. It is supposed that increasing the population by inserting new individuals without replacing the old population maintains diversity in solutions for a global search, and the death operator provides the ability to search the neighborhood of the optimal solution for a local search.

For mixed lines, this chapter proposes a two-phase method based on the pair-matrix design [9] and simulation optimization with GAs [6, 12] (Fig. 9.2.2). It determines the design plan except for the sequence based on the pair-matrix strategy and simulation optimization with GAs as a stochastic assembly line for a single model [1] at Phase 1, and determines the sequence based on the simulation optimization with GAs or Tabu search [12] at Phase 2.

Based on Fig. 9.2.2, Phase 1 is used to decide the cycle time, d, the look-ahead time, c_i and the working zones, W_i, based on the pair-matrix design as a stochastic assembly line for the single model. Phase 2 is used to determine the sequence related to the Traveling Salesman Problem [13] by GAs or Tabu search designs as a mixed line.

The sequencing problem in the two-phase design at Phase 2 is defined as coordination of the sequence to maximize the sum of the differences of the mean service time between adjacently sequenced models at the bottleneck station.

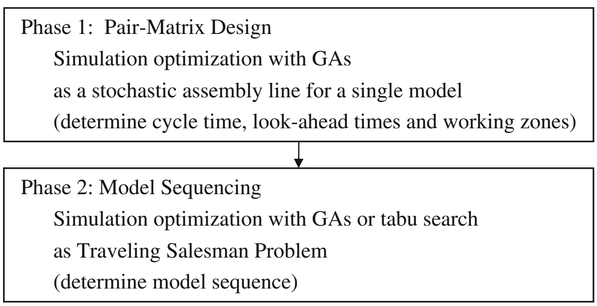


Fig. 9.2.2 2-phase method

9.2.3 Setting of Look-Ahead

9.2.3.1 Effect of Design Factors

In this chapter, the generalized CSPS model [5] is used as a unit station for a detailed process design. The control factors such as design factor, ε_j, look-ahead time, c_i and working zone, W_i, are decided in the model. Here, the effect of these factors should be considered by using the traditional GA design for the single model [1].

The design factor, ε_j, is the moving speed coefficient that is set properly to station, i. Without the design factor (equivalent to $\varepsilon_j = 1.0$), the delay time means the distance between the operator and the arrival item. With the design factor, the delay time is given as the distance multiplied by the design factor.

The parameter settings are as follows:

Regular arrival, Erlang service (phase $k = 3$), $T_0 = 8,400$[min .], $N_0 = 4,200$[pcs], $d = 1.0$[min .], mean of total assembly time; 4.6[min.], $K = 5$, $p = 10$[US\$], $\varepsilon_j = 0.5$, $\alpha_i = 100$[US\$/ min .], $\beta_{1i} = 1.0$[US\$/ min .], $\beta_{2i} = 1.0$[US\$/pcs], $\beta_{3i} = 0.5$[US\$/pcs], $LL_{max} = 20$, $SO_i = 0.2$ $(i = 1, 2, \ldots, K)$.

Figure 9.2.3 shows the behavior of net reward, EN, for the design factor, ε_j. When the working zones, W_i, are fixed to $2.0_{\overline{x_j}}$, the design factors, ε_j, are set to 0.2, 0.5, 0.8, and 1.0. Except for the case of $\varepsilon_j = 1.0$, the reward is maximized when the ratio of look-ahead time to working zone is 50%. Similar to the case without line-length constraints in Chapter 5.1, the operating cost, EC, also decreases in the case with line-length constraints. It seems that the differences of the reward, EN, among different design factors, ε_j, are larger when c_i / W_i is larger.

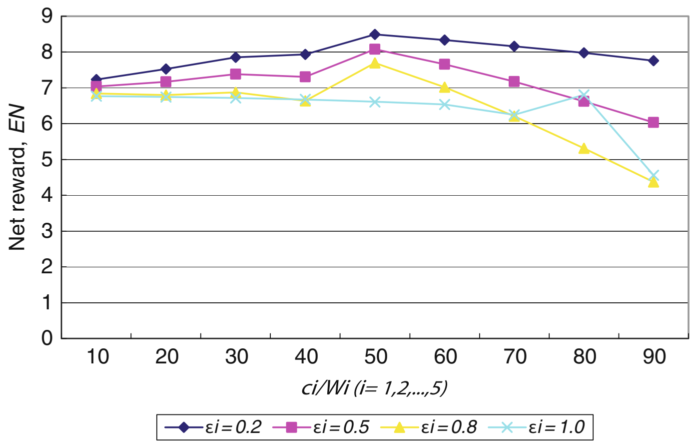


Fig. 9.2.3 Behavior of net reward, EN, for the design factor, ε_j $(W_i = 2.0\overline{X_j})$

9.2.3.2 Look-Ahead and Working Zones

When $W_i > \overline{x_i}$, there is a specific length of look-ahead time that maximizes the net reward. The net rewards, EN, are maximized as $EN^* = 8.1$ and $EN^* = 7.7$, when $c_i/W_i = 50\%$ in $W_i = 2.0\overline{X_j}$ and $c_i/W_i = 80\%$ in $W_i = W_{amaxi}$ $(i = 1, 2, \ldots, 5)$ respectively, because the delay and overflow costs are minimized by designing the appropriate look-ahead time, c_i.

9.2.4 Optimal Design Example

9.2.4.1 Design Problem Example

To investigate the effect of our design method, we used a balancing example from the literature [8] (Fig. 9.2.4). This balancing problem is applied when the service time of stations for each model has stochastic variations, and it is extended to our design problem with buffers.

The parameter settings are as follows:

Regular arrival, Erlang service (phase $k = 3$), $T_0 = 4,500$[min.], $N_0 = 200$[pcs], $CT = 22.5$[min.], $LL_{max} = 300$
Number of product models: $M = 3$,
Product quantity for each product, A: 100[pcs], B: 60[pcs], C: 40[pcs],
Mean of total assembly time for each product, A: 60[min.], B:71[min.], C:71[min.]
Prices of each product, A: 100[US$], B: 96[US$], C: 106[US$]

Also, the mean of the service times for each model at each station by the number of stations is shown in Table 9.2.1. The experiments are coded in C language and implemented on a PC with a Celeron processor running at 800 MHz.

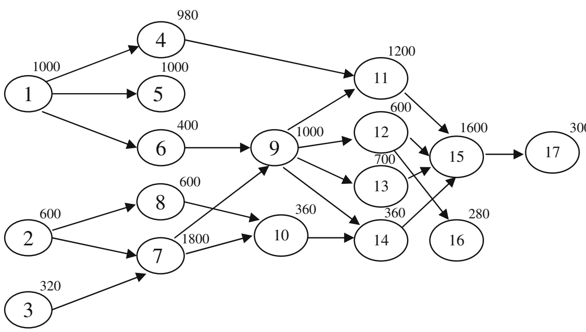


Fig. 9.2.4 Example of combined precedence diagram

Table 9.2.1 Mean of service times for each model at each station

K	$\bar{x}_{1m}$	$\bar{x}_{2m}$	$\bar{x}_{3m}$	$\bar{x}_{4m}$	$\bar{x}_{5m}$	$\bar{x}_{6m}$	$\bar{x}_{7m}$
3	(20,23,28)	(26,18,18)	(14,30,25)				
4	(17,10,25)	(12,28,12)	(17,16,16)	(14,17,18)			
5	(13,13,21)	(16,9,16)	(5,26,16)	(15,15,10)	(11,8,8)		
6	(10,10,18)	(10,13,10)	(9,13,13)	(17,5,5)	(3,22,17)	(11,8,8)	
7	(10,10,10)	(10,13,10)	(0,4,12)	(9,15,9)	(17,5,5)	(3,16,17)	(11,8,8)

9.2.4.2 2-Phase Design Results

For mixed lines, this chapter proposes a two-phase method based on the pair-matrix table and simulation optimization with GAs and tabu search (Fig. 9.2.2). The pair-matrix table [9] is a strategic map showing profit (mean net reward), EN, and the lead time, LT, (line length, LL) at the same time with different demand (arrival)/supply (production) speeds (CT, K), and it is used for positioning of a profit-maximal plan.

At Phase 1, the pair-matrix table is drawn for obtaining a profit-maximal plan, in which it decides the optimal design variables, such as cycle time, look-ahead time buffers, and working zones except for the sequence based on the simulation optimization with GAs as a stochastic assembly line for a single model. At Phase 2, the sequence is determined only by the simulation optimization with GAs or tabu search [12] as a mixed line.

Table 9.2.2 shows an example of the pair-matrix table by using [1], and the profit-maximal plan is positioned at Phase 1. On the basis of the profit-maximal plan, Tables 9.2.3 and 9.2.4 show an optimal design example based on the Adam-Eve GA design and the two-phase design with Adam-Eve GA (Fig. 9.2.2), respectively. Table 9.2.5 shows the optimal net rewards, EN^*, and computational times based on the two-phase and GA designs.

Since the computational time of the two-phase designs with GAs is about 10 seconds only at Phase 2 by reaching the net reward limitation, the total computational time of the proposed two-phase design, including both Phase 1 and Phase 2 is shorter than that of the time of the GA designs. From Table 9.2.5, the two-phase designs are superior to the traditional GA and Adam-Eve GA designs by more than 16% in terms of the net reward and by more than 43% in terms of the computational time.

In the two-phase designs, it can be seen that the difference among the three kinds of combinations of the optimization methods is slight in terms of the net reward, because it is considered that the sequence has a smaller impact on the objective function of the net reward, EN, than the other control factors. Therefore, the two-phase method with Adam-Eve GA at Phase 1 and Tabu search at Phase 2 is superior to the other methods in terms of the computational time.

Table 9.2.2 Profit-maximal plan (positioning)

$CT \setminus K$		3	4	5	6	7	8
20.0	d				16.20	14.00	14.30
	ER				6.17	7.14	6.99
	EC				3.73	3.86	4.46
	EN				2.44	3.28	2.53
	LT				228.38	211.68	205.28
	ROW				0.01	0.02	0.01
21.0	d			19.20	15.30	14.80	12.50
	ER			5.21	6.54	6.76	**8.00**
	EC			2.47	3.78	4.05	4.53
	EN			2.74	2.76	2.71	3.47
	LT			256.68	196.05	<u>**187.06**</u>	225.42
	ROW			0.01	0.01	0.01	0.02
22.0	d		18.30	16.80	13.50	17.00	13.10
	ER		5.46	5.95	7.41	5.88	7.63
	EC		2.31	2.65	3.83	4.15	5.42
	EN		3.15	3.30	**3.58**	1.73	2.21
	LT		254.07	236.25	253.00	226.43	239.63
	ROW		0.01	0.01	0.01	0.01	0.01
23.0	d		22.20	16.00	15.10	15.70	16.30
	ER		4.50	6.25	6.62	6.37	6.13
	EC		1.97	3.12	3.14	4.47	5.43
	EN		2.53	3.13	3.48	1.90	0.70
	LT		175.49	263.66	237.25	212.46	195.69
	ROW		0.01	0.01	0.01	0.01	0.00
24.0	d		22.20	19.30	15.10	14.40	15.50
	ER		4.50	5.18	6.62	6.94	6.45
	EC		1.85	2.51	3.42	4.06	5.24
	EN		2.65	2.67	3.20	2.88	1.21
	LT		212.13	202.74	205.40	195.19	204.92
	ROW		0.01	0.01	0.02	0.01	0.01
25.0	d	25.00	21.20	16.80	15.00	16.70	16.20
	ER	4.00	4.72	5.95	6.67	5.99	6.17
	EC	**1.80**	1.88	2.86	3.78	4.38	4.99
	EN	2.20	2.84	3.09	2.89	1.61	1.18
	LT	238.54	245.74	<u>**247.09**</u>	244.58	203.21	194.15
	ROW	0.01	0.01	0.01	0.01	0.01	0.01

Profit-maximal plan (positioning)

d^*=13.5 (cycle time)

Buffers						
	c_1^*	c_2^*	c_3^*	c_4^*	c_5^*	c_6^*
	10.75	10.46	27.32	12.75	21.69	3.29
	W_1^*	W_2^*	W_3^*	W_4^*	W_5^*	W_6^*
	39.82	31.69	49.68	42.49	48.19	41.13

Table 9.2.3 Optimal design example: Adam-Eve GA design

K	EN^*	ER^*	EC^*	d^*	c_{1^*} W_{1^*}	c_{2^*} W_{2^*}	c_{3^*} W_{3^*}	c_{4^*} W_{4^*}	c_{5^*} W_{5^*}	c_{6^*} W_{6^*}	c_{7^*} W_{7^*}	LL	Sequence
					11.13	9.92	13.44	8.67	9.16				
5	2.44	5.55	3.11	18.0	65.47	47.23	61.09	48.18	20.81			242.78	BAACBAABAC
					0.83	5.63	15.64	4.85	18.42	13.04			
6	3.21	6.37	3.16	15.7	41.75	46.88	40.09	37.31	49.78	43.48		259.29	BABCACAABA
					5.58	7.91	7.72	11.67	12.08	9.22	15.18		
7	3.56	7.19	3.63	13.9	17.99	32.97	15.76	40.24	37.76	41.90	24.49	211.11	AAACACBBAB

Table 9.2.4 Optimal design example: Two-phase design with Adam-Eve GA

K	EN^*	ER^*	EC^*	d^*	c_{1^*} W_{1^*}	c_{2^*} W_{2^*}	c_{3^*} W_{3^*}	c_{4^*} W_{4^*}	c_{5^*} W_{5^*}	c_{6^*} W_{6^*}	c_{7^*} W_{7^*}	LL	Sequence
					20.73	22.16	3.97	13.44	1.15				
5	2.83	6.02	3.19	16.6	57.57	44.31	56.75	55.99	19.20			233.82	BABABAACAC
					16.62	10.49	4.48	13.86	15.90	5.09			
6	4.16	7.63	3.47	13.1	50.36	31.78	49.74	49.51	44.16	33.92		259.47	CABACAABAB
					11.99	15.81	2.60	15.32	5.25	1.06	17.89		
7	3.05	7.35	4.30	13.6	41.35	49.40	15.30	43.77	47.73	26.50	41.61	265.66	AACBAABCAB

Table 9.2.5 Optimal net rewards, EN^*, and computational times: Two-phase and GA designs

	Simulation optimization			
Design method	Single model	sequence	Net reward EN^*	Computationl time t
	Traditional GA	Traditional GA	2.78	96
2-phase	Adam-Eve GA	Adam-Eve GA	2.79	95
	Adam-Eve GA	Tabu search	2.78	89
Traditional GA	Traditional GA		2.38	171
Adam-Eve GA	Adam-Eve GA		2.31	257

References

1. Abe, K., Yamada, T. and Matsui, M., A Design Problem of Assembly Line Systems using Genetic Algorithm under the BTO Environment, *IEEJ Transactions on Electronics, Information and Systems*, 124(10), 2006–2013, 2004
2. Abe, K., Yamada, T. and Matsui, M., A Design Approach to Stochastic Mixed Line with Look-Ahead, *Journal of Japan Society of Logistics Systems*, 7(2), 3–10, 2007
3. Bard, J.F., Dar-El, E.M. and Shtub, A., An Analytic Framework for Sequencing Mixed Model Assembly Lines, *International Journal of Production Research*, 30(1), 35–48, 1992
4. Bard, J.F., Shtub, A. and Joshi, S.B., Sequencing Mixed-Model Assembly Lines to Level Parts Usage and Minimize Line Length, *International Journal of Production Research*, 32(10), 2431–2454, 1994
5. Feyzbakhsh, S.A., Matsui, M. and Itai, K., Optimal Design of a Generalized Conveyor-Serviced Production Station: Fixed and Removal Item Cases, *International Journal of Production Economics*, 55(2), 177–189, 1998
6. Feyzbakhsh, S.A. and Matsui, M., Adam-Eve-like Genetic Algorithm: A Methodology for Optimal Design of a Simple Flexible Assembly System, *Computers & Industrial Engineering Journal*, 36(2), 233–258, 1999
7. Gen, M. and Cheng, R., *Genetic Algorithms and Engineering Design*, Wiley, NY, *Journal*, 1997
8. Kuroda, M., *Line Balancing and Its Applications*, Nikkankogyo Shinbunsya, Tokyo, Japan, 1984 (in Japanese)
9. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
10. Matsui, M., Management Game Theory: Manufacturing vs. Service Enterprise Type, *International Journal of Productivity and Quality Management*, 1(1/2), 103–115, 2006
11. Ponnambalam, S.G., Aravindan, P. and Rao, M.S., Genetic Algorithms for Sequencing Problems in Mixed Model Assembly Lines, *Computer & Industrial Engineering Journal*, 45, 669–690, 2003
12. Sait, S.M. and Youssef, H., *Iterative Computer Algorithms with Applications in Engineering*, Wiley-IEEE Computer Society, 2000
13. Yamamoto, Y. and Kubo, M., *An Introduction to Traveling Salesman Problem*, Asakurashoten, Tokyo, Japan, 1997 (in Japanese)

Chapter 10
NonAssembly Type

10.1 Job-Shop Enterprise and Ellipse Strategy

10.1.1 Introduction

Generally, job-shop production systems consist of a sales center with order selection and a production center with scheduling. These centers have a close relationship, but complete collaboration for maximal profit and delivery speed would be difficult in practice.

This problem necessarily relates to the interface problem between marketing and production in the supply-chain management (SCM) age. In [3, 4], a game model made in the conflict between marketing and production was first issued in the process of problem finding, but was left unexamined for a long time.

For a job-shop, Matsui [6, 7] presented a game-theoretical model for the collaborative control problem of sales and production centers. The management goal was to maximize the net reward (= reward − cost) under a distributed environment. Recently, the game formulation was developed for the periodic type [13] and dynamic type [5, 10] under no due date.

This chapter [11] introduces a strategic management/design approach by applying the two-stage design method in [8], and presents the setting problem of economic lead time in the job-shop model of periodic and semidynamic types. Through the two-stage design, the above control problem is introduced to Stage 1 (economics), and the four optimal variables are regarded as the economic traffic.

In Stage 2 (reliability), the economic lead time is set under the economic traffic in Stage 1. This method is a graphical solution method for two-level problems and provides a scientific basis for lead time setting or due date.

10.1.2 Management/Design Problem

10.1.2.1 Job-Shop Model with Sales

Suppose that a job-shop production system consists of a sales center with order selection and a production center with switch-over (Fig. 6.1.1). The sales center pursues the maximization of accepted price, *ER*, while the production center pursues the minimization of operating cost, *EC*.

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_18,

Details of the job-shop model of periodic and semidynamic types are summarized from [10, 13] as follows:

(1) The arrival of job-orders follows the Poisson distribution with rate λ. Also, the processing times of the two types have the exponential distribution with rate μ_1 and μ_2 ($> \mu_1$), respectively.
(2) The estimated price, S, might have a general distribution, but the exponential distribution with rate α is assumed for simplicity.
(3) The estimated price, S, is independent of the processing time, X_k, of type k $(= 1,\ 2)$.
(4) The sales center has the two selection criteria, $c_1,\ c_2$, in order to select (accept/subcontract) the job-orders on the basis of estimated price.
(5) The production center has two control levels, $i_1,\ i_2,\ (i_1\ \geq\ i_2)$ in order to switch over the two processing types on the basis of the number of backlogs. The switch-over time is assumed to be zero.
(6) When the processing type is k, the job-orders over c_k are accepted, and the arrival rate of accepted orders is given by $\lambda(c_k)$.
(7) The cost structure is processing cost at rate, r_k $(k = 1,\ 2)$, holding cost at rate, h, idle cost at rate, $r0$, and fixed switch-over cost, K.
(8) The number of backlog, i $(= 0,\ 1,\ 2,\ \ldots)$, is the number of accepted orders that wait for the processing at decision epochs.
(9) The state of the system is generally given by $(i,\ k)$, a set of the number of backlogs, i, and processing type, k.
(10) The model of periodic and semi-dynamic types is distinguished at the epoch of order-selection. The former decides the selection at each completion epochs of processing, while the latter decides the selection at arrival epochs of job-orders.
(11) Any rejected job orders are assumed to be lost or transferred to the subcontractor without comeback.

10.1.2.2 Management/Design Formulation

The management goal of a job-shop is to maximize the net reward (marginal profit), $EN\ [F]$, which is the mean accepted reward, $ER\ [F_1]$, minus the mean operating cost, $EC\ [F_2]$, under a constraint of the delivery or due date:

$$F(\,\boldsymbol{c} : \hat{\boldsymbol{\imath}}(\boldsymbol{c})) = F_1(\,\boldsymbol{c} : \hat{\boldsymbol{\imath}}(\boldsymbol{c})) - F_2(\,\boldsymbol{c}; \hat{\boldsymbol{\imath}}(\boldsymbol{c})). \qquad (10.1.1)$$

where $\boldsymbol{i} = (i_1,\ i_2)$ and $\boldsymbol{c} = (c_1,\ c_2)$.

However, constraints such as the due date must be considered. We treat here a condition of lead time instead of due date. The lead time means the sojourn time from the arrived time to the delivery time for accepted orders.

For periodic and semidynamic types, the mean lead time, W, is given by the embedding approach in Chapters 6.1 and 6.2. The basic equation used is

$$
\begin{array}{lll}
\text{Upper level:} & \max\limits_{c} F(\boldsymbol{c};\ \hat{\boldsymbol{i}}(\boldsymbol{c})), & \text{(Net reward)} \\
 & s.t.\ 0 \le \boldsymbol{c} \le \boldsymbol{c}_0, & \text{(Selection criteria)} \\
 & \quad \lambda(c_2) \le \mu_1, & \text{(Traffic intensity)} \\
\text{Lower level:} & F(\boldsymbol{c};\ \hat{\boldsymbol{i}}(\boldsymbol{c})) = \max\limits_{i} F(\boldsymbol{c}; \boldsymbol{i}), & \text{(Net reward)} \\
 & s.t.\ 0 \le \boldsymbol{i} \le \boldsymbol{i}_0,\ i_2 - i_1 \le 0, & \text{(Control level)} \\
 & \quad W(\boldsymbol{c}; \boldsymbol{i}) \le LT_0 & \text{(Due date)} \\
\multicolumn{3}{l}{\text{where } \boldsymbol{i}_0, \boldsymbol{c}_0 \text{ are fixed value vectors, and } LT_0 \text{ is a constant value.}}
\end{array}
$$

Fig. 10.1.1 Two-level formulation of a job-shop problem

$$\text{Mean leadtime } (W) = \frac{\text{Total mean holding time}}{\text{Mean number of processed units}} \tag{10.1.2}$$

and the results are omitted and seen in [11].

This job-shop problem (10.1.1), (10.1.2) is characterized by a two-level approach [1], and is formulated in Fig. 10.1.1. However, a solution method such as the Barrier Method would not be practical.

10.1.3 Two-Stage Design

10.1.3.1 Design Procedure

A graphical/practical solution is given by applying the two-stage method [8] instead of solving the two-level problems above. This method can give the economic lead time under the maximization of the net reward, *EN*, given by (marginal profit, *EN*) = (mean accepted price, *ER*) − (mean operating cost, *EC*). These subobjective functions EN $[F]$; ER $[F_1]$ and EC $[F_2]$ are available from [10, 13].

The two-stage design procedure for job-shop models is outlined in Fig. 10.1.2. At Stage 1, the economic traffic, f = $(c_1, c_2;\ i_1, i_2)$, is decided by the maximization of the net reward. At Stage 2, the economic lead time, LT, is set under the eco-

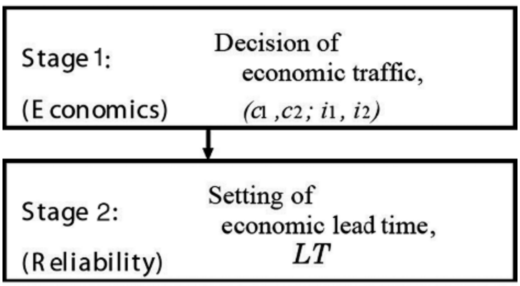


Fig. 10.1.2 Two-stage design procedure

nomic traffic at Stage 1. If the due date is unsatisfactory ($LT > LT_0$), the procedure is feedback at Stage 1.

10.1.3.2 Periodic versus Semidynamic

An example of a two-stage design for a periodic type is given here, and it is similar to that of the semidynamic type. The system parameters and basic traffic variables are set as follows:

Arrival rate $\lambda = 3{\cdot}0$,
Processing rate $\mu_1 = 1{\cdot}0,\ \mu_2 = 2{\cdot}0$,
Holding cost rate $h = 0{\cdot}05$,
Idle cost rate $r_0 = 0{\cdot}1$,
Processing cost rate $r_1 = 0{\cdot}5,\ r_2 = 1{\cdot}75$,

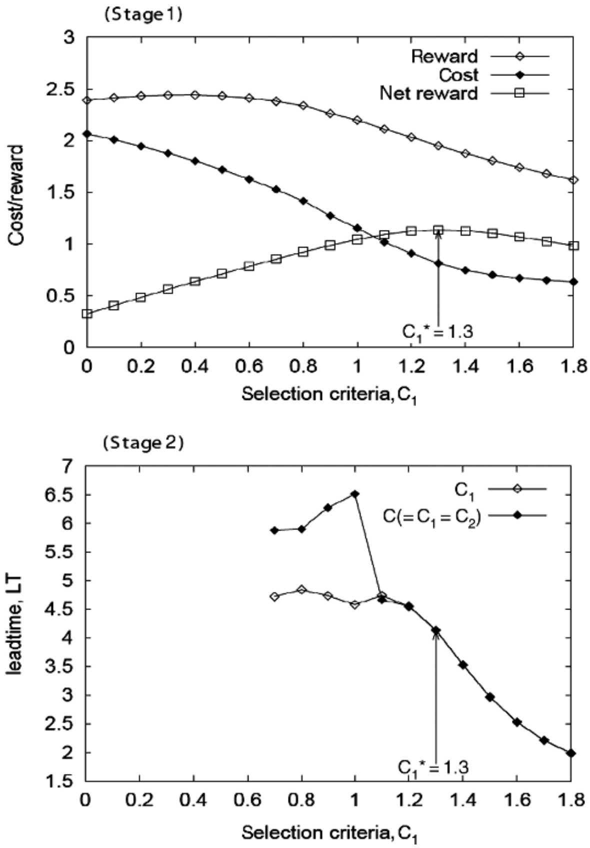


Fig. 10.1.3 Two-stage design in c, c_1: Periodic type

Fixed switching cost $K = 3{\cdot}0$,
Price rate $\alpha = 1{\cdot}0$,
$c_1 = 1.3,\ c_2 = 1.4$,
$i_1 = 13,\ i_2 = 3$.

First, the two-stage design for periodic type is shown in Figs. 10.1.3 and 10.1.4. The case of a semidynamic type is similar to that shown in Figs. 10.1.3 and 10.1.4 (and is omitted here). From Figs. 10.1.3 and 10.1.4, it is ascertained that the economic traffic $(c_1^*,\ i_1^*)$ exists, and then the economic lead time, LT^*, is found under c_1^* and i_1^*. The increase in c_1, or decrease in i_1 is also effective with the shortening of the economic lead time, LT^*.

The economic lead time, LT^*, under the periodic versus the semidynamic type is finally discussed. Tables 10.1.1 and 10.1.2 give a summary of the economic traffics and lead times under arrival rate $\lambda = 1.0(1.0)6.0$. It is ascertained that the semidy-

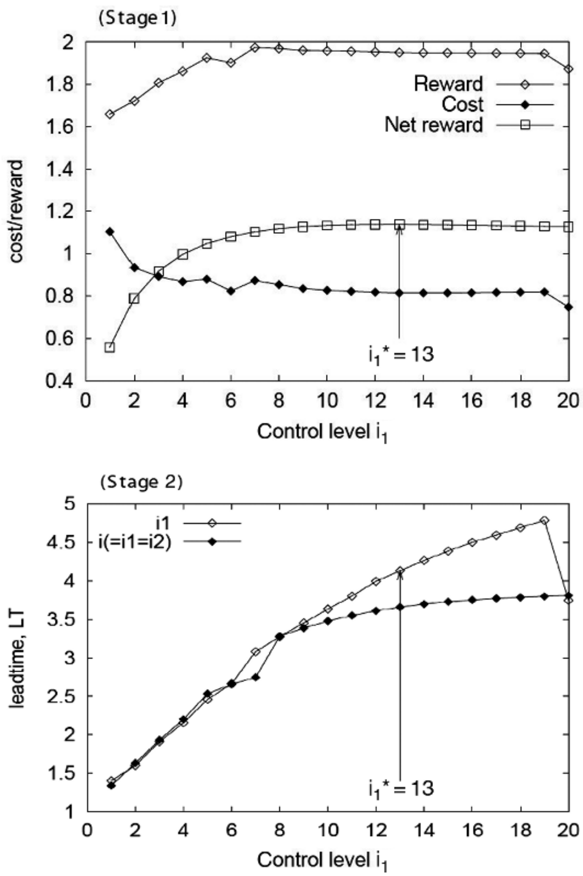


Fig. 10.1.4 Two-stage design in i, i_1: Periodic type

Table 10.1.1 Economic traffic and lead time: Periodic type

λ	f^* (Periodic)	EN	Lead time. LT*
1.0	(0.6, 1.3; 19.7)	0.4485	2.2160
2.0	(1.0, 1.4; 14.4)	0.8605	3.4958
3.0	(1.3, 1.4; 13.3)	1.1367	4.1326
4.0	(1.5, 1.4; 11.2)	1.3439	4.2709
5.0	(1.6, 1.7; 11.1)	1.5126	4.6907
6.0	(1.6, 1.8; 10.1)	1.6680	4.7394

Table 10.1.2 Economic traffic and lead time: Semidynamic type

λ	f^* (Semidynamic)	EN (%)	Lead time. LT* (%)
1.0	(0.6, 1.4; 19.6)	0.4978 (10)	1.2160 (45)
2.0	(1.0, 1.4; 15.4)	0.9414 (9)	2.5510 (27)
3.0	(1.3, 1.4; 13.3)	1.2566 (10)	3.1592 (24)
4.0	(1.5, 1.4; 12.2)	1.5063 (11)	3.5656 (17)
5.0	(1.6, 1.4; 11.1)	1.7268 (12)	3.9099 (17)
6.0	(1.6, 1.4; 9.0)	1.9405 (14)	3.8833 (18)

namic type is superior to the periodic type in terms of both profit (*EN*) and lead time (LT^*). The superiority (%) increases in profit but decreases in lead time according to the increase of λ.

10.1.4 Management Strategy

10.1.4.1 Pair-Matrix Table

For management strategies, the pair-matrix table in [8] is introduced here as the strategy map on traffic axes ($c_1,\ i_1$). The pair-matrix table consists of rewards (economics) and buffer/lead time (reliability), and it is a graphical/practical method for management strategies of design, and is obtained by use of the two-stage design method in Fig. 10.1.3.

Tables 10.1.3 and 10.1.4 show the pair-matrix tables of periodic and semidynamic types, respectively. Strategy c_1=1.3 and i_1=13 is best for both the types. Strategy $c_1\ \uparrow$ or $i_1\ \downarrow$ is also desirable for the decrease in lead time. Note that the net reward (economics) involves a kind of trade-off relationship with lead time (reliability).

10.1.4.2 Variety of Strategies

A variety of management strategies for the periodic and semidynamic types are obtained from Tables 10.1.3 and 10.1.4, respectively. They include a pair-pole,

Table 10.1.3 Pair-matrix table: Periodic type and ellipse

c_1	i_1	10	11	12	13	14	15	16
1.0	ER	2.1980$_{max}$	2.1973	2.1967	2.1826	2.1825	2.1824	2.1823
	EC	1.1530	1.1529	1.1562	1.1487	1.1571	1.1673	1.1790
	EN	1.0449	1.0444	1.0404	1.0339	1.0254	1.0151	1.0033
	LT	4.5825	4.9308	5.2849	5.6457	6.0123	6.3833	6.7584$_{max}$
	c_2, i_2	1.2, 1	1.2, 1	1.2, 1	1.3, 1	1.3, 1	1.3, 1	1.3, 1
1.1	ER	2.1125	2.1116	2.1108	2.1100	2.1100	2.1094	2.1088
	EC	1.0216	1.0194	1.0204	1.0237	1.0296	1.0362	1.0441
	EN	1.0908	1.0921	1.0903	1.0863	1.0804	1.0732	1.0647
	LT	4.4352	4.7429	5.0536	5.3667	5.6003	5.9209	6.2425
	c_2, i_2	1.3, 2	1.3, 2	1.3, 2	1.3, 2	1.3, 1	1.3, 1	1.3, 1
1.2	ER	2.0364	2.0348	2.0333	2.0320	2.0267	2.0260	2.0255
	EC	0.9150	0.9108	0.9091	0.9094	0.9069	0.9101	0.9139
	EN	1.1214	1.1240	1.1242	1.1226	1.1198	1.1160	1.1115
	LT	4.0650	4.3097	4.5506	4.7871	5.0136	5.2403	5.4614
	c_2, i_2	1.3, 2	1.3, 2	1.3, 2	1.3, 2	1.4, 2	1.4, 2	1.4, 2
1.3	ER	1.9587	1.9566	1.9541	1.9505	1.9497	1.9490	1.9483
	EC	0.8265	0.8213	0.8175	0.8138	0.8137	0.8142	0.8152
	EN	1.1321	1.1352	1.1365	1.1367$_{max}$	1.1360	1.1347	1.1331
	LT	3.6348	3.8042	3.9949	4.2660	4.2660	4.3895	4.5033
	c_2, i_2	1.3, 2	1.3, 2	1.3, 3	1.4, 3	1.4, 3	1.4, 3	1.4, 3
1.4	ER	1.8818	1.8801	1.8787	1.8766	1.8759	1.8753	1.8749
	EC	0.7577	0.7533	0.7505	0.7478	0.7470	0.7466	0.7465
	EN	1.1240	1.1267	1.1281	1.1287	1.1288	1.1287	1.1283
	LT	3.2161	3.3119	3.3960	3.4660	3.5294	3.5835	3.6294
	c_2, i_2	1.3, 3	1.3, 3	1.3, 3	1.4, 3	1.4, 3	1.4, 3	1.4, 3
1.5	ER	1.8101	1.8084	1.8076	1.8066	1.8062	1.8059	1.8057
	EC	0.7095	0.7060	0.7041	0.7026	0.7020	0.7017	0.7015$_{min}$
	EN	1.1006	1.1024	1.1034	1.1039	1.1041	1.1042	1.1041
	LT	2.8007$_{min}$	2.8582	2.8955	2.9240	2.9479	2.9666	2.9810
	c_2, i_2	1.3, 3	1.3, 4	1.3, 4	1.4, 4	1.4, 4	1.4, 4	1.4, 4

$(ER^*,\ EC^*)$, consisting of sales maximization, ER^*, at (1.0, 10), and production-minimization, EC^*, at (1.5, 16) points, our favorite strategy for demand-to-supply management is shown in the ellipse plane.

Alternatively, a neighborhood of the strategy, c_1=1.5 and i_1=10, in Table 10.1.3 is far from that of the economic lead time, $LT^*(= 4.266)$, and is better than the decrease in lead time or due date, $LT0 = 2.81$. This search method is useful for the formulation in Fig. 10.1.2, and would be practical for discontinuity of the number of backlogs, i, and so forth.

This pair-matrix table would, therefore, be useful as a strategy map for management/design, and the ellipse shape with pair-pole in [8] is found again. Note that the overall optimization, EN*, at $(c_1^*,\ i_1^*) = (1.3,\ 13)$, is positioned at the midpoint of pair-pole, (1.0, 10) and (1.5, 16).

Table 10.1.4 Pair-matrix table: Semidynamic type and ellipse

c_1	i_1	10	11	12	13	14	15	16
1.0	ER	2.1542_{max}	2.1563	2.1581	2.1597	2.1611	2.1623	2.1635
	EC	0.9911	0.991	0.9947	1.0012	1.0101	1.0208	1.0329
	EN	1.1631	1.1652	1.1634	1.1584	1.151	1.1416	1.1305
	LT	3.6973	4.049	4.4062	4.7683	5.1351	5.5062	5.8814_{max}
	c_2, i_2	1.3, 1	1.3, 1	1.3, 1	1.3, 1	1.3, 1	1.3, 1	1.3, 1
1.1	ER	2.0723	2.0739	2.0753	2.0683	2.0698	2.0712	2.0725
	EC	0.8605	0.8586	0.8601	0.8557	0.8619	0.8696	0.8786
	EN	1.2118	1.2152	1.2152	1.2125	1.2079	1.2016	1.1939
	LT	3.4238	3.7347	4.0479	4.3546	4.6725	4.9916	5.3119
	c_2, i_2	1.3, 1	1.3, 1	1.3, 1	1.4, 1	1.4, 1	1.4, 1	1.4, 1
1.2	ER	1.9805	1.9755	1.9766	1.9777	1.9786	1.9794	1.9802
	EC	0.7393	0.7296	0.729	0.7303	0.7331	0.7369	0.7415
	EN	1.2412	1.2459	1.2477	1.2474	1.2455	1.2425	1.2386
	LT	3.1348	3.3635	3.6004	3.833	4.0609	4.2838	4.5013
	c_2, i_2	1.3, 2	1.4, 2	1.4, 2	1.4, 2	1.4, 2	1.4, 2	1.4, 2
1.3	ER	1.8805	1.8773	1.8778	1.8782	1.8785	1.8773	1.8777
	EC	0.6322	0.6244	0.6222	0.6216	0.6219	0.6214	0.623
	EN	1.2483	1.253	1.2556	1.2566_{max}	1.25[illegible]6	1.2559	1.2547
	LT	2.6739	2.8722	3.0204	3.1592	3.2887	3.4043	3.5155
	c_2, i_2	1.3, 3	1.4, 3	1.4, 3	1.4, 3	1.4, 3	1.5, 3	1.5, 3
1.4	ER	1.7776	1.7755	1.7755	1.7755	1.7755	1.775	1.7751
	EC	0.5445	0.5387	0.5364	0.5352	0.5347	0.534	0.5342
	EN	1.233	1.2368	1.2391	1.2403	1.2408	1.241	1.2409
	LT	2.2377	2.3236	2.4049	2.4889	2.547	2.5948	2.6378
	c_2, i_2	1.3, 3	1.4, 3	1.4, 3	1.4, 4	1.4, 4	1.5, 4	1.5, 4
1.5	ER	1.6752	1.6741	1.6739	1.6738	1.6737	1.6735	1.6735
	EC	0.476	0.4723	0.4707	0.4697	0.4692	0.4687	0.4687_{min}
	EN	1.1992	1.2018	1.2033	1.2041	1.2045	1.2047	1.2048
	LT	1.8225_{min}	1.8629	1.8987	1.9275	1.9537	1.9698	1.9832
	c_2, i_2	1.3, 4	1.4, 4	1.4, 4	1.4, 4	1.4, 5	1.5, 5	1.5, 5

10.1.5 Actual Situation

As the managerial strategies for backlog control, the following four types are considered [12].

A: All acceptance.
B: Traditional strategy: If the backlog is over the prescribed value (here, 5 (processing time)), any order is rejected. Thus, there is not any switch-over strategy.
C: Modeling strategy (in this chapter).
D: Revised strategy: The estimated price per sales is changed to the estimated price per unit time.

In Company A, the symmetrical frequency of estimated price and the cyclical arrival pattern for orders are assumed. In the above situation, the four managerial strategies are compared by simulation. Figures 10.1.6 and 10.1.7 show the relative

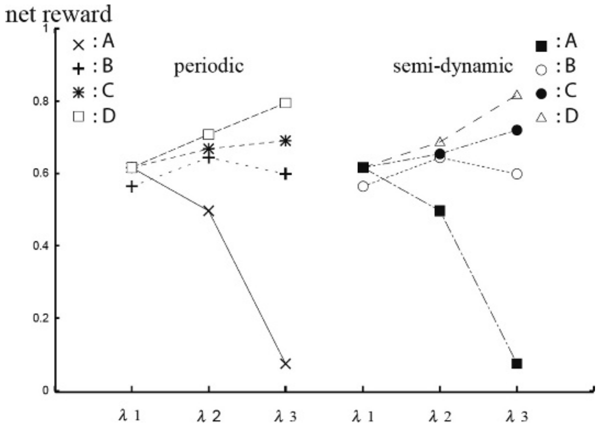


Fig. 10.1.5 Net reward at stage 1

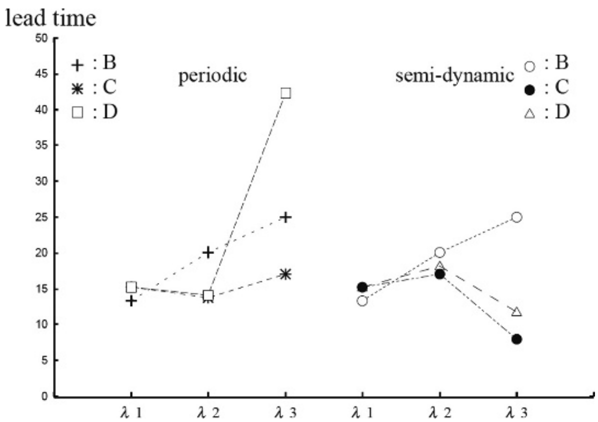


Fig. 10.1.6 Economic leadtime at stage 2

effects of the four strategies at the three different arrival rates: $\lambda_1=0.219$, $\lambda_2=0.264$ and $\lambda_3=0.411$. It is shown that the lead time of Type A in Fig. 10.1.5 is divergent and thus omitted.

From Figs. 10.1.5 and 10.1.6, it is ascertained that the modeling strategy (C) is effective and valid. Furthermore, note that the revised strategy (D) is superior to that of Type C. Thus, the proposed model would be valid and practical. Problem between sales and production centers would be very interesting [2, 9].

References

1. Aiyoshi, E. and Shimizu, K., Hierarchical Decentralized Systems and its New Solution by a Barrier Method, *IEEE Transactions on Systems, Man and Cybernetics*, 11, 444–449, 1981

2. Ceroni, J., Nof, S. and Matsui, M., Communication Based Coordination Modeling in Distributed Manufacturing Systems, *International Journal of Production Economics*, 60–61, 281–287, 1999
3. Davis, K.R., The Process of Problem Finding: A Production-Marketing Example, *Interfaces*, 8, 82–86, 1977
4. Eliashberg, J. and Steinberg, R., Marketing-Production Joint Decision-Making. In: J. Eliashberg and G.L. Lilien (eds.), *Marketing*, North-Holland, Amsterdam, 827–880, 1993
5. Kanbara, K., Tamaki, K. and Matsui, M., Queueing Analysis and Optimal Control of a Job-Shop Production System of Dynamic Type, *Journal of Japan Industrial Management Association*, 49(5), 327–337, 1998 (in Japanese)
6. Matsui, M., A Game-Theoretic Consideration of Order-Selection and Switch-Over Policy, *Preprints of the Japan Industrial Management Association*, Fall Meeting, 48–49, 1983 (in Japanese)
7. Matsui, M., On a Joint Policy of Order-Selection and Switch-Over, *Journal of Japan Industrial Management Association*, 39(2), 83–89, 1988 (in Japanese)
8. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting. *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
9. Matsui, M., Aita, S., Nof, S., Chen, J. and Nishibori, Y., Analysis of Cooperation Effects in Two-Center Production Models, *International Journal of Production Economics*, 84, 101–112, 2002
10. Matsui, M., Kaneda, K. and Kanbara, K., Optimal Control of a Job-Shop Production System: Periodic Versus Dynamic Type, *International Journal of Production Research*, 38(13), 2951–2966, 2000
11. Matsui, M. and Nakada, Y., Strategic Management/Design Approach to a Job-Shop Production System. *International Journal of Production Research*, 41(14), 3257–3271, 2003
12. Matsui, M., Nakada, Y., Yasuda, M., Kamigaki, T. and Ohshio, H., 2-Stage Design for a Job-Shop Production System with Backlog Control and Its Application Study, *Journal of Japan Industrial Management Association*, 53(2), 170–177, 2002 (in Japanese)
13. Matsui, M., Yang, G. and Miya, T., Optimal Control of a Job-Shop Production System with Order-Selection and Switch-Over. *International Journal of Production Research*, 37(1), 73–90, 1999

10.2 Flexible Enterprise and Ellipse Strategy

10.2.1 Introduction

The flexible manufacturing system (FMS) used in production consists of a set of identical and/or complementary, numerically controlled machines connected through an automated transportation system [12]. This Central Server System (CSS) is usually controlled by a network of computers on site, for example, in a job shop [1].

This chaper [11] considers a Central Server Model (CSM) incorporating four routings and a sales center in operations management. The central server corresponds to an FMS parts warehouse, regarded as a sales/profit center. Based on Chapter 8 [3, 10], inventory, busy, idle, and blocking factors are taken as operating costs, and the operating cost sum is obtained analytically as the (expected) operating cost by [6, 7].

This two-center operating problem was first formulated by Matsui [4, 5], and was modeled as a Management Game Model (MGM) by Matsui [7]. The sales center generally seeks to maximize sales revenue, while the production center seeks to minimize operating cost. The two-center problem involves the self-optimized solution which is not necessarily realised in profit maximization.

We start by discussing the behaviors of these costs in a production center (CSS), then consider the problem of maximizing the marginal profit – net reward = sales price – operating cost – under lead time (time reliability). We use Matsui's two-stage design [6, 7] instead of multiobjective programming. Based on [9], we apply the two-stage design and the pair-matrix table to CSM, and the ellipse shape is refound in a CSM with four routing strategies.

10.2.2 CSM with Sales

10.2.2.1 Explanations of Models

The CSM is introduced as a two-center model consisting of sales and production/service centers (Fig. 10.2.1). The two-centers are a production center with

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_19,

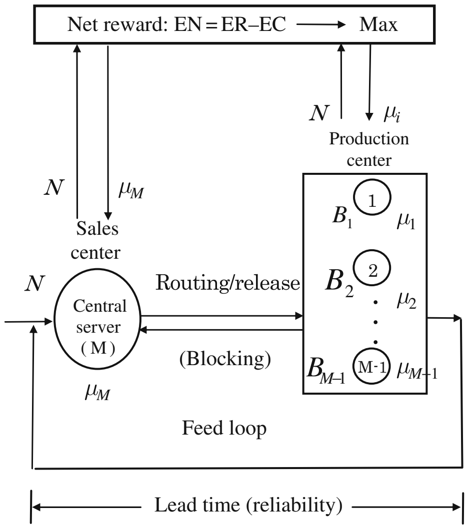


Fig. 10.2.1 Central server-center model

(M-1) processing stations and a sales center with one transporter. Each station has one or more machines, for example, NC machine tools and machining centers, N parts are fixed to pallets, and the central server is assumed to have unlimited capacity.

Limited local buffers hold parts when processing machines are busy. When one or all of the limited local buffers is full, new parts carried from the transporter are blocked, that is, a "blocking" event occurs. When no parts are being processed, the machine is "idle."

The main problem is to maximize marginal profit economics: Net profit (*EN*) = Sales price (*ER*) − Operating cost (EC) Under lead time (reliability).

The four main routing rules involve four FMS similar to CSMs considered as queueing networks. The first is the fixed-routing model (*FR*), the second the dynamic-routing model (*DR*), the third the ordered-entry routing model (*OE*), and the fourth the hybrid-routing model (HR).

In the fixed-routing model, routing probabilities for carrying parts from the central server to each processing station are given and fixed. Parts are carried to the destination automatically, regardless of whether the local buffer is full. The analysis assumes that fixed-routing probabilities correspond to real distribution of routes between stations for given sets of parts, as seen in the FMS studies [12, 13, etc.].

In the dynamic-routing model, the routing mechanism is designed to send parts to the relatively shortest queue in the station that has the largest number of empty buffer spaces compared to capacity. If all stations are full, parts stay in the central buffer to be delivered later. In the analysis, routing is determined stochastically as seen in the FMS-like studies [14, 15, etc.], and others.

In the ordered-entry (sequentially-transferred) model, a part is routed to Station 1 from the central server based on probability, q, and to the load/unload station based on probability, (1–q). Parts are serviced immediately. If Station 1 is in service, the part waits at a local buffer. The part goes to Station 2 if the local buffer of station 1 is full. The part goes to Station 3 if the local buffer of Station 2 is full, as seen in the Flexible Assembly System (FAS) [3].

The part is kept as follows until a processing station with a vacancy is found in the local buffer. The part is returned to the end of the infinite buffer of the central server without being serviced if all local buffers are full, that is, are blocked.

In the hybrid-routing (HR) model, consisting of fixed-routing and ordered-entry (OE) routing (see Appendix A), any part can be transferred from the central server to each station with fixed probability and also transferred to the next station sequentially if blocked at any station, as seen in the order-release problem of job shops [1].

10.2.2.2 Cost/Profit Formulation

We introduce an (expected) operating cost analytically obtained from closed queueing network theory. Operating cost, *EC*, is defined as follows:

$$EC = \alpha_1 ZK + \alpha_2 KD + \alpha_3 YU + \alpha_4 BC \tag{10.2.1}$$

where *ZK*, is the amount of inventory, *KD*, the busy rate, *YU*, the idle rate, and *BC*, is the blocking probability. α_1, is the inventory cost coefficient, α_2 the busy cost coefficient, α_3 idle cost coefficient, and α_4 the blocking cost coefficients.

Parts are delivered to the processing station automatically. If the local buffer is full when a new part is transferred to the station, the part is blocked and returned to the central server. This can detract from system productivity, and is taken as a blocking penalty cost.

Idle cost occurs when the machine is idle. Inventory cost is defined as the cost of parts in the system, equal to constant N. Busy cost is the cost spent on processing. The sum of inventory, busy, idle, and blocking costs is regarded as the operating cost, analytically obtained by closed queueing networks of the CSS [3, 10, 13, 14].

ZK, KD, YU, and *BC* are given using state probabilities of system $\pi(\mathbf{n})$, in which S is:

$$S = \{\ (n_1, \cdots,\quad n_i, \cdots,\quad n_M) | \sum_{i=1}^{M} n_i = N, \quad n_i \geq 0, \quad i = 1, \cdots, M\ \}.$$

Then,

$$ZK = N \tag{10.2.2}$$

where n_i is the number of parts at station i in the steady state.

$$KD = \sum_{i=1}^{M-1} \sum_{\mathbf{n} \in S, n_i \neq 0} \pi(\mathbf{n}), \tag{10.2.3}$$

$$YU = \sum_{i=1}^{M-1} \sum_{\mathbf{n} \in S, n_i = 0} \pi(\mathbf{n}), \tag{10.2.4}$$

and BC is omitted here for simplicity, but it is available from the state probabilities of the system and the references provided.

Various studies [13, 14, etc.] have highlighted the problem that maximum buffer capacity increases with increasing numbers of parts. When it increases, however, it is possible to increase idleness and, in turn, the efficiency of the system. Blocking, another negative factor, becomes negligible.

Next, we introduce the reward at the sales center (warehouse) in the CSM. The sales center releases demand to the production/service center by a transporter or a truck. The expected reward per unit time *ER* at a sales center is given under sales price, p, by

$$ER = p \times TH \tag{10.2.5}$$

and net reward (marginal profit), *EN*, is found from Eqs. (10.2.1) and (10.2.5) as follows:

$$EN = ER - EC \tag{10.2.6}$$

The formulation problem for the management goal is given as follows:

$$\text{Goal}: EN = ER - EC \rightarrow \max \qquad \text{(Economics)} \tag{10.2.7}$$

$$\text{Subject to}: \text{ Constraints of manufacturing resources and lead time.} \quad \text{(Reliability)} \tag{10.2.8}$$

The two-stage method of [6, 7] is applicable to this problem.

10.2.3 Operating Cost

10.2.3.1 Performance and Parameters

We discuss operating cost behavior under performance evaluations and the parameter settings below. Basic parameters are assumed as follows [3]:

$$\text{Number of stations } (M): \ M = 4.$$

That is, there are 3 processing stations and 1 central server.

$$\text{Service rates } (\mu_i) : \mu_1 = \mu_2 = \mu_3 = 40,\ \mu_4 = 100$$

Routing probabilities:
Parts in station, M, are assigned to station, i, following the routing probabilities, q_{M_i}. If limited local buffers are full, parts are blocked and re-circulated.

- Fixed routing:

$$q_{M1} = q_{M2} = q_{M3} = 0.3 \quad \text{and} \quad q_{MM} = 0.1$$

- Dynamic routing: Routing follows priority $\widehat{q}_{M_i}$:

$$\widehat{q}_{Mi} = \frac{(B_i - n_i)\big/ B_i}{\sum_{i=1}^{M-1} (B_i - n_i)\big/ B_i} \quad i = 1, 2, ..., M-1, \tag{10.2.9}$$

- Ordered-entry routing:

$$q = q_{M1} = 0.9 \quad \text{and} \quad q_{MM} = 1 - q = 0.1,$$

where q_{MM} is set heuristically from many trials.

- Hybrid routing:

$$q_{M1} = q_{M2} = q_{M3} = 0.3 \quad \text{and} \quad q_{MM} = 0.1$$

Number of parts (kanban):

$$1 \le N \le 10$$

Capacity of limited buffers:

$$\sum B_i \le 9 \quad and \quad B_M = N$$

Number of servers: All stations only have one server.
Cost coefficients:

$$\alpha_1 = 0.35, \quad \alpha_2 = 0.3, \quad \alpha_3 = 2.5, \quad \alpha_4 = 1.0, \quad \text{and} \quad p = 0.1$$

10.2.3.2 Four Behaviors

Consider that operating cost is regarded as a function of the number of parts, N. From operating cost behavior, we deduce the optimal or economical number of parts

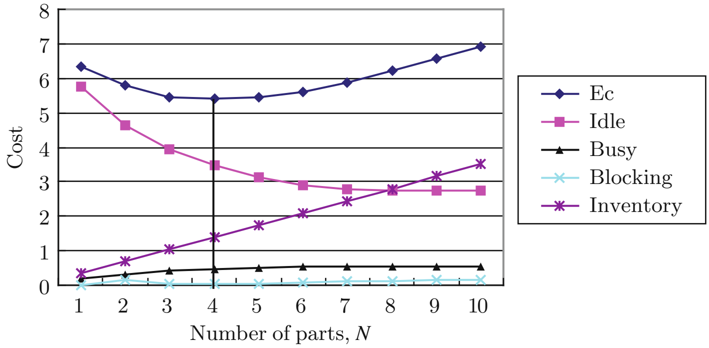


Fig. 10.2.2 Operating cost behavior: fixed

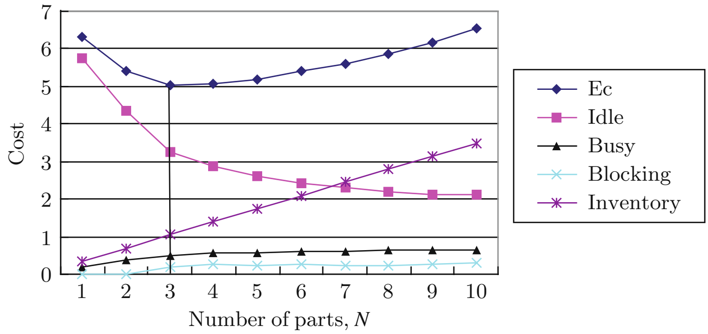


Fig. 10.2.3 Operating cost behavior: ordered-entry

based on cost criteria, and assign the number of limited buffers to each station. The effect of blocking cost, idle cost, inventory cost, and busy cost is found at the same time. The operating cost behavior for each routing is shown in Figs. 10.2.2 and 10.2.3.

10.2.4 Design Method

10.2.4.1 Two-Stage Design

The lead time of a system under net reward behavior is of interest because the FMS requires a shorter lead time to deliver products. The problem is simultaneous determination of economic traffic and lead time, and is given by a two-stage design in multi-objective programming (Fig. 10.2.4).

The main merit of this is to give a solution map instead of only an optimal point.

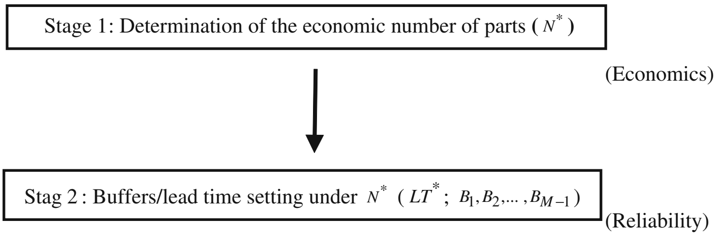


Fig. 10.2.4 Two-stage design

Stage 1: Economic number of parts
The economic number of parts (kanban) is first decided by maximizing the net reward (10.2.7). For operating cost, the existence of the economic number of parts, N^* is shown in Figs. 10.2.2 and 10.2.3.

Stage 2: Lead time setting
The lead time of the system generally increases with the increasing number of parts. Scientific lead time is set based on the economic number of parts, N^* and limited local buffers, Bi, and is called the economic lead time. Economic lead time is determined from Little's formula as follows:

$$LT^* = N^* / TH, \tag{10.2.10}$$

where system throughput, *TH*, is given from the busy rate of station i, V_i, by

$$TH = \sum_{i=1}^{M-1} \mu_i V_i. \tag{10.2.11}$$

Figures 10.2.5 and 10.2.6 show the behavior of the system's net reward and lead time for three routing types. The economic lead time is set using the corresponding optimal number of parts at the first stage. Optimal operational design for operation is given in Table 10.2.1.

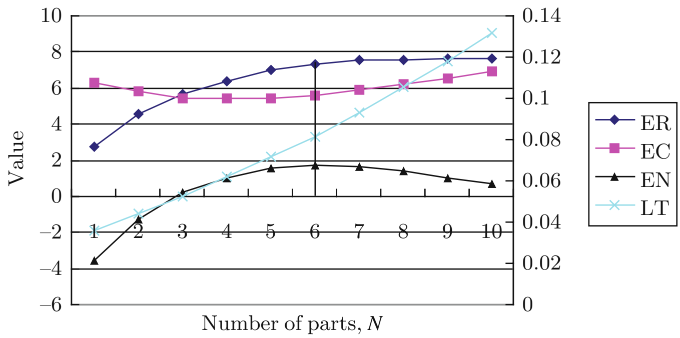


Fig. 10.2.5 Two-stage design: fixed

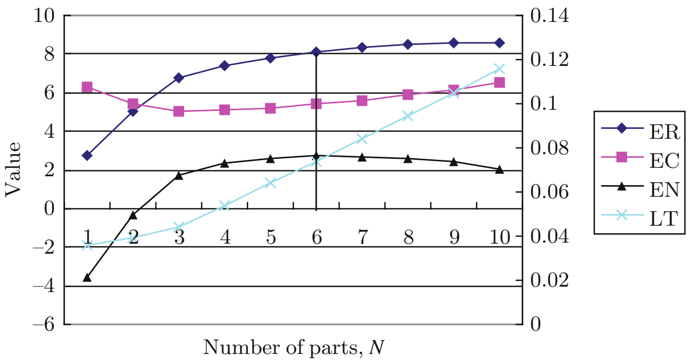


Fig. 10.2.6 2-stage design: ordered-entry

Table 10.2.1 Optimal design comparisons

Routing		Fixed (FR)	Dynamic (DR)	Ordered-entry (OE)	Hybrid (HR)
Expected reward		7.3435	7.4474	8.1138	9.4708
	Blocking	0.0825	0.0063	0.2546	0.0819
Cost	Idle	3.0267	2.8454	2.4289	1.5808
	Inventory	2.1000	2.1000	2.1000	2.8000
	Busy	0.5260	0.5586	0.6085	0.7103
Operating cost		5.6188	5.5103	5.392	5.1730
Net reward		1.7247	1.9371	2.7219	4.2978
Stage I	Number of parts	6	6	6	8
Stage II	Throughput	73.435	74.474	81.138	94.708
	Lead time	0.0817	0.0806	0.0739	0.0845
	B_1, B_2, B_3	3,3,3	3,3,3	1,2,3	2,3,3

The figures show that the expected reward and lead time increase as the number of parts increases, and that the net reward has a maximum. The ordered-entry type is generally better than fixed-and dynamic-types in term of net reward and lead time, but inferior to the hybrid-routing type.

10.2.4.2 Routing Comparison

Figures 10.2.7 and 10.2.8 summarize the two-stage design, and Table 10.2.1 compares optimal design, maximizing throughputs of routings in the parameter given. Based on the figures and table, ordered-entry routing appears to have lower operating cost and higher profit than fixed- and dynamic-routing models, which is similar to the case of heterogeneous servers.

The economic lead time of ordered-entry routing is shorter than that of the fixed or dynamic, but longer than that of hybrid routing. For further comparison [8], it is noted that OE routing would be more optimal in light traffic.

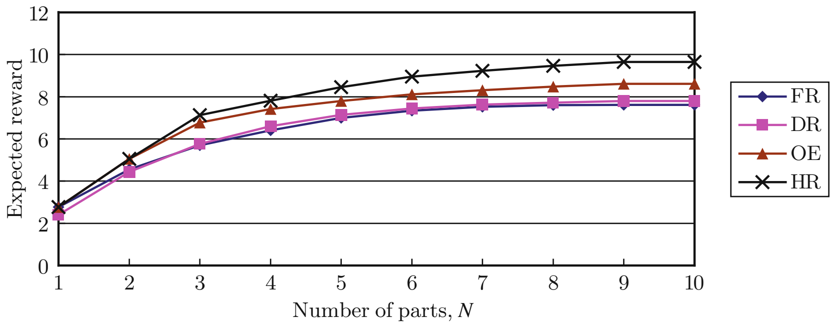


Fig. 10.2.7 Economic comparison of routings

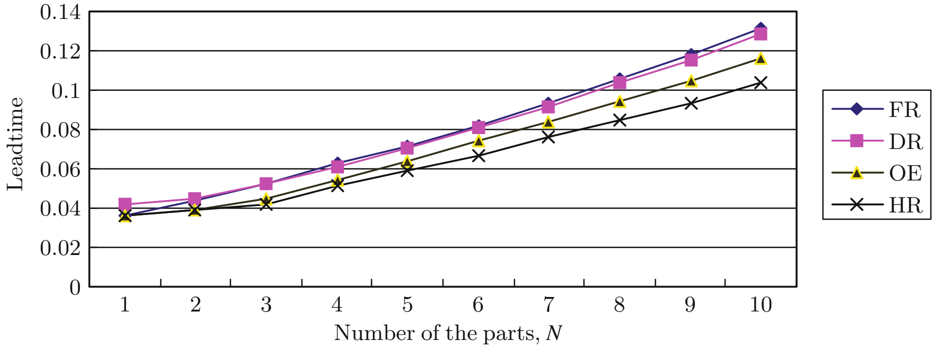


Fig. 10.2.8 Comparative lead time of routings

10.2.5 Ellipse Theory

10.2.5.1 Pair Matrix Table

In this section, we discuss management design for the pair-matrix table for $M = 4$, obtained by the two-stage design (Fig. 10.2.6). The map has two profit/cost (economics) and buffer/lead time (reliability) values in each element (*N*, *m*), where service rates are all the same, for example, $1/\mu_i = m,\ i = 1, 2, \cdots, M-1$.

Tables 10.2.2 and 10.2.3 are pair-matrix tables (*N*, *m*), under all combinations in fixed (*FR*) and ordered-entry (*OE*) routing. Based on [3], we assume that $q_1 = q_2 = q_3 = 0.3$ and $q_4 = 0.1$ in fixed routing and $q = 0.9$ in ordered-entry routing.

Tables 10.2.2 and 10.2.3 show that optimization exists for each (*N*, *m*), and optimal couples are $(N^*,\ m^*) = (6,\ 0.0250)$. Economic lead time LT^* is longer for larger N and m, and has a trade-off relationship to net reward.

A pair-pole exists consisting of sales-maximization ER^* at (10, 0.0100) and production-minimization EC^* at (3, 0.2000) (Tables 10.2.2 and 10.2.3). These ellipses with pair-poles $(ER^*,\ EC^*)$ in the pair-matrix table were first found in [7, 9].

Table 10.2.2 Pair-matrix table: fixed type and ellipse

Demand \ Supply			m					
			0.0100	0.0125	0.0250	0.0500	0.1000	0.2000
	1	ER	4.7368	4.2353	2.7692	1.6364	0.9000	0.4737
		EC	6.8079	6.6853	6.3269	6.0500	5.8700	5.7658
		EN	-2.071[illegible]	-2.4500	-3.5577	-4.4136	-4.9700	-5.2921
		TH	47.3684	[illegible]2.3529	27.6923	16.3636	9.0000	4.7368
		LT	0.0211	0.[illegible]36	0.0361	0.0611	0.1111	0.2111
		B_t	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1
	2	ER	7.0082	6.4421	4.557	2.9388	1.7027	0.9213
		EC	6.6582	6.4284	[illegible].7894	5.0445	4.5051	4.1762
		EN	0.3500	0.0137	-1.[illegible]324	-2.1057	-2.8024	-3.2550
		TH	70.0820	64.4211	45.5[illegible]96	29.3878	17.0270	9.2126
		LT	0.0285	0.0310	0.0439	0.0681	0.1175	0.217[illegible]
		B_t	2 2 2	2 2 2	1 1 1	1 1 1	1 1 1	1 1 1
	3	ER	8.1033	7.6425	5.6966	[illegible].5367	2.2500	1.2857
		EC	6.7673	6.4483	5.4539	4.[illegible]929	3.806[illegible]	3.0361
		EN	1.3361	1.1941	0.2427	-1.[illegible]563	-1.[illegible]567	[illegible]
		TH	81.0332	76.4246	56.9657	35.36[illegible]6	[illegible].5000	12.8571
		LT	0.0370	0.0393	0.0527	0.0848	0.1333	0.2333
		B_t	3 3 3	3 3 3	2 2 2	2 2 [illegible]	1 1 1	1 1 1
	4	ER	8.6018	8.3008	6.4066	4.1[illegible]55	2.4231	1.3455
		EC	7.0137	6.6262	5.3945	4.4176	[illegible].7843	3.1280
		EN	1.5881	1.6746	1.0121	-0.2720	-1.[illegible]612	-1.7825
		TH	86.0181	83.0081	64.0662	41.4555	24.[illegible]308	13.4551
		LT	0.0465	0.0482	0.062[illegible]	0.0965	0.16[illegible]1	0.2973
		B_t	3 3 3	3 3 3	3 3 3	2 2 2	1 1 2	1 1 2
N	5	ER	[illegible].7704	8.5732	6.[illegible]917	4.5866	2.6546	1.4156
		EC	7.3301	6.9076	[illegible].4425	4.3638	3.5411	3.1050
		EN	1.[illegible]403	1.6656	1.5492	0.2228	-0.8865	-1.6894
		TH	87.[illegible]040	85.7318	69.9174	45.8662	26.5463	1[illegible].1557
		LT	0.05[illegible]0	0.058[illegible]	0.0715	0.1090	0.1884	0.[illegible]532
		B_t	3 3 [illegible]	3 3 3	3 3 3	2 2 2	2 2 2	2 2 2
	6	ER	8.817[illegible]	8.[illegible]673	7.3435	4.7899	2.7692	1.4[illegible]1
		EC	7.6714	7.2352	5.6188	4.4439	3.7348	3.3[illegible]2
		EN	1.1457	1.4320	1.7247	0.3461	-0.9656	-1.[illegible]846
		TH	88.1713	86.6727	[illegible]	47.8994	27.6923	1[illegible].6512
		LT	0.0680	[illegible].0692	0.0817	0.1253	0.2167	0.4095
		B_t	3 3 3	3 3 3	3 3 3	2 3 3	2 2 2	2 2 2
	7	ER	8.82[illegible]9	8.[illegible]921	7.5293	5.0593	2.8051	1.4629
		EC	8.0[illegible]99	7.5[illegible]02	5.8867	4.5073	3.87[illegible]7	3.6016
		EN	0.[illegible]070	1.112[illegible]	1.6427	0.5520	-1.[illegible]716	-2.1387
		TH	88.2690	86.921[illegible]	75.2933	50.5926	28.0515	14.6292
		LT	[illegible].0793	0.0805	0.093	0.1384	[illegible].2495	0.4785
		B_t	3 3 3	3 3 3	3 3 3	3 3 3	3 3 3	2 3 3
	8	ER	8.8284	8.6968	[illegible].5953	5.2045	2.8917	1.4862
		EC	8.3697	7.9294	6.[illegible]117	4.74[illegible]	4.0861	3.8516
		EN	0.4586	0.7674	1.3[illegible]36	0.4[illegible]11	-1.1944	-2.3654
		TH	88.2836	86.9680	75.95[illegible]5	5[illegible].0452	28.9169	14.8621
		LT	0.0906	0.0920	0.1053	0.1537	0.2767	0.5383
		B_t	3 3 3	3 3 3	3 3 3	3 3 3	3 3 3	3 3 3
	9	ER	8.8285	8.6974	7.61[illegible]	[illegible].2615	2.9250	1.4942
		EC	8.7197	8.2794	6.[illegible]586	5.[illegible]788	4.4465	4.2355
		EN	0.1088	0.4180	[illegible].0528	0.1[illegible]27	-1.5215	-2.7413
		TH	88.2851	86.9738	76.1143	52.615[illegible]	29.2500	14.9421
		LT	0.1019	0.103[illegible]	0.1182	0.1711	0.3077	0.6023
		B_t	[illegible]	3 [illegible] 3	3 3 3	3 3 3	[illegible] 3 3	3 3 3
	10	ER	8.8285	[illegible].6974	7.6114	5.2615	2.[illegible]250	1.4942
		EC	9.06[illegible]	8.6294	6.9109	5.4740	4.99[illegible]2	4.9509
		EN	[illegible].2412	0.0680	0.7005	-0.2125	-2.0652	-3.4567
		TH	88.2851	86.9738	76.1143	52.6154	29.2500	[illegible]
		LT	0.1133	0.1150	0.1314	0.1901	0.3419	0.66[illegible]8
		B_t	3 3 3	3 3 3	3 3 3	3 3 3	3 3 3	3 3 3
				9				

Table 10.2.3 Pair-matrix table: Ordered-entry type and ellipse

Supply / Demand			m					
			0.0100	0.0125	0.0250	0.0500	0.1000	0.2000
	1	ER	4.7368	4.2353	2.7692	1.6364	0.9000	0.4737
		EC	6.8079	6.6853	6.3269	6.0500	5.8700	5.7658
		EN	[illegible]	−2.4500	−3.5577	−4.4136	−4.9700	−5.2921
		TH	[illegible]	42.3529	27.6923	16.3636	9.0000	4.7368
		LT	0.0211	0.0236	0.0361	0.0611	0.1111	0.2111
		B_t	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1
	2	ER	7.4187	[illegible]	5.0595	3.1680	1.7822	0.9448
		EC	6.5679	[illegible]	5.4173	4.7152	4.2792	4.0431
		EN	0.8508	[illegible]	−0.3578	−1.5472	−2.4970	−3.0983
		TH	74.1866	69.3484	50.5946	31.6800	17.8218	9.4475
		LT	0.0270	0.0288	0.0395	0.0631	0.1122	0.2117
		B_t	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1
	3	ER	8.5494	8.2869	[illegible]	4.5639	2.6424	[illegible]
		EC	6.7948	6.4213	[illegible]	3.6848	2.8322	2.3855
		EN	1.7546	1.8656	[illegible]	0.8791	[illegible]	−0.9727
		TH	85.4935	82.8693	[illegible]	45.6389	[illegible]	14.1284
		LT	0.0351	0.0362	0.0443	0.0657	0.1135	0.2123
		B_t	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1
	4	ER	[illegible]	8.6226	7.4244	[illegible]	2.7587	1.4425
		EC	7.0223	6.6125	5.0794	[illegible]	2.9394	2.6085
		EN	[illegible]	2.0101	2.345	[illegible]	−0.1808	−1.1661
		TH	[illegible]	86.2264	74.2437	[illegible]	27.5867	14.4245
		LT	[illegible]	0.0464	[illegible]	[illegible]	0.1450	0.2773
		B_t	1 2 1	1 2 1	[illegible]	1 1 2	1 1 2	1 1 2
	5	ER	[illegible]	8.8551	[illegible]	5.2210	2.8582	1.4695
N		EC	[illegible]	6.9244	5.1792	3.6981	3.0702	2.8396
		EN	1.5820	1.9307	2.6221	1.5229	−0.2120	[illegible]
		TH	89.0226	[illegible]	78.0122	52.2098	28.5820	[illegible]
		LT	0.0562	[illegible]	0.0641	0.0958	[illegible]	[illegible]
		B_t	1 3 1	[illegible]	1 2 2	1 2 2	[illegible]	1 2 2
	6	ER	8.9701	[illegible]	8.1138	5.4430	[illegible]	[illegible]
		EC	7.6629	[illegible]	[illegible]	3.7995	[illegible]	3.0807
		EN	1.3072	[illegible]	2.7219	1.6435	[illegible]	−1.5865
		TH	[illegible]	[illegible]	[illegible]	54.4300	[illegible]	14.9422
		LT	[illegible]	[illegible]	0.0739	0.1102	0.2038	0.4015
		B_t	[illegible]	[illegible]	1 2 3	2 2 2	[illegible]	2 2 2
	7	ER	[illegible]	[illegible]	8.3093	5.6030	[illegible]	1.4965
		EC	[illegible]	7.5270	5.601	3.9912	[illegible]	3.4211
		EN	0.9956	1.4257	2.7082	1.6118	[illegible]	−1.9246
		TH	89.7742	89.5262	83.0925	56.0304	29.6604	[illegible]
		LT	0.0780	0.0782	0.0842	0.1249	0.2360	[illegible]
		B_t	2 4 1	2 3 2	[illegible]	[illegible]	2 2 3	[illegible]
	8	ER	8.9896	8.9732	[illegible]	[illegible]	2.9805	[illegible]
		EC	8.3255	7.8545	[illegible]	[illegible]	3.8533	[illegible]
		EN	0.6641	1.1187	[illegible]	[illegible]	−0.8728	[illegible]
		TH	89.8958	89.7317	[illegible]	56.8854	29.8052	[illegible]
		LT	0.0890	0.0892	0.0943	0.1406	0.2684	[illegible]
		B_t	2 5 1	2 4 2	[illegible]	2 3 3	2 3 3	2 3 3
	9	ER	8.9952	8.9845	[illegible]	5.7699	2.9901	1.4996
		EC	8.6725	8.1920	[illegible]	[illegible]	4.1823	4.1073
		EN	0.3226	0.7926	2.4424	[illegible]	−1.1922	−2.6077
		TH	89.9517	[illegible]	86.1098	[illegible]	29.9006	14.9959
		LT	0.1001	[illegible]	0.1045	[illegible]	0.3010	0.6002
		B_t	2 6 1	[illegible]	2 2 5	2 3 4	3 3 3	3 3 3
	10	ER	8.9952	8.9845	8.611	5.7699	2.9901	1.4996
		EC	[illegible]	8.5437	6.5618	5.2234	5.2001	5.2907
		EN	[illegible]	0.4409	2.0492	0.5465	[illegible]	−3.7911
		TH	[illegible]	89.8455	86.1098	57.6993	[illegible]	14.9959
		LT	0.1112	0.1113	0.1161	0.1733	[illegible]	0.6668
		B_t	2 6 1	2 5 2	2 2 5	2 3 4	3 3 3	3 3 3

Similar to that of the economics, ellipses in reliability are found from pair-pole $(LT_{\min},\ LT_{\max})$, Tables 10.2.2 and 10.2.3. Overall net reward, EN^*, at (6, 0.0250), is positioned at the midpoint of pair-poles, (10, 0.0100) and (3, 0.2000). This phenomenon with four poles is called ellipse-cross theory.

10.2.5.2 Ellipse Strategy

Under the pair-matrix table, we can choose appropriate management strategy $(N^*,\ m^*)$ for demand and supply. Profit and lead time strike a tradeoff. If a manager wants shorter lead time, economic traffic (*N, m*) should be changed to lessen profit. Economic lead time $LT^* = 0.0739$ at (6, 0.0250) (Table 10.2.3), for example, would not be allowed by a customer with permissible lead time $LT_0 = 0.05$, and thus, the number of parts may be changed from $N = 6$ to $N = 4$.

This ellipse strategy is effective in the strategic-reconfigurable problem of manufacturing systems beyond [2]. The pair-matrix table may address the flexible combination of the number of pallets, *N* and machines M (m), under demand speed and production (supply) speed. The production manager would then be able to choose a better configuration for demand and supply by simulation.

The superiority of routing rules depends on the positions in map (*N, m*) and are obtained from Tables 10.2.2, 10.2.3, etc. By three comparisons of economic reward and lead time, it can be seen that hybrid routing is better under both criteria, and maximum $EN^* = 4.9932$ at $(N^*,\ m^*) = (9,\ 0.01)$. Note that dynamic routing may be superior to ordered-entry routing in the case of unlimited local buffers.

References

1. Herrmann, J.W., Order Release, In: P.M. Swamidass (ed.), *Encyclopedia of Production and Manufacturing Management*, Kluwer, Boston, pp. 495–501, 2000
2. Koren, Y., Heisel, U., Jovane, F., Moriwaki, T., Pritschow, G., Ulsoy, G. and Van Brussel, H., Reconfigurable Manufacturing Systems, *CIRP Annals*, 48(2), 527–540, 1999
3. Ma, J. and Matsui, M., Performance Evaluation of a Flexible Machining/Assembly System and Routing Comparisons, *International Journal of Production Research*, 40(7), 1713–1724, 2002
4. Matsui, M., A Game-Theoretic Consideration of Order-Selection and Switch-Over policy, *Preprints of Japan Industrial Management Association*, Fall Meeting, 48–49, 1983 (in Japanese)
5. Matsui, M., On a Joint Policy of Order-Selection and Switch-Over, *Journal of Japan Industrial Management Association*, 39(2), 83–87, 1988 (in Japanese)
6. Matsui, M., Optimal Economic Design of Production and Queueing Systems, *Abstracts of the Third Conference of the Association of Asian-Pacific Operational Research Societies within IFORS (APORS'94)*, Fukuoka, Japan, 266, 1994
7. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
8. Matsui, M., Kobayashi, M. and Yamashita, H., Evaluation of Earliest vs. Ordered – Entry Routing in Central Sever Model, *Preprints of Japan Industrial Management Association*, Spring Meeting, 164–165, 2004 (in Japanese)

9. Matsui, M. and Nakada, Y., Strategic Management/Design Approach to a Job-Shop Production System, *International Journal of Production Research*, 41(14), 3257–3271, 2003
10. Matsui, M., Uehara, S. and Ma, J., Performance Evaluation of Flexible Manufacturing Systems with Finite Local Buffers: Fixed and Dynamic Routings, *International Journal of Flexible Manufacturing Systems*, 13(4), 405–424, 2001
11. Matsui, M. and Wang, L., An Economic/Lead-Time Design Comparison and Map for Central Sever Systems including FMS, *International Journal of Automation Technology*, 1(1), 35–44, 2007
12. Solberg, J.J., A Mathematical Model of Computerized Manufacturing Systems, *4th International Conference on Production Research (ICPR)*, Tokyo, Japan, 22–30, 1977
13. Uehara, S. and Matsui, M., The Performance Evaluation of Flexible Manufacturing Systems with Limited Local Buffers and its Design Problem, *Journal of Japan Industrial Management Association*, 45(5), 467–471, 1994 (in Japanese)
14. Uehara, S. and Matsui, M., The Performance Evaluation of Flexible Manufacturing Systems with Dynamic Routing and its Optimal Configurations, *Journal of Japan Industrial Management Association*, 47(2), 126–134, 1996 (in Japanese)
15. Yao, D.D. and Buzacott, J.A., Models of Flexible Manufacturing Systems with Limited Local Buffers, *International Journal Production Research*, 24(1), 107–108, 1986

Part VI
Demand and Supply Risk Chain

Chapter 11
2MGM Chains and Balancing

11.1 Serial SCM and Balancing

11.1.1 Introduction

A significant number of researches have dealt with supply chain management (SCM) [1, 3]. Many studies have focused on the bullwhip effects and win-win strategy problems in the supply chain. The latter is generally treated as a problem of coordination/contract in enterprises.

This problem is here considered as a supply chain balancing issue in profit (economics) and lead time (reliability) [6]. Then, the supply chain is assumed to be the two-chain model consisting of the Management Game Models (MGMs) of service (sales) and manufacturing types [5, 7].

For balancing issues, the concept of integral optimization is first introduced in Chapter 2.2. The integral optimization in profit and lead time (workload) is the condition of integral balancing in a win-win strategy. This condition is discussed on the basis of the pair-matrix table (map) in MGM [9].

11.1.2 Balancing Problem

11.1.2.1 General Problem

The object of SCM is outlined in Fig. 11.1.1. The problem of SCM is to optimize the profit totally through the supply chain shown in Fig. 11.1.1, and to speed up the management by the reduction of lead time.

This problem is typically formulated as follows :

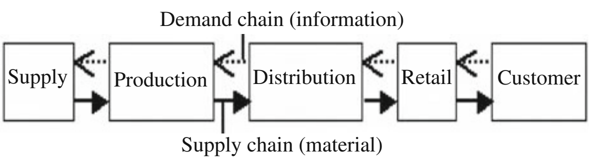


Fig. 11.1.1 The object of SCM

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_20,

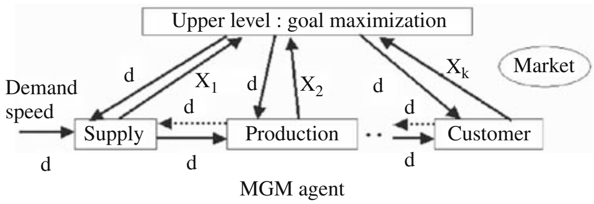


Fig. 11.1.2 Two-level of SCM structure: Is duality division possible?

$$\text{Goal: Marginal Profit} = \text{Revenue} - \text{Operating Cost} \rightarrow \max \tag{11.1.1}$$

$$\text{Constraints: Resource, Lead time, Environment, and soon.} \tag{11.1.2}$$

In this case, the collaboration of cost reduction and demand creation is important, and the cooperative game approach is introduced.

The SCM has a two-level structure [4] as shown in Fig. 11.1.2. If the structure is possible in duality division, the SCM can be handled in the conventional frame. However, it is impossible in duality division at a glance, and thus, it is the interest of this study.

This problem is optimistically the gain-sharing problem of the inter-enterprise, while it seems pessimistically to be the risk allocation problem such as the stock. For the reason, it is valuable to consider the upper level that adjusts the balancing of inter-enterprise (MGM agent).

11.1.2.2 M-M SCM Model

In [6], examples of MGM modeling are classified into two types: Series and parallel types of MGMs. For the series type, a general formulation and example are given in [8] under M/M enterprise type.

For win-win exploration, the focused series type is the Marketing-Manufacturing SCM model (M-M SCM). This model consists of a two-chain SCM of Marketing-MGM (MGM1) and manufacturing MGM (MGM2). The simple SCM and Assembly SCM models of marketing and manufacturing types also exist.

These two-chain SCM model is common as shown in Fig. 11.1.3. Figure 11.1.3 shows that customers arrive at demand speed, d, and are delivered at the speed, d. Under the condition, the pricing setting, p_i, and stock level, N_1, are considered.

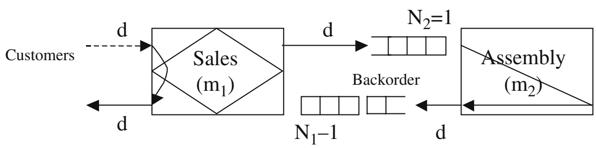


Fig. 11.1.3 Marketing-manufacturing SCM model

11.1.3 Formulation and Objectives

11.1.3.1 SCM Formulation

The objective functions in MGMs are as follows:

ER_i: Mean sales reward per unit time
EC_i: Mean operating cost per unit time
EN_i ($= ER_i - EC_i$): Net reward (marginal profit)
BT_i: Mean workload

where $i = \text{MGM}1,\ 2$.

Then, the M-M SCM model is generally formulated in [6, 8] as follows:

$$\text{Main goal}: MEN = (ER_1 + ER_2) - (EC_1 + EC_2) \to \max \tag{11.1.3}$$

$$\text{or, Dual goal}: DEN = (ER_1 - EC_1)^+ + (ER_2 - EC_2)^+ \to \max \tag{11.1.4}$$

(Economics)

subject to :

$$W = BT_1 + BT_2 \to \max. \qquad \text{(Reliability)} \tag{11.1.5}$$

Especially, if the following conditions are satisfied:

$$EN_1 \fallingdotseq EN_2 \text{ and } BT_1 \fallingdotseq BT_2, \tag{11.1.6}$$

It is said that the integral balancing would hold. Then, $p_2 = (EN_1 + EN_2)/2$, and this condition indicates stronger balancing than with Win-Win.

11.1.3.2 Objective Functions

The MGMs in the respective companies are assumed to be an *M/M* queueing type [2]. For Markovian queus with back-orders, the following notation is introduced:

d: Mean interarrival time of customers (cycle time)
m_1: Mean processing time of marketing-MGM
m_2: Mean processing time of manufacturing-MGM
N_1: Stock level of products at marketing-MGM
N_2: Stock level in process at manufacturing-MGM
K: Number of workstations in manufacturing (assembly line)
α_{0i}: Cost coefficient of back-orders
α_{1i}: Cost coefficient of inventory

α_{2i}: Cost coefficient of busy rate
α_{3i}: Cost coefficient of idle rate

where $i = 1,\ 2$. Note that $\alpha_{12} > \alpha_{13}$ and $\alpha_{12} = \varepsilon/m_1^2$ for marketing-MGM, and $\alpha_{22} < \alpha_{23}$ for manufacturing-MGM, which ε is a coefficient [7].

In SCM formulation, the common marketing enterprise is based on *M/M/*1 (N) queues with back-orders, and the manufacturing enterprises are based on *M/M/1* (K) queues with back-orders. Capacity (K) in *M/M/1* (K) corresponded here to the number of series processes.

In formulations (11.1.3)–(11.1.5), the objective functions are easily given from the queueing theory as follows:

(i) Marketing Case

$$ER_1 = \frac{p_1 - p_2}{d}, \tag{11.1.7}$$

$$ER_2 = \frac{p_2 - p_3}{d}. \tag{11.1.8}$$

(ii) Simple SCM Case ($K = 1$)

$$\begin{aligned} EC_i &= \alpha_{0i}\frac{(N_i+1)\rho_i^{N_i+1}}{1-\rho_i^{N_i+1}} + \alpha_{1i}\rho_i\frac{1-(N_i+1)\rho_i^{N_i}+N_i\rho_i^{N_i+1}}{(1-\rho_i)(1-\rho_i^{N_i+1})} \\ &\quad + \alpha_{2i}\rho_i + a_{3i}(1-\rho_i), \end{aligned} \tag{11.1.9}$$

$$BT_i\,(= m_iL_i) = m_i\rho_i\frac{1-(N_i+1)\rho_i^{N_i}+N_i\rho_i^{N_i+1}}{(1-\rho_i)(1-\rho_i^{N_i+1})}, \tag{11.1.10}$$

where $\rho_i = {}^{m_i}\!/_{d}$ *and* $i = 1,\ 2$.

(iii) Assembly SCM Case ($K \neq 1$)

$$\begin{aligned} EC_1 &= \alpha_0\frac{(N_1+1){\rho_1}^{N_1+1}}{1-{\rho_1}^{N_1+1}} + \alpha_1\rho_1\frac{1-(N_1+1){\rho_1}^{N_1}+N_1{\rho_1}^{N_1+1}}{(1-\rho_1)(1-{\rho_1}^{N_1+1})} \\ &\quad + \alpha_2\rho_1 + \alpha_3(1-\rho_1), \end{aligned} \tag{11.1.11}$$

$$EC_2 = \alpha_0 \frac{(K+1){\rho_2}^{K+1}}{1-{\rho_2}^{K+1}} + \alpha_1 K + \alpha_2 K \rho_2 + \alpha_3 \left\{ K - \rho_2 \frac{1 - K{\rho_2}^{K-1} + (K-1){\rho_2}^{k}}{(1-\rho_2)(1-{\rho_2}^{K})} \right\}, \tag{11.1.12}$$

$$BT_1 = m_1 \times L_1 = m_1 \rho_1 \frac{1-(N_1+1){\rho_1}^{N_1} + N_1 {\rho_1}^{N_1+1}}{(1-\rho_1)(1-{\rho_1}^{N_1+1})}, \tag{11.1.13}$$

$$BT_2 = m_2 \times K. \tag{11.1.14}$$

11.1.4 Simple SCM Case

11.1.4.1 Parameter Setting

For the simple SCM case, a numerical example is considered here. Its parameter setting is as seen in Table 11.1.1. In particular, the setting of stock level, N_1, is noted from the view of Figs. 11.1.4 and 11.1.5.

In Fig. 11.1.4, the back-order in the marketing enterprise becomes larger when the processing time, m_1, is larger, and it is near the demand speed, $d(= 1.0)$. However, the effect of back-orders decreases according to the increase of N_1.

Table 11.1.1 Parameter setting: Single case

$d = 1.00$	Marketing	Manufacuturing
N	10	1
p	$p_1 = 20$	$p_2 = 14$, $p_3 = 6$
α_0	1	0.66
α_1	1	1
α_2	$\varepsilon = 1.0$	1
α_3	1	10

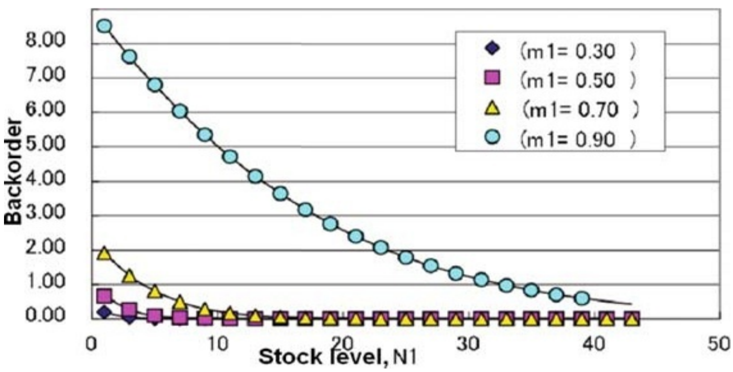


Fig. 11.1.4 Effect of capacity N_1 by m_1

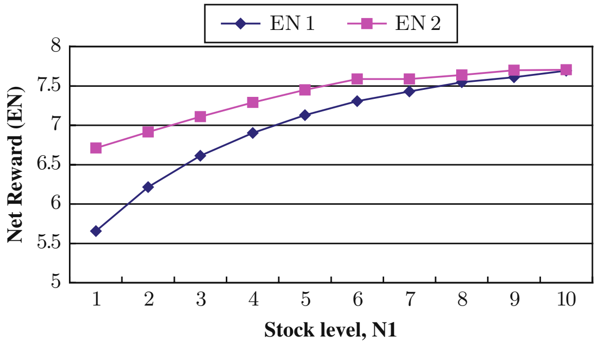


Fig. 11.1.5 Effect of capacity N_1 in EN_1 and EN_2 ($m_1 = 0.32$)

Then, it is seen in Fig. 11.1.5 that the difference of EN_1 and EN_2 is smaller according to the increase of N_1, and is near zero when the stock level, N_1, is larger than 10. Thus, the stock level, N_1, is set to 10 as shown in Table 11.1.1.

11.1.4.2 Integral Balancing

The balancing example of marketing and manufacturing enterprises is possible at the parameter setting shown in Table 11.1.1. The behavioral map in (m_1, m_2) balancing is seen in Fig. 11.1.6, and the integral balancing in economics (EN) and reliability (BT) exists in the area of $m_1 < m_2$.

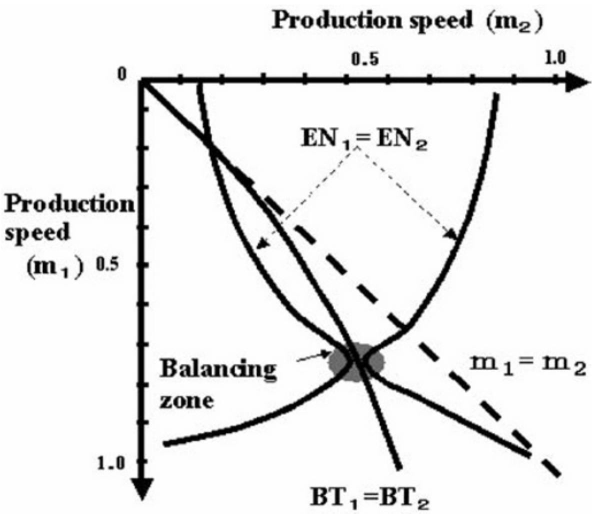


Fig. 11.1.6 Behavioral map in balancing

Table 11.1.2 Ellipse theory of SCM: simple case ($K = 1$)

m1		m2	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
	BT1	BT2	0.009	0.033	0.069	0.114	0.167	0.225	0.288	0.356	0.426
	EN1	EN2	[illegible]	−0.422	0.339	1.063	1.727	2.283	2.620	2.409	−0.001
0.10	0.011	BT1+BT2	0.020	0.248	0.267	0.286	0.306	0.326	0.346	0.367	[illegible]
	−5.011	EN1+EN2	−6.215	−5.433	−4.672	−3.948	−3.284	−2.729	−2.391	−2.602	−5.012
0.20	0.050	BT1+BT2	0.059	0.248	0.267	[illegible]	0.306	0.326	0.346	0.367	0.387
	−0.050	EN1+EN2	[illegible]	−0.472	0.289	1.013	[illegible]	[illegible]	2.570	2.359	−0.051
0.30	0.129	BT1+BT2	[illegible]	0.287	0.306	0.325	[illegible]	0.365	0.385	0.406	0.426
	1.538	EN1+EN2	0.334	1.116	1.877	2.601	3.265	[illegible]	4.158	3.947	[illegible]
0.40	0.266	BT1+BT2	0.276	0.300	0.336	[illegible]	0.433	0.491	0.555	0.622	[illegible]
	2.233	EN1+EN2	1.029	[illegible]	2.572	3.296	3.960	4.516	[illegible]	4.642	2.232
0.50	0.497	BT1+BT2	0.506	0.531	[illegible]	0.612	0.664	0.722	[illegible]	[illegible]	0.924
	2.500	EN1+EN2	1.296	2.078	[illegible]	3.563	4.227	4.783	5.120	[illegible]	2.499
0.60	0.876	BT1+BT2	0.885	[illegible]	[illegible]	0.990	1.043	1.101	[illegible]	[illegible]	1.302
	2.433	EN1+EN2	1.229	2.012	2.772	[illegible]	4.160	4.716	[illegible]	4.842	2.432
0.70	1.478	BT1+BT2	[illegible]	1.511	1.547	[illegible]	1.645	[illegible]	1.766	1.834	[illegible]
	1.938	EN1+EN2	[illegible]	1.516	2.277	3.001	[illegible]	4.221	4.558	4.347	[illegible]
0.80	2.373	BT1+BT2	2.382	2.406	2.442	2.487	[illegible]	2.598	2.661	2.729	2.799
	0.550	EN1+EN2	−0.654	0.128	0.889	[illegible]	2.277	[illegible]	3.170	2.959	0.549
0.90	3.572	BT1+BT2	3.582	3.606	3.642	3.687	3.739	3.797	[illegible]	3.928	3.999
	−4.211	EN1+EN2	−5.415	−4.633	[illegible]	−3.148	−2.484	−1.929	−1.591	[illegible]	−4.212

Then, an example of (m_1, m_2)-balancing is shown in Table 11.1.2, and is here called the ellipse theory of SCM on the table of balance matrix. The balancing point is seen at $m_1 = 0.42$ and $m_2 = 0.66$, and attains the maximum value of total net reward $(EN_1 + EN_2)$.

11.1.5 Assembly SCM Case

11.1.5.1 Parameter Setting

For the assembly of SCM case, a numerical example is also considered. This parameter setting is seen in Table 11.1.3. In this case, the setting of processing stages, K, is noted from the view of Figure 11.1.7.

In Fig. 11.1.7, it is seen that the optimal processing time, m_2^*, maximizing the net reward, EN_2, exists, and is different for each K. For simplicity, the number of workstations in the assembly line is set here to $K = 3$.

Table 11.1.3 Parameter setting: Assembly case

$d = 0.58$	Marketing	Manufacuturing
N_1, K	$N_1 = 25$	K = 3
p	$p_1 = 25$	$p_2 = 17$, $p_3 = 7$
α_0	1	2
α_1	1	1
α_2	$\varepsilon = 2.0$	1
α_3	11	10

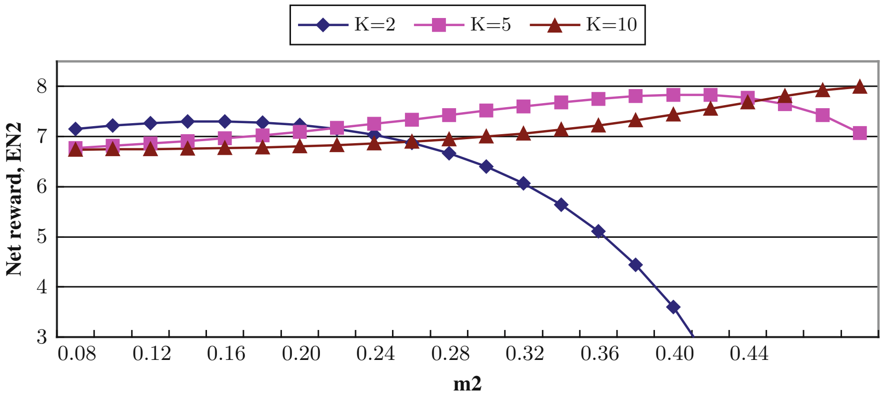


Fig. 11.1.7 Effect of work stations, K, by m_2

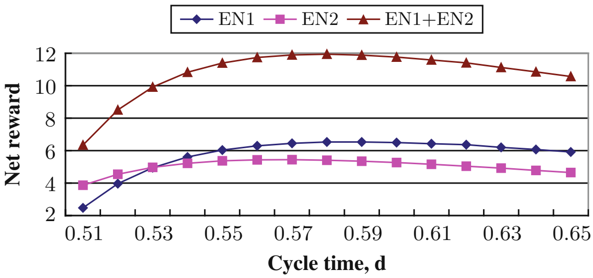


Fig. 11.1.8 Cycle time and net reward

Table 11.1.4 Ellipse theory of SCM: assembly case ($K = 3$)

m1		m2	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
	BT1	BT2	0.300	0.450	0.600	0.750	0.900	1.050	1.200	1.350	1.500
	EN1	EN2	6.710	6.958	7.185	7.370	7.484	7.486	7.298	6.725	5.094
0.20	0.105	BT1+BT2	0.410	0.560	0.710	0.860	1.010	1.160	1.310	1.460	1.610
	5.784	EN1+EN2	12.494	12.744	12.974	13.154	13.264	13.274	13.084	12.514	10.874
0.23	0.151	BT1+BT2	0.451	0.601	0.751	0.901	1.051	1.201	1.351	1.501	1.651
	6.181	EN1+EN2	12.891	13.141	13.371	13.551	13.661	13.671	13.481	12.911	11.271
0.26	0.211	BT1+BT2	0.511	0.661	0.811	0.961	1.111	1.261	1.411	1.561	1.711
	6.553	EN1+EN2	13.263	13.513	13.743	13.923	14.033	14.043	13.853	13.283	11.643
0.29	0.290	BT1+BT2	0.590	0.740	0.890	1.040	1.190	1.340	1.490	1.640	1.790
	6.893	EN1+EN2	13.603	13.853	14.083	14.263	14.373	14.383	14.193	13.623	11.983
0.32	0.393	BT1+BT2	0.693	0.843	0.993	1.143	1.293	1.443	1.593	1.743	1.893
	7.190	EN1+EN2	13.900	14.150	14.380	14.560	14.670	14.680	14.490	13.920	12.280
0.35	0.531	BT1+BT2	0.831	0.981	1.131	1.281	1.431	1.581	1.731	1.881	2.031
	7.427	EN1+EN2	14.137	14.387	14.617	14.797	14.907	14.917	14.727	14.157	12.517
0.38	0.715	BT1+BT2	1.015	1.165	1.315	1.465	1.615	1.765	1.915	2.065	2.215
	7.576	EN1+EN2	14.286	14.536	14.766	14.946	15.056	15.066	14.876	14.306	12.666
0.41	0.963	BT1+BT2	1.263	1.413	1.563	1.713	1.863	2.013	2.163	2.313	2.463
	7.592	EN1+EN2	14.302	14.552	14.782	14.962	15.072	15.082	14.892	14.322	12.682
0.44	1.297	BT1+BT2	1.597	1.747	1.897	2.047	2.197	2.347	2.497	2.647	2.797
	7.388	EN1+EN2	14.098	14.348	14.578	14.758	14.868	14.878	14.688	14.118	12.478
0.47	1.739	BT1+BT2	2.039	2.189	2.339	2.489	2.639	2.789	2.939	3.089	3.239
	6.786	EN1+EN2	13.496	13.746	13.976	14.156	14.266	14.276	14.086	13.516	11.876
0.50	2.304	BT1+BT2	2.604	2.754	2.904	3.054	3.204	3.354	3.504	3.654	3.804
	5.336	EN1+EN2	12.046	12.296	12.526	12.706	12.816	12.826	12.636	12.066	10.426
0.53	2.993	BT1+BT2	3.293	3.443	3.593	3.743	3.893	4.043	4.193	4.343	4.493
	1.514	EN1+EN2	8.224	8.474	8.704	8.884	8.994	9.004	8.814	8.244	6.604

11.1.5.2 Ellipse Theory of SCM

The balancing example of marketing and assembly enterprises is possible at the parameter setting shown in Table 11.1.3. The optimal demand speed (cycle time) is set to $d_2^* = 0.58$ at the total profit of win-win from Fig. 11.1.8.

Similar to Table 11.1.2, the ellipse theory of SCM is again seen on the balance-matrix table in Table 11.1.4. It is noted that the ellipse in economics (EN) intersects the ellipse in reliability (BT) for both cases.

References

1. Beamon, B.M., Supply Chain Design and Analysis: Models and Methods, *International Journal of Production Economics*, 55, 281–294, 1998
2. Cox, D.R. and Smith, W.L., *Queues*, Chapman & Hall, London, 1961
3. de Kok, A.G. and Graves, S.C. (eds.), *Supply Chain Management: Design, Coordination and Operation*, Elsevier, Amsterdam, 2003
4. Lasdon, L.S., *Optimization Theory of Large Systems*, Macmillan, NY, 1970
5. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Prancing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
6. Matsui, M., MGM-Modeling and Balancing Problem in Supply Chain Management, *Proceedings of APIEMS 2004*, Gold Coast, Australia, 2004 (on CD-ROM)
7. Matsui, M., Management Game Theory: Manufacturing vs. Service Enterprise Type, *International Journal of Productivity and Quality Management*, 1(1/2), 103–115, 2006
8. Matsui, M. and Ichihara, S., A Game Approach to SCM: Modeling, Formulation and Integral Optimization, *Journal of Japan Society of Logistics Systems*, 4(1), 67–80, 2003 (in Japanese)
9. Matsui, M. and Motohashi, M., A Basic Study for Strategic Supply Chain Balancing, *Journal of Japan Society of Logistics Systems*, 7(1), 21–31, 2007

11.2 Make-or-Buy and Retail SCMs

11.2.1 Introduction

In modern society, enterprises are inter-connected with each other, and the supply chain forms a flow/value network of enterprises. Generally, the profitability of supply chain structures would be different in an institutional/sustainable environment. Multiechelon systems are well known as a traditional model of supply chain structures [1].

There are the problems of flow coordination and information sharing in a supply chain [15]. The literature of coordination focuses on the management of incentive conflicts with contracts [3]. On the other hand, that of information focuses on the Bullwhip effect in the multistage system [4].

Our coordination approach deals with autonomous balancing by the sharing of cycle-time information. For this study, we recently examined a fundamental approach in [8] by the station-centered approach [6, 13]. A new challengeable trial is already seen in a two-serial supply chain [10, 11].

Then, the win-win problem in a supply chain is extended to a world of multiple win-win relations, and also, this problem is related to an equilibrium/balancing condition and network flow/value of an invisible hand [16]. Our main concern deals with the win-win balancing and how it can cause all enterprises to achieve the maximal profit in the institutional view [10].

This chapter treats another type of win-win strategy in a parallel supply chain, and discusses the ellipse hypothesis of SCM for win-win balancing [9, 12]. This hypothesis originated in [7, 10], and means the ellipse-cross theory that the ellipse shape with pair-poles of economics is cross to that with pair-poles of reliability in balance matrix. At the cross point, the total profit becomes maximal, even-profit, and even-workload.

This interesting hypothesis is considered here by the two Markovian models. These models are two simple types of make-or-buy and supply-retailers network systems, and it would be better to treat them by a system-centered approach. This study contributes to the development of an equilibrium/balancing condition in the institutional system of SCM.

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_21, © Springer Science+Business Media, LLC 2009

11.2.2 Overview of the Research

11.2.2.1 Balancing View

The type of the problem is an institutional system of a global supply chain shown in Fig. 11.2.1. The classical coordination of each enterprise is usually tried by price, resource [5], contract/gaming [3] and so on.

Our coordination approach involves autonomous balancing in profit/time by cycle-time sharing. There are the two types of series and ordered-entries in a supply chain [8]. An approach to a series type is seen in [10, 12]. For the ordered-entry type, the types of manufacturing and sales are seen in Fig. 11.2.1, and are treated here.

11.2.2.2 Ellipse Theory of SCM

The ellipse theory of enterprises was first found in a pair-matrix table for a two-center model consisting of sales and production centers [10, 11]. The pair matrix is formed by an input (demand) variable in column and output (supply) in row. This theory also involves the ellipse-cross theory of economics and reliability.

The theory of economics has two poles of revenue maximum and cost minimum, and the profit maximum is located at their medium zone. Also, the theory of reliability has the two poles of lead time minimum and maximum. Then, the two medium zones are the cross-region in two ellipses.

Recently, the ellipse hypothesis of SCM is proposed in a series chain by Matsui and Omori [11]. Figure 11.2.2 shows the ellipse-cross theory of economics and reliability on the balance matrix formed by the respective processing speeds of enterprises.

11.2.3 Two Parallel Models

For the study, we present two parallel models consisting of heterogeneous enterprises (agents). These situations were assumed under a different institutional

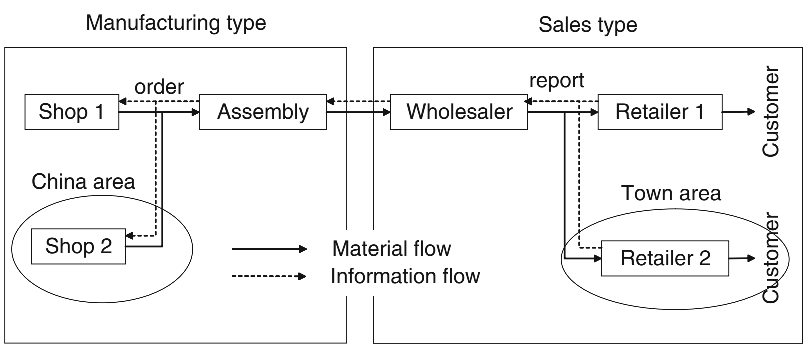


Fig. 11.2.1 An institutional system of supply chain

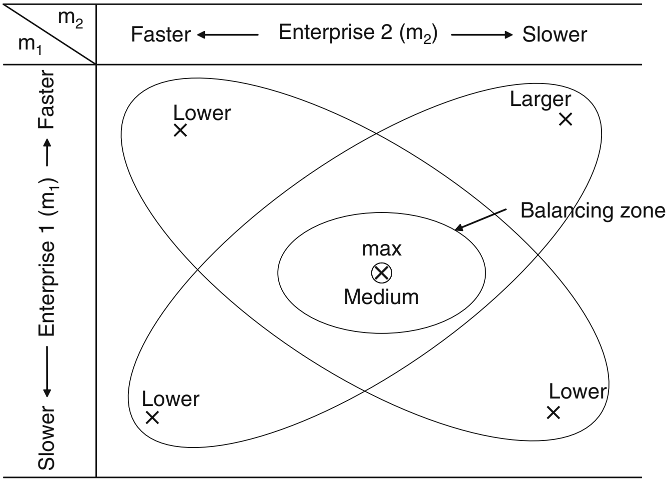


Fig. 11.2.2 Ellipse hypothesis of SCM

environment in past researches. One parallel model is a manufacturing type of make-or-buy, and the other is a sales type of supplier-retailers.

11.2.3.1 Manufacturing Type

The first model consists of two communicated make-to-order enterprises as shown in Fig. 11.2.3. Suppose that Job-shop 1 is a domestic and high-cost shop, while Job-shop 2 is in China and a low-cost shop. Profitable orders are accepted at Job-shop 1, and rejected orders are accepted at Job-shop 2.

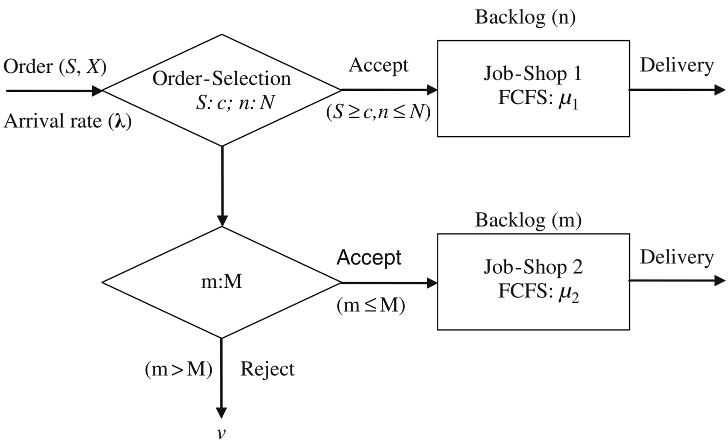


Fig. 11.2.3 Manufacturing type model

The following assumptions and notations are added:

1. The arrival patterns of orders is a Poisson distribution with rate λ.
2. The marginal profit of orders, S, has an exponential distribution with a mean of 1.
3. The processing time of the shops is the exponential distribution with rates, μ_1 and μ_2, respectively.
4. At Job-shop 1, the arriving orders are screened until the stock level of backlog is N, by selection criterion, c ($0 \leq c \leq \propto$). The rejected orders are removed to Job-shop 2, and are accepted till the stock level of backlog is M. The overflow rate from Enterprise 2, v, is lost.

Thus, Job-shop 1 decides the make-or-buy action without comeback by a selection criterion (input speed), c, and it may have the stock level of backlog, N. Job-shop 2 may have the stock level of backlog, M, and if the number of backlogs are over M, then an arrived order is lost. Job-shop 2 communicates with Job-shop 1, but both are in a noncooperative relation.

11.2.3.2 Sales Type

The second model is a multi-echelon system, and consists of a supplier and two order retailers as shown in Fig. 11.2.4. The following assumptions and notations are added:

1. The demand patterns at retailers are a Poisson distribution with rates, μ_1 and μ_2, respectively.
2. The retailers sell the goods at price, p_2. If each stock of the retailers is sold out, an arriving customer is lost to the respective retailers. The number of lost items is denoted by $Ki,\ i = 1,\ 2$.
3. The truck is first routed from the supplier to Retailer 1, and if it is replenished until stock level, N, it removes to Retailer 2 with negligible delay.
4. The overflow rate from Retailer 2, v, is returned to the supplier.

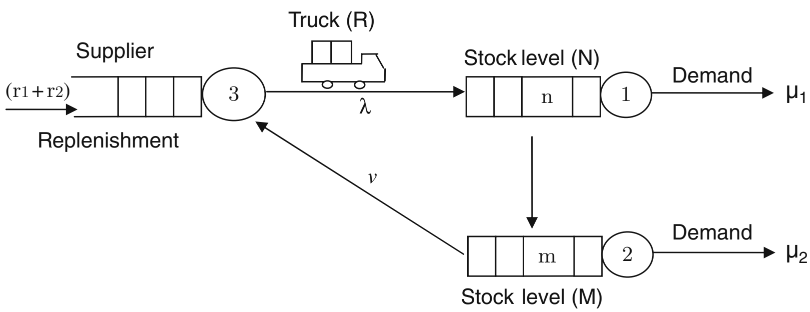


Fig. 11.2.4 Retailer type model

The supplier has an infinite capacity, but the two heterogeneous retailers have the stock level of N and M, respectively, in VMI manner. Also, the supplier has a truck with capacity (travel time) R, and replenishes the goods (at price p_1) to the retailers at the approximate rate (input speed), λ.

Also, the goal is the integral balancing of the system. Integral balancing means that both economics (profit) and reliability (lead time) hold in win-win balancing. For economics, the objective criterion is the positive sum of each profit in the enterprises. This integral profit is represented as follows:

$$DEN = (ER_1 - EC_1)^+ + (ER_2 - EC_2)^+ \to \max_{c \text{ or } \lambda}, \tag{11.2.1}$$

where ER_i and EC_i are the revenue and operating cost per unit time of enterprise $i\ (=1,\ 2)$, respectively. If the difference $(ER_\mathrm{i} - EC_\mathrm{i})$ is positive, DEN is replaced by MEN.

For reliability, the mean workload is used as the other balancing measure instead of lead time, and is given by

$$BT_i = L_i/\mu_i,\ i = 1, 2 \tag{11.2.2}$$

where L_i is the mean number of units, and μ_i is the processing rate, and the objective criterion is the optimization of the sum:

$$BT = BT_1 + BT_2 \to \min_{c \text{ or } \lambda}. \tag{11.2.3}$$

11.2.4 Markovian Analysis

The two types of models are a Markovian queueing network and may be analyzed by the corresponding birth and death processes [14]. Let us denote the state of the system by a pair (n, m), in which $n\ (\le N)$ and $m\ (\le M)$ is the number of backlogs (goods) in Job-shops (retailers) 1 and 2, respectively.

Then, the steady-state probabilities, $\pi(n, m)$'s, may be given by the system of equilibrium equations, in which the transition rates are summarized in Table 11.2.1. These equations are easily solved by a personal computer, and the steady-state probabilities are obtained computationally.

Table 11.2.1 A summary of transition rates

State transition	Manufacturing type	Retailers' type
$(\mathrm{n},\ \mathrm{m}) \to (\mathrm{n}+1,\ \mathrm{m})$	λ_e^{-c}	λ
$(\mathrm{n},\ \mathrm{m}) \leftarrow (\mathrm{n}+1,\ \mathrm{m})$	μ_1	μ_1
$(\mathrm{n},\ \mathrm{m}) \to (\mathrm{n},\ \mathrm{m}+1)$	$\lambda(1-e^{-c})$	$0(n < N),\ \lambda(n = N)$
$(\mathrm{n},\ \mathrm{m}) \leftarrow (\mathrm{n},\ \mathrm{m}+1)$	μ_2	μ_2

11.2.4.1 Manufacturing Type

By using the steady-state probabilities, $\pi(n, m)$'s, the objective functions of production type are easily obtained as follows:

$$ER_1 = \lambda(1 + c)e^{-c} \sum_{m=0}^{M} \sum_{n=0}^{N-1} \pi(n, m), \tag{11.2.4a}$$

$$ER_2 = \lambda\{\sum_{m=0}^{M-1} \pi(N, m) + (1 - e^{-c} - ce^{-c}) \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \pi(n, m)\}, \tag{11.2.4b}$$

$$EC_1 = \alpha_{11} L_1 + \alpha_{21} BP_1 + \alpha_{31}(1 - BP_1), \tag{11.2.5a}$$

$$EC_2 = \alpha_{12} L_2 + \alpha_{22} BP_2 + \alpha_{32}(1 - BP_2), \tag{11.2.5b}$$

where $\alpha_{i,j},\ i = 1,\ 2,\ 3,\ j = 1,\ 2$, are cost coefficients, the busy probabilities, BP_1 and BP_2, are, respectively,

$$BP_1 = \sum_{n=1}^{N} \sum_{m=0}^{M} \pi(n, m), \tag{11.2.6a}$$

$$BP_2 = \sum_{n=0}^{N} \sum_{m=1}^{M} \pi(n, m). \tag{11.2.6b}$$

and the mean number of backlogs, L_1 and L_2, are respectively,

$$L_1 = \sum_{m=1}^{M} \sum_{n=0}^{N} n\pi(n, m), \tag{11.2.7a}$$

$$L_2 = \sum_{n=0}^{N} \sum_{m=1}^{M} m\pi(n, m), \tag{11.2.7b}$$

in Job-shops 1 and 2.

In addition, the mean workloads of job-shops, BT_1 and BT_2, are given directly by the Eq. (11.2.2). These objective criteria are used as the balancing measure of the two job-shops.

11.2.4.2 Sales Type

Similar to the case of manufacturing type, the objective functions of the sales type are easily obtained by using the steady-state probabilities $\pi(n, m)$'s as follows:

$$ER_i = (p_2 - p_1) r_i, \qquad i = 1, 2. \tag{11.2.8}$$

$$EC_i = \alpha_{0i} K_i + \alpha_{1i} L_i + \alpha_{2i} BP_i + \alpha_{3i}(1 - BP_i), \tag{11.2.9}$$

where BP_i's and L_i's are similar to those of Eqs. (11.2.6) and (11.2.7), respectively, and the mean rate of lost sales, LS_1 and LS_2, is given respectively by

$$LS_1 = \sum_{m=0}^{M} \mu_1 \pi(0, m), \tag{11.2.10a}$$

$$LS_2 = \sum_{n=0}^{N} \mu_2 \pi(n, 0), \tag{11.2.10b}$$

In addition, the mean workloads of retailers, BT_1 and BT_2, are given instead of Eq. (11.2.2) by

$$BT_i = L_i / r_i, \quad i = 1, 2. \tag{11.2.11}$$

These objective criteria are used as the balancing measure of the two retailers.

For the supplier, the objective functions of reward and cost are given respectively as follows:

$$ER_3 = p_1(r_1 + r_2), \tag{11.2.12}$$

$$EC_3 = \beta_1 \nu + \beta_2 \lambda R, \tag{11.2.13}$$

where R is the capacity of truck, β_1 and β_2 are cost coefficients, the sales rates, r_1 and r_2, are respectively

$$r_1 = \sum_{m=0}^{M} \sum_{n=1}^{N} \mu_1 \pi(n, m), \tag{11.2.14a}$$

$$r_2 = \sum_{n=0}^{N} \sum_{m=1}^{M} \mu_2 \pi(n, m), \tag{11.2.14b}$$

and the overflow rate from Retailer 2 is as follows:

$$\nu = \lambda - (r_1 + r_2). \tag{11.2.15}$$

11.2.5 Balancing Consideration

For both the types, the problem of ellipse hypothesis is discussed from the point of view that integral balancing of the profit maximization in cooperation is attainable, even if, each agent pursues the self goal in non-cooperation. In [10], it is found that each of the unit-optimizations gives the total optimization in sum nearly, and a realization of an ellipse hypothesis is seen in serial SCM examples [11].

11.2.5.1 Manufacturing Type

This treatment would be tried here for two types of models in parallel SCM, but the problem is not so simple. First, a numerical example is given and considered for a production type. This parameter setting is as follows:

$$\begin{aligned} \lambda = 3.0,\ \mu_1 = 1.0,\ \mu_2 = 2.5 \\ \alpha_{11} = 0.1,\ \alpha_{12} = 0.1 \\ \alpha_{21} = 0.4,\ \alpha_{22} = 0.2 \\ \alpha_{31} = 0.5,\ \alpha_{32} = 0.5 \end{aligned}$$

where $\alpha_{2i} < \alpha_{3i}$ is assumed in utilization [10].

In addition, the setting: $M = 2N$ is added for simplicity. For larger N, Job-Shop 1 becomes better, but the total SCM becomes worse. Thus, it would be intuitively suggested that $N < M$.

Figures 11.2.5 and 11.2.6 show a balancing example on profit and workload, respectively. However, the integral balancing is not seen there. The balancing in

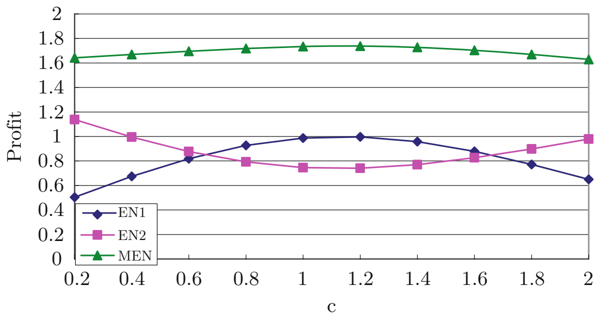


Fig. 11.2.5 Balancing in profit: $\lambda = 3.0,\ N = 3$

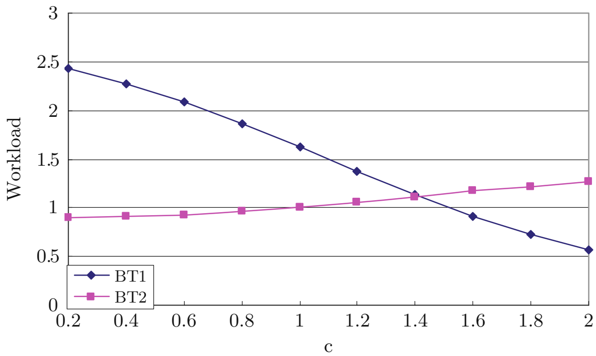


Fig. 11.2.6 Balancing in workload: $\lambda = 3.0,\ N = 3$

profit is attainable at c = 0.6 and 1.6, but the profit maximization occurs at c = 1.2, and the balancing in workload occurs at c = 1.4.

A feature map is seen in the balance matrix (c, N) of the production type. Table 11.2.2 partly shows the ellipse theory of SCM in the meaning that the profit maximization occurs at the ellipse-cross point. However, it is not complete in win-win balancing, and the win-win strategy for the production type would be variant.

11.2.5.2 Sales Type

As in the production type, the ellipse hypothesis is considered in the sales type also. Assume the situation that Retailer 1 is located closer to town than Retailer 2. For this type, a numerical example is given and considered.

The parameter setting here is as follows:

$$p_1 = 1.0, \qquad p_2 = 1.9$$
$$\mu_1 = \mu_2 = 1.2$$
$$\alpha_{0i} = 0.7, \qquad i = 1, 2$$

Table 11.2.2 Balance matrix: manufacturing type

c	N		1		2		3		4		5		6	
0.2	EN1	EN2	0.3528	1.0160	0.5100	1.1242	0.5039	1.1376	0.4416	1.1320	0.3573	1.1196	0.2639	1.1043
	BT1	BT2	0.7107	0.3651	1.5304	0.6541	2.4263	0.9025	3.3698	1.1206	4.3407	1.3107	5.3263	1.4740
	EN	BT	1.3688	1.0758	1.6342	2.1845	1.6415	3.3288	1.5736	4.4905	1.4768	5.6515	1.3681	6.8003
0.4	EN1	EN2	0.4350	0.9531	0.6442	1.0129	0.6741	0.9946	0.6357	0.9690	0.5664	0.9445	0.4821	0.9223
	BT1	BT2	0.6679	0.3724	1.4315	0.6662	2.2714	0.9103	3.1676	1.1199	4.1030	1.3011	5.0639	1.4570
	EN	BT	1.3881	1.0403	1.6572	2.0976	1.6687	3.1817	1.6047	4.2875	1.5109	5.4041	1.4044	6.5209
0.6	EN1	EN2	0.4954	0.9082	0.7507	0.9266	0.8186	0.8768	0.8106	0.8282	0.7649	0.7877	0.6981	0.7546
	BT1	BT2	0.6221	0.3798	1.3193	0.6829	2.0832	0.9284	2.9036	1.1313	3.7702	1.3018	4.6732	1.4460
	EN	BT	1.4036	1.0019	1.6773	2.0022	1.6954	3.0115	1.6388	4.0349	1.5526	5.0720	1.4528	6.1192
0.8	EN1	EN2	0.5334	0.8801	0.8242	0.8684	0.9263	0.7921	0.9509	0.7212	0.9351	0.6630	0.8953	0.6163
	BT1	BT2	0.5741	0.3870	1.1962	0.7036	1.8641	0.9591	2.5753	1.1641	3.3265	1.3285	4.1140	1.4608
	EN	BT	1.4134	0.9611	1.6926	1.8998	1.7184	2.8233	1.6721	3.7394	1.5981	4.6549	1.5116	5.5748
1	EN1	EN2	0.5493	0.8671	0.8612	0.8392	0.9876	0.7462	1.0389	0.6593	1.0517	0.5865	1.0420	0.5274
	BT1	BT2	0.5246	0.3938	1.0656	0.7271	1.6229	1.0025	2.1964	1.2248	2.7859	1.4005	3.3913	1.5363
	EN	BT	1.4163	0.9184	1.7004	1.7927	1.7338	2.6254	1.6981	3.4212	1.6382	4.1864	1.5694	4.9276
1.2	EN1	EN2	0.5443	0.8673	0.8612	0.8376	0.9975	0.7403	1.0625	0.6473	1.0928	0.5674	1.1039	0.5008
	BT1	BT2	0.4747	0.4003	0.9325	0.7519	1.3736	1.0553	1.7981	1.3122	2.2061	1.5256	2.5979	1.6994
	EN	BT	1.4116	0.8749	1.6987	1.6844	1.7377	2.4289	1.7098	3.1104	1.6602	3.7318	1.6047	4.2973
1.4	EN1	EN2	0.5205	0.8788	0.8267	0.8599	0.9580	0.7697	1.0223	0.6801	1.0553	0.5999	1.0720	0.5297
	BT1	BT2	0.4252	0.4062	0.8021	0.7767	1.1326	1.1127	1.4197	1.4160	1.6666	1.6887	1.8770	1.9333
	EN	BT	1.3993	0.8314	1.6866	1.5788	1.7277	2.2453	1.7024	2.8357	1.6552	3.3554	1.6017	3.8103
1.6	EN1	EN2	0.4808	0.8993	0.7633	0.9011	0.8784	0.8258	0.9316	0.7447	0.9576	0.6666	0.9705	0.5920
	BT1	BT2	0.3772	0.4117	0.6790	0.8005	0.9140	1.1697	1.0923	1.5223	1.2244	1.8607	1.3203	2.1868
	EN	BT	1.3800	0.7889	1.6644	1.4795	1.7042	2.0837	1.6764	2.6146	1.6242	3.0852	1.5625	3.5071
1.8	EN1	EN2	0.4282	0.9267	0.6784	0.9556	0.7714	0.8985	0.8100	0.8265	0.8267	0.7489	0.8341	0.6676
	BT1	BT2	0.3315	0.4167	0.5671	0.8224	0.7263	1.2224	0.8291	1.6203	0.8931	2.0183	0.9317	2.4173
	EN	BT	1.3549	0.7482	1.6339	1.3895	1.6699	1.9486	1.6365	2.4495	1.5757	2.9115	1.5016	3.3490
2	EN1	EN2	0.3663	0.9592	0.5797	1.0180	0.6500	0.9787	0.6753	0.9135	0.6847	0.8343	0.6882	0.7447
	BT1	BT2	0.2888	0.4212	0.4683	0.8420	0.5718	1.2688	0.6277	1.7048	0.6565	2.1512	0.6708	2.6081
	EN	BT	1.3255	0.7099	1.5977	1.3103	1.6287	1.8406	1.5888	2.3325	1.5190	2.8077	1.4329	3.2789

* $EN_i = ER_i - EC_i, \ i = 1, \ 2$

$$\alpha_{1i} = 0.03, \qquad i = 1, 2$$
$$\alpha_{3i} = 0.1, \qquad i = 1, 2$$
$$\alpha_{21} = 0.3, \qquad \alpha_{22} = 0.2$$
$$\beta_1 = 0.25, \qquad \beta_2 = 0.1$$

where $\alpha_{2i} > \alpha_{3i}$ is assumed in availability [11].

In addition, the setting, $N + M = 8$, is added for simplicity. This setting focuses on the arrangement of N and M.

Figure 11.2.7 shows a balancing example in profit at λ = 3.2 for both the suppliers and retailers. However, this balancing does not include workload and is not complete (Fig. 11.2.8). That is, it is noted that the balancing in profit becomes possible in a situation of high cost for Retailer 1 and high workload for Retailer 2.

These feature maps are seen in the balance matrix (λ, N) of the sales type (Table 11.2.3). From Table 11.2.3, the ellipse theory of SCM holds partly in the meaning that the profit maximization occurs at positioning (3.2, 3), but this is not at the ellipse-cross point. A new finding is that the two ellipses of economics and reliability are non-cross in supplier-retailers type.

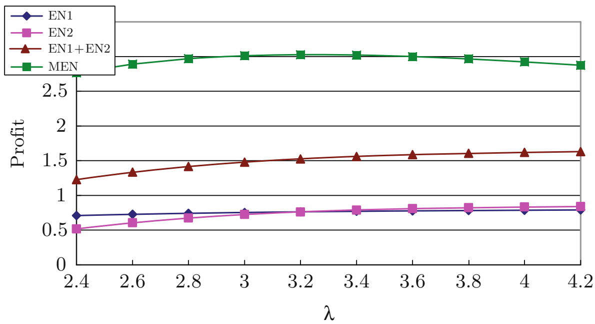


Fig. 11.2.7 Balancing in profit: $N = 3,\ M = 5$ (MEN $= EN_1 + EN_2 + EN_3$)

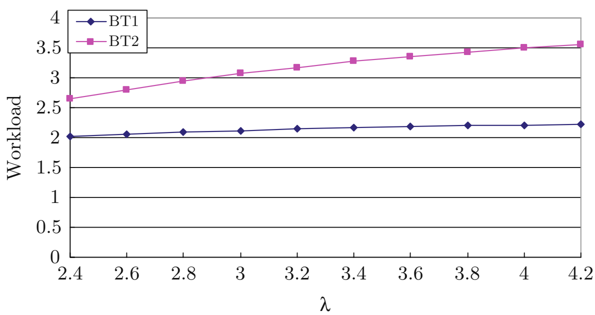


Fig. 11.2.8 Non-Balancing in workload: $N = 3,\ M = 5$

Table 11.2.3 Balance matrix: sales type

λ	N	1		2		3		4		5		6	
2.4	(EN1, EN2)	0.2667	0.7546	0.5943	0.6310	0.7093	0.5180	0.7458	0.4160	0.7479	0.3026	0.7339	0.1427
	BT1,BT2	0.8333	4.1251	1.3889	3.2060	2.0238	2.6485	2.7222	2.1826	3.4677	1.7328	4.2460	1.2829
	(REN, EN3)	1.0212	1.3853	1.2253	1.5311	1.2273	1.5387	1.1618	1.5008	1.0506	1.4314	0.8765	1.3181
	MEN,BT	2.4066	4.9584	2.7564	4.5949	2.7660	4.6723	2.6626	4.9048	2.4820	5.2005	2.1946	5.5290
2.6	(EN1, EN2)	0.2984	0.7813	0.6218	0.6981	0.7280	0.6073	0.7566	0.5161	0.7530	0.4061	0.7352	0.2415
	BT1,BT2	0.8333	4.3757	1.4035	3.4234	2.0583	2.8026	2.7775	2.2803	3.5415	1.7856	4.3345	1.3029
	(REN, EN3)	1.0797	1.3668	1.3200	1.5388	1.3352	1.5545	1.2727	1.5171	1.1591	1.4446	0.9766	1.3240
	MEN,BT	2.4465	5.2091	2.8587	4.8269	2.8897	4.8609	2.7898	5.0578	2.6037	5.3271	2.3006	5.6375
2.8	(EN1, EN2)	0.3270	0.7963	0.6452	0.7447	0.7427	0.6751	0.7643	0.5962	0.7561	0.4922	0.7354	0.3265
	BT1,BT2	0.8333	4.5807	1.4167	3.6138	2.0886	2.9413	2.8247	2.3695	3.6028	1.8340	4.4062	1.3214
	(REN, EN3)	1.1233	1.3358	1.3899	1.5273	1.4177	1.5509	1.3605	1.5160	1.2482	1.4432	1.0619	1.3187
	MEN,BT	2.4591	5.4140	2.9173	5.0304	2.9687	5.0299	2.8766	5.1942	2.6914	5.4368	2.3806	5.7276
3	(EN1, EN2)	0.3529	0.8042	0.6651	0.7763	0.7543	0.7255	0.7699	0.6594	0.7579	0.5632	0.7351	0.3996
	BT1,BT2	0.8333	4.7473	1.4286	3.7780	2.1154	3.0649	2.8654	2.4502	3.6542	1.8785	4.4650	1.3384
	(REN, EN3)	1.1570	1.2963	1.4414	1.5014	1.4799	1.5318	1.4293	1.5005	1.3211	1.4294	1.1347	1.3038
	MEN,BT	2.4533	5.5806	2.9428	5.2065	3.0117	5.1803	2.9299	5.3156	2.7506	5.5327	2.4385	5.8034
3.2	(EN1, EN2)	0.3764	0.8080	0.6823	0.7972	0.7637	0.7626	0.7740	0.7089	0.7589	0.6217	0.7346	0.4624
	BT1,BT2	0.8333	4.8828	1.4394	3.9184	2.1392	3.1740	2.9006	2.5230	3.6978	1.9191	4.5139	1.3542
	(REN, EN3)	1.1844	1.2510	1.4795	1.4646	1.5263	1.5005	1.4829	1.4733	1.3806	1.4055	1.1970	1.2809
	MEN,BT	2.4353	5.7162	2.9441	5.3578	3.0268	5.3132	2.9562	5.4235	2.7861	5.6169	2.4778	5.8681
3.4	(EN1, EN2)	0.3978	0.8095	0.6971	0.8110	0.7713	0.7895	0.7770	0.7474	0.7595	0.6696	0.7339	0.5163
	BT1,BT2	0.8333	4.9937	1.4493	4.0381	2.1604	3.2699	2.9313	2.5883	3.7351	1.9561	4.5551	1.3687
	(REN, EN3)	1.2074	1.2016	1.5080	1.4201	1.5608	1.4599	1.5243	1.4369	1.4291	1.3732	1.2502	1.2512
	MEN,BT	2.4090	5.8270	2.9281	5.4873	3.0207	5.4303	2.9612	5.5196	2.8023	5.6912	2.5015	5.9239
3.6	(EN1, EN2)	0.4175	0.8098	0.7100	0.8198	0.7775	0.8090	0.7792	0.7772	0.7597	0.7089	0.7332	0.5628
	BT1,BT2	0.8333	5.0850	1.4583	4.1398	2.1795	3.3538	2.9583	2.6468	3.7672	1.9900	4.5902	1.3822
	(REN, EN3)	1.2273	1.1494	1.5298	1.3698	1.5865	1.4122	1.5564	1.3932	1.4686	1.3341	1.2960	1.2159
	MEN,BT	2.3766	5.9183	2.8996	5.5982	2.9988	5.5333	2.9496	5.6052	2.8027	5.7572	2.5119	5.9724
3.8	(EN1, EN2)	0.4356	0.8093	0.7213	0.8254	0.7826	0.8231	0.7808	0.8004	0.7597	0.7412	0.7325	0.6029
	BT1,BT2	0.8333	5.1609	1.4667	4.2265	2.1967	3.4273	2.9822	2.6992	3.7952	2.0209	4.6203	1.3947
	(REN, EN3)	1.2449	1.0950	1.5467	1.3154	1.6057	1.3593	1.5812	1.3439	1.5009	1.2895	1.3355	1.1758
	MEN,BT	2.3399	5.9942	2.8621	5.6932	2.9651	5.6239	2.9251	5.6814	2.7904	5.8160	2.5113	6.0151

* $MEN = EN_1 + EN_2 + EN_3$

Remarks

Respite of considerable trials, this chapter shows that the integral balancing does not necessarily hold and will be non-complete in parallel SCM. Probably, the win-win strategy for parallel SCM is an not autonomous but compromise solution in trade-off, and would not be unique and alternative in balancing. The further search should be tried for parallel SCM in integral balancing view. We would hope the development of multiple win-win problem in complex supply chains. The invisible hand in SCM [16] is not simple and may be faced with Braess' paradox [2].

References

1. Axsäter, S., Supply Chain Operations: Serial and Distribution Inventory Systems, In: A.G. de Kok and S.C. Graves (ed.), *Supply Chain Management: Design Coordination and Operation*, Elsevier, Amsterdam, 2003

2. Braess, D., Über ein Paradoxen aus der Verkehrsplanung, Unterehmensforshung, 12, 258–268, 1968
3. Cachon, G., Supply Chain Coordination with Contracts, In: A.G. de Kok and S.C. Graves (eds.), *Supply Chain Management: Design, Coordination and Operation*, Elsevier, Amsterdam, 2003
4. Chen, F., Information Sharing and Supply Chain Coordination, In: A.G. de Kok and S.C. Graves (eds.), *Supply Chain Management: Design, Coordination and Operation*, Elsevier, Amsterdam, 2003
5. Lasdon, L.S., *Optimization Theory for Large Systems*, Macmillan, New York, 1970
6. Matsui, M., Conveyor-Serviced Production System (II): 2-Level Mathematical Formulation and Application, *Preliminary Report of the Operations Research Society of Japan*, Autumn, 92–93, 1982 (in Japanese)
7. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53, 1–9, 2001
8. Matsui, M., MGM-Modeling and Balancing Problem in Supply Chain Management, *Proceedings of APIEMS 2004*, Gold Coast, Australia, 2004 (on CD-ROM).
9. Matsui, M. and Dai, Y., Parallel SCM: Balancing of Make-or-Buy and Retailer Types, *International Workshop on Institutional View of Supply Chain Management*, Tokyo Institute of Technology, Japan, 2006
10. Matsui, M. and Ichihara, S., A Game Approach to SCM: Modeling, Formulation and Integral Optimization, *Journal of Japan Society of Logistics Systems*, 4(1), 67–80, 2003 (in Japanese)
11. Matsui, M. and Motohashi, M., A Basic Study for Strategic Supply Chain Balancing, *Journal of Japan Society for Logistics Systems*, 7(1), 21–31, 2007
12. Matsui, M. and Omori, T., Parallel SCM: A Make-or-Buy Chain Model and Integral Optimization, *Workshop on Inventory Control and Production Planning & Management 2002*, Tokyo Institute of Technology, Japan, 2002
13. Matsui, M., Shingu, T. and Makabe, H., Conveyor-Serviced Production System: An Analytic Framework for Station-centered Approach by Some Queueing Formulas, *Preliminary Report of the Operations Research Society of Japan*, Autumn, 104–107, 1977 (in Japanese)
14. Neuts, M.F., *Matrix-Geometric Solutions in Stochastic Models*, The Johns Hopkins University Press, Maryland, 1981
15. Sahin, F. and Robinson, E.P., Flow Coordination and Information Sharing in Supply Chains: Review, Implications, and Directions for Future Research, *Decision Sciences*, 33, 505–536, 2002
16. Smith, A., *The Wealth of Nations*, Encyclopedia Britannica, 194, 1952

Chapter 12
Manufacturing SCM

12.1 Push Versus Pull System

12.1.1 Introduction

Since 1978 [10], many studies have focused on the pull system [1, 4] in contrast to the traditional push system. A comparison of the push versus pull system is seen in [11], but it is not seen in lot production.

We consider a single-stage lot/cell production in the push [6] and pull [2, 5] queueing systems. It is assumed to have a Poisson arrival and exponential service in batch, and it introduces the expected operating cost in [7, 8].

This chapter presents three economic queueing models of push and pull types, considers an economic comparison of the push versus pull system, and gives a strategic management/design consideration to lot production [9].

12.1.2 Models for Lot Production

12.1.2.1 Assumptions and Notation

Consider the three-queueing systems of the single-stage lot/cell production with finite capacity as shown in Figs. 12.1.1–12.1.3. Figure 12.1.1 shows the push model of a build-to-order (BTO) type, Fig. 12.1.2 shows the push model of a Omote-Kanban type in Japanese naming, and Fig. 12.1.3 shows the pull model of a Kanban type [10]. For simplicity, a Poisson arrival and exponential service in batch are assumed.

The symbols used are seen below.

D: Total amount of demand
N: Number of Kanban/capacity of the stage
Q: Batch size
m: Mean processing time
r: Fixed setup time
$\lambda = D/Q$: Mean arrival rate
$\mu = 1/(r + mQ)$: Mean processing rate
$\rho = \lambda/\mu = D(m + r/Q)$: Traffic intensity

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_22,

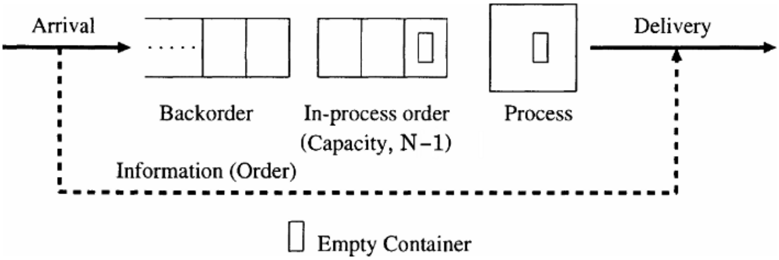


Fig. 12.1.1 Push model (build-to-order type)

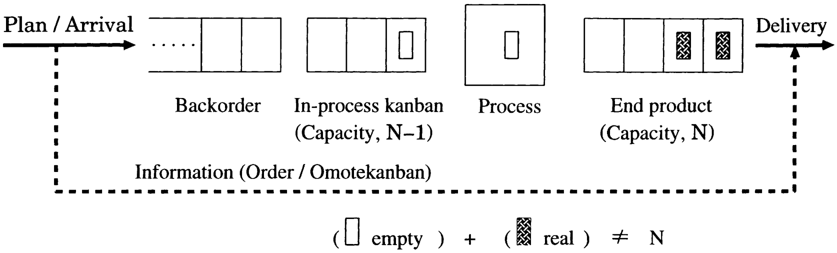


Fig. 12.1.2 Push model (Omote-Kanban type)

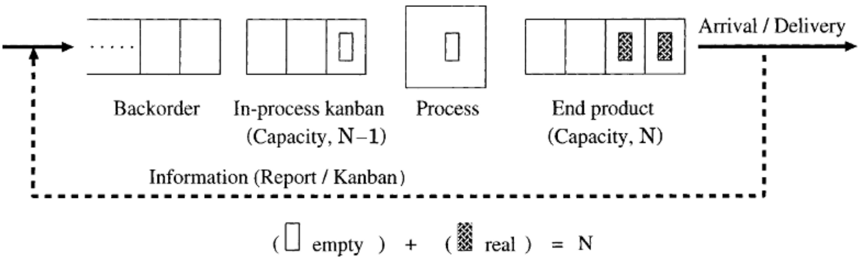


Fig. 12.1.3 Pull model (Kanban type)

α_0: Coefficient of backorder cost
α_1: Coefficient of inventory- carrying cost
α_1': Coefficient of order-holding cost
α_2: Coefficient of busy cost
α_3: Coefficient of idle cost

12.1.2.2 Push and Pull Models

An explanation of the Figs. 12.1.1–12.1.3 is given below (Table 12.1.1). The BTO model in Fig. 12.1.1 is a typical type of the single-stage queueing system with back-order. Usually, orders are lined up for processing, and are treated and delivered (pushed) according to the schedule.

Table 12.1.1 Types of push and pull models

Types		Control	M/I Flow	Kanban
Push	BTO (Fig. 12.1.1)	Feed-forward	Same direction	Nothing
	Omote-Kanban/VMI (Fig. 12.1.2)	Feed-forward	Same direction	$\neq N$
Pull	Kanban (Fig. 12.1.3)	Feedback	Dual direction	$= N$

The Omote-Kanban model in Fig. 12.1.2 uses the Omote-Kanban type as order (push) information. When an order is received, information in Kanban is sent (fed-forwarded) to the stock area, and the corresponding product is delivered from there simultaneously.

And, the model is controlled to replenish the stock continuously by the processing of the order in the system. The backorder only occurs if any product is not in the stock area when a new order is received. This model is similar to that of the vender-managed inventory (VMI) type.

The Kanban model in Fig. 12.1.3 is a typical apparatus for JIT in a Toyota system [10]. When an order arrives, the corresponding product is delivered (pulled) from the stock station, and information is sent (feed backed) to the waiting area simultaneously.

For economic comparison, the cost function is introduced as an objective criterion. Generally, it is assumed that the operating cost consists of waiting cost, busy cost, and idle cost, and it is a function of traffic variables [8].

Then, the expected operating costs, EC_1 and EC_2, for respective BTO and Kanban types are from [8] as follows:

$$\begin{aligned} EC_1 =& \alpha_0\,(\text{backorder}) + \alpha_1{}'\,(\text{order} - \text{holding}) \\ &+ \alpha_2\,(\text{busy}) + \alpha_3\,(\text{idle})\,, \quad \text{BTO type} \end{aligned} \tag{12.1.1}$$

$$\begin{aligned} EC_2 =& \alpha_0\,(\text{backorder}) + \alpha_1\,(\text{inventory} - \text{carrying}) \\ &+ \alpha_2\,(\text{busy}) + \alpha_3\,(\text{idle})\,, \quad \text{Kanban types} \end{aligned} \tag{12.1.2}$$

where the busy and idle terms are the respective probabilities in the steady state.

These costs are regarded as a function of the traffic variables: the batch size, Q, and mean processing time, m, while, as a function of the buffer variables: the fixed setup time, r, and the number of Kanban, N. In addition, the lead time is introduced later as another criterion of reliability.

12.1.3 Operating Cost

12.1.3.1 BTO Type

Under Poisson assumption, the three functions of the expected operating cost are given from Eqs. (12.1.1) and (12.1.2) below, and are ascertained to be convex in ρ

(m or r). For the BTO type, it is similar to a $M/M/1\,(N)$ system, and is obtained from [3, 9] as follows:

$$EC_A = \alpha_0 Q \frac{(N+1)\,\rho^{N+1}}{1-\rho^{N+1}} + \alpha_1{}' Q\rho \frac{1-(N+1)\,\rho^{N} + N\rho^{N+1}}{(1-\rho)\left(1-\rho^{N+1}\right)} + \alpha_2\rho + \alpha_3\,(1-\rho)\,,\ N < \infty. \tag{12.1.3}$$

Figures 12.1.4 and 12.1.5 show the cost behaviors of Eq. (12.1.3) in the respective, m and r. From Figs. 12.1.4 and 12.1.5, it is seen that there are the optimal processing time, m^*, and setup time, r^*, respectively. Also, it is ascertained that the inventory-carrying cost decreases according to the reduction of setup time.

12.1.3.2 Kanban Types

For Kanban types, the expected operating cost is considered here. First, the Omote-Kanban type is a variant of the $M/M/1\,(N)$ system, and the expected operating costs, EC_B, for Omote-Kanban type is obtained from [3, 8] as follows:

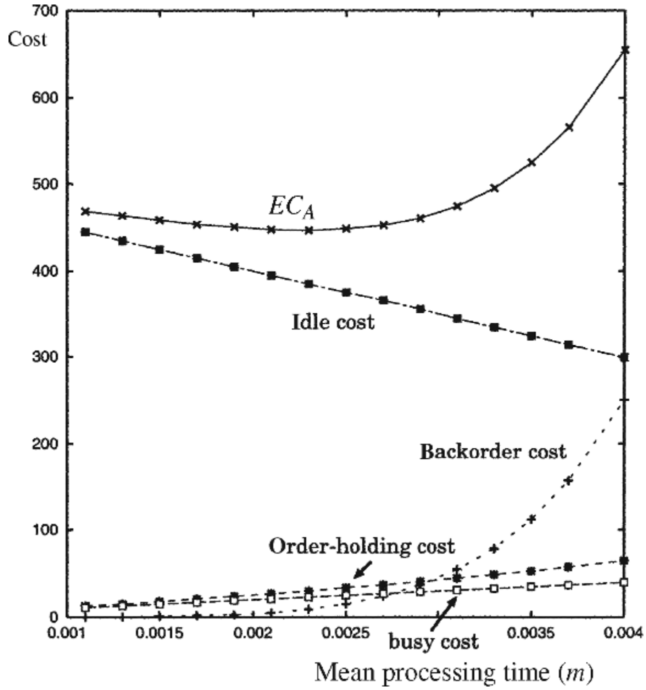


Fig. 12.1.4 Push model (BTO type) in m : $N = 5, D = 100, Q = 100, r = 0.001$; $\alpha_0 = 100, \alpha_1 = 1, \alpha_2 = 100, \alpha_3 = 500$

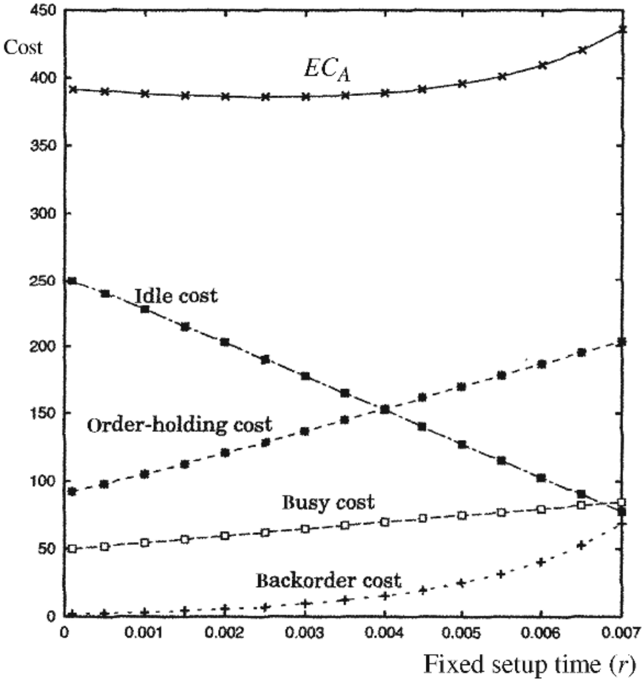


Fig. 12.1.5 Push model (BTO type) in r : $N = 5, D = 1000, Q = 20, m = 0.0005$; $\alpha_0 = 1, \alpha_1 = 5, \alpha_2 = 100, \alpha_3 = 500$

$$\begin{aligned} EC_B &= \alpha_0 Q \frac{(N+1)\,\rho^{N+1}}{1-\rho^{N+1}} \\ &\quad + \alpha_1 Q \left[N - \frac{\rho\left(1-\rho^N\right)}{1-\rho} \right] \frac{1}{1-\rho^{N+1}} + \alpha_2 \rho + \alpha_3 (1-\rho),\ N < \infty. \end{aligned} \tag{12.1.4}$$

Also, the (Ura-) Kanban type is a $M/M/1\,(N)$ system with blocking, and the expected operating cost, EC_C, are obtained from [2, 5, 8] as follows:

$$\begin{aligned} EC_C = \alpha_0 Q \frac{\rho^{N+1}}{1-\rho} + \alpha_1 Q \left[N - \frac{\rho\left(1-\rho^N\right)}{1-\rho} \right] \\ + \alpha_2 \rho + \alpha_3 (1-\rho),\ N < \infty. \end{aligned} \tag{12.1.5}$$

Figures 12.1.6 and 12.1.7 show the cost behaviors of Eqs. (12.1.4) and (12.1.5) in the Kanban types, respectively. From Figs. 12.1.6 and 12.1.7, the optimal processing time, m^*, are seen in both types.

Finally, it is noted that the function, EC, has the optimal traffic, ρ^*, and is dual with respect to, m, and r, for ρ^*. For example, Table 12.1.2 shows that EC_C has ${EC_C}^* = 357.04$ at $\rho^* = 0.87$, and is dual with respect to, m and r, for $\rho^* = 0.87$.

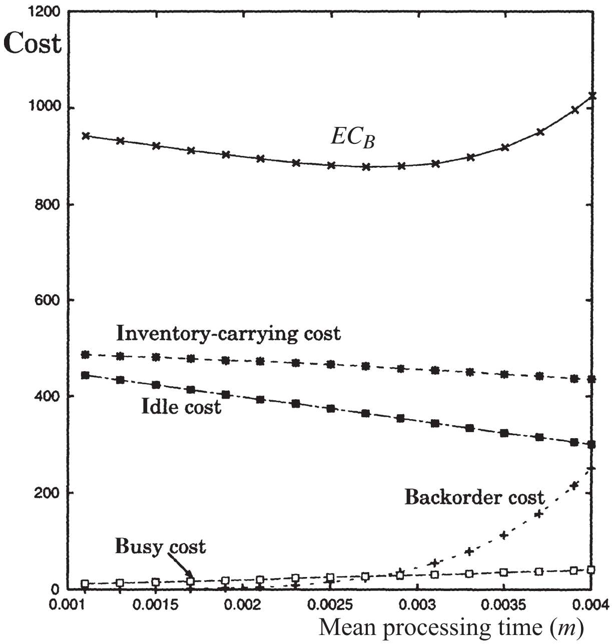


Fig. 12.1.6 Push model (Omote-Kanban type) in m : $N = 5, D = 100, Q = 100, r = 0.001;$ $\alpha_0 = 100, \alpha_1 = 1, \alpha_2 = 100, \alpha_3 = 500$

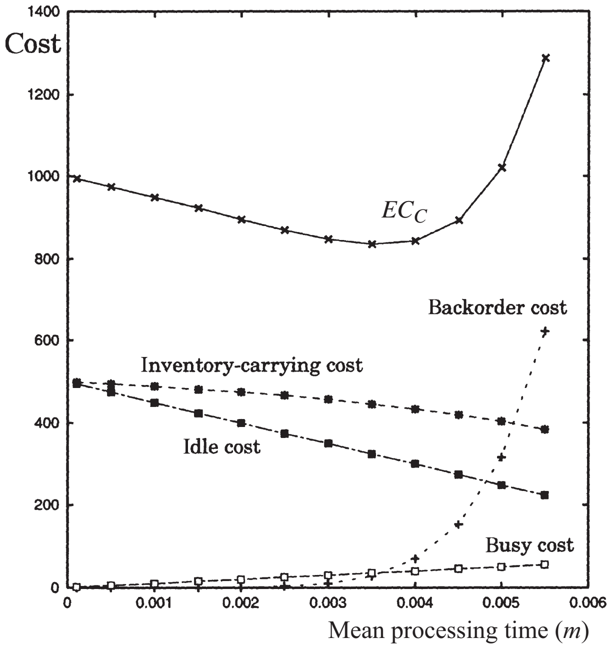


Fig. 12.1.7 Pull model (Kanban type) in m : $N = 5, D = 100; Q = 100, r = 0.001;$ $\alpha_0 = 100, \alpha_1 = 1, \alpha_2 = 100, \alpha_3 = 500$

Table 12.1.2 Dual structure of EC_B for m and r : $N = 5, D = 1000, Q = 20;\ \alpha_0 = 1, \alpha_1 = 5, \alpha_2 = 100, \alpha_3 = 300$

setup time (r)		mean processing time(m) 0.00005	0.00010	0.00015	0.00020	0.00025	0.00030	0.00035	0.00040	0.00045	0.00050	0.00055
0.0074	ρ=	0.42	0.47	0.52	0.57	0.62	0.67	0.72	0.77	0.82	0.87	0.92
	EC=	644.7	619.8	592.6	563.0	530.8	495.9	458.6	420.0	383.1	357.0	375.5
0.0084	ρ=	0.47	0.52	0.57	0.62	0.67	0.72	0.77	0.82	0.87	0.92	0.97
	EC=	619.8	592.6	563.0	530.8	495.9	458.6	420.0	383.1	357.0	375.5	704.6
0.0094	ρ=	0.52	0.57	0.62	0.67	0.72	0.77	0.82	0.87	0.92	0.97	
	EC=	592.6	563.0	530.8	495.9	458.6	420.0	383.1	357.0	375.5	704.6	
0.0104	ρ=	0.57	0.62	0.67	0.72	0.77	0.82	0.87	0.92	0.97		
	EC=	563.0	530.8	495.9	458.6	420.0	383.1	357.0	375.5	704.6		
0.0114	ρ=	0.62	0.67	0.72	0.77	0.82	0.87	0.92	0.97			
	EC=	530.8	495.9	458.6	420.0	383.1	357.0	375.5	704.6			
0.0124	ρ=	0.67	0.72	0.77	0.82	0.87	0.92	0.97				
	EC=	495.9	458.6	420.0	383.1	357.0	375.5	704.6				
0.0134	ρ=	0.72	0.77	0.82	0.87	0.92	0.97					
	EC=	458.6	420.0	383.1	357.0	375.5	704.6					
0.0144	ρ=	0.77	0.82	0.87	0.92	0.97						
	EC=	420.0	383.1	357.0	375.5	704.6						
0.0154	ρ=	0.82	0.87	0.92	0.97							
	EC=	383.1	357.0	375.5	704.6							

12.1.4 Push Versus Pull

12.1.4.1 Effect of Setup Time

In a Toyota system, the setup time reduction is critical. However, it occurs under some constraints that the inventory cost does not decrease necessarily according to the reduction of setup time [12].

Figures 12.1.8 and 12.1.9 show the cost behavior with respect to the setup time, r, in the respective Kanban types. From Figs. 12.1.8 and 12.1.9, it is seen that the shorter the setup time is, the larger the inventory-carrying cost is, and the optimal setup time, r^*, exists for cost minimization.

From Figs. 12.1.5, 12.1.8, and 12.1.9, the type effects in setup time reduction are obvious and inverse. The inverse relationship between the setup time and inventory holding cost occurs under a change of only r and the other fixed parameters.

This inverse property is very interesting, and also is ascertained from Eqs. (12.1.3) and (12.1.5) as follows: For the BTO type,

$$\lim_{r\to 0}(\text{Order} - \text{holding}) = \lim_{\rho\to Dm}(\text{Order} - \text{holding}) = \text{Constant},$$
$$\lim_{r\to\infty}(\text{Order} - \text{holding}) = \lim_{\rho\to 1}(\text{Order} - \text{holding}) \to \infty.$$

For the Kanban type,

$$\lim_{r\to 0}(\text{Inventory} - \text{carrying}) = \lim_{\rho\to Dm}(\text{Inventory} - \text{carrying}) = \text{Constant},$$
$$\lim_{r\to\infty}(\text{Inventory} - \text{carrying}) = \lim_{\rho\to 1}(\text{Inventory} - \text{carrying}) \to \infty.$$

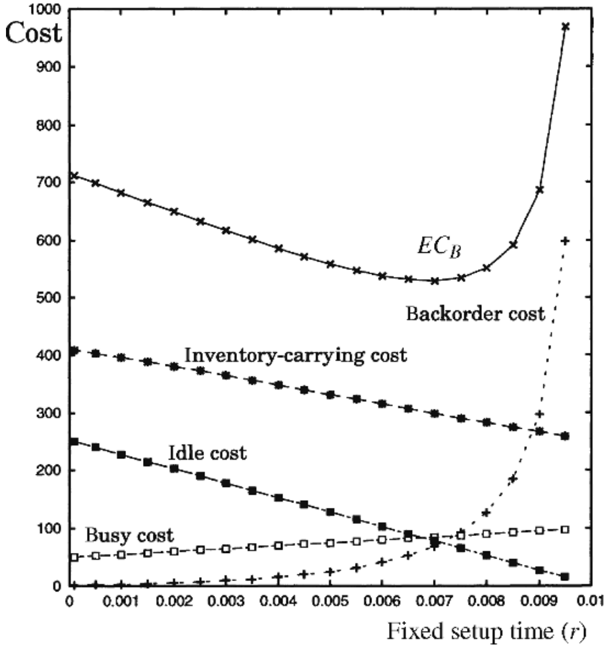


Fig. 12.1.8 Push model (Omote-Kanban type) in r : $N = 5, D = 1000, Q = 20, m = 0.0005$; $\alpha_0 = 1, \alpha_1 = 5, \alpha_2 = 100, \alpha_3 = 500$

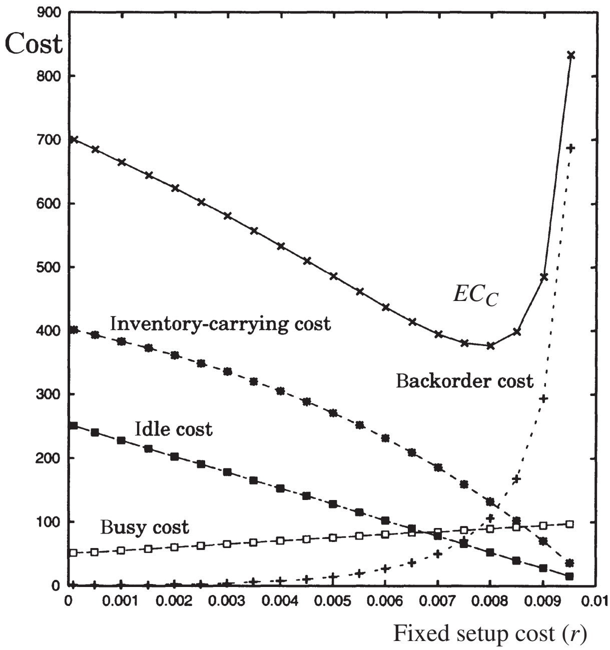


Fig. 12.1.9 Pull model (Kanban type) in r : $N = 5, D = 1000, Q = 20, m = 0.0005$; $\alpha_0 = 1$, $\alpha_1 = 5, \alpha_2 = 100, \alpha_3 = 500$

12.1.4.2 Inventory Versus Backorder

Next, let us consider the push versus pull system from the viewpoint of inventory versus backorder cost. Figures 12.1.10 and 12.1.11 show the cost behaviors of $(EC_A - EC_C)$ in, m, for BTO and Kanban types, respectively.

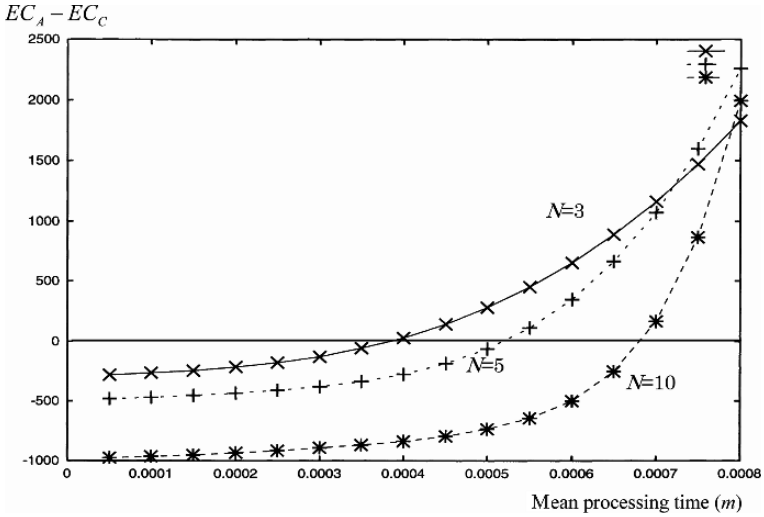


Fig. 12.1.10 BTO (EC_A) versus Kanban (EC_C) under $\alpha_0 \geq \alpha_1 = \alpha_1{}'$: $D = 1000, Q = 20, r = 0.001$; $\alpha_0 = 100, \alpha_1 = 5, \alpha_2 = 100, \alpha_3 = 500$

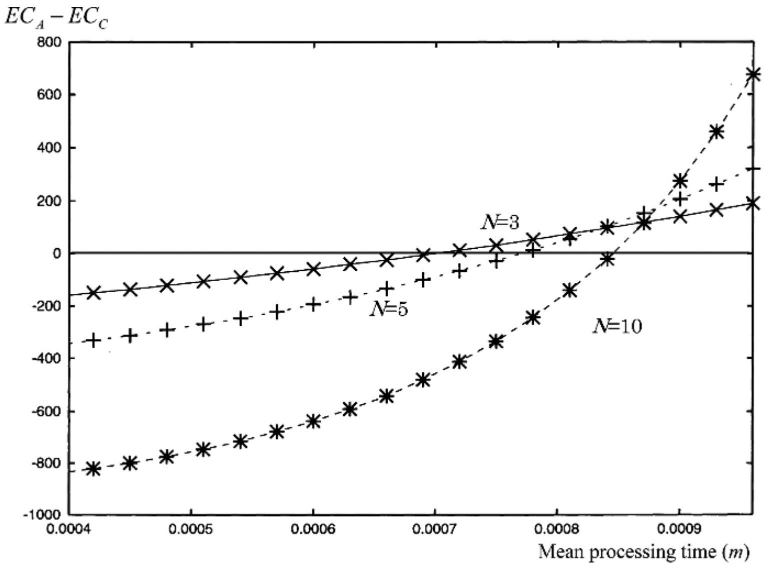


Fig. 12.1.11 BTO (EC_A) versus Kanban (EC_C) under $\alpha_0 < \alpha_1 = \alpha_1{}'$: $D = 1000, Q = 20, r = 0.001$; $\alpha_0 = 1, \alpha_1 = 5, \alpha_2 = 100, \alpha_3 = 500$

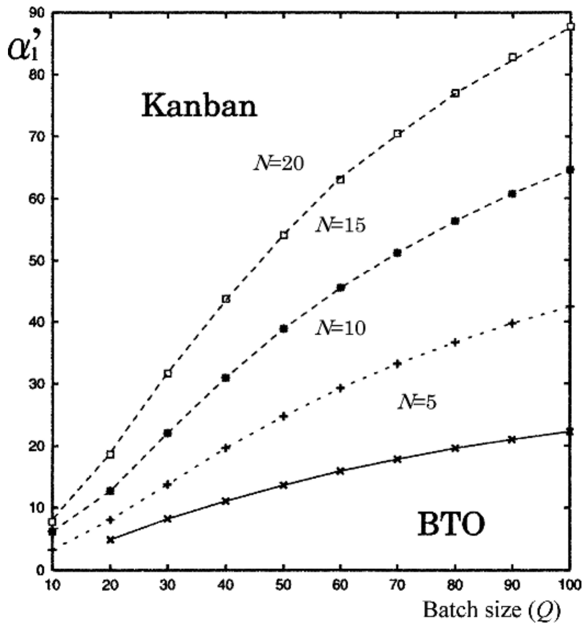


Fig. 12.1.12 BTO versus Kanban under $\alpha_0 > \alpha_1{}' > \alpha_1 (= 1) :\ D = 1000, r = 0.005;\ \alpha_0 = 100, \alpha_1 = 1, \alpha_2 = 100, \alpha_3 = 500$

From the Figs. 12.1.10 and 12.1.11, it is seen that the BTO type is better than the Kanban type under the smaller, m, and the Kanban type is better than the BTO type under the larger, m. In addition, it is ascertained that the Kanban type is better for the larger backorder cost shown in Fig. 12.1.11.

Also, Fig. 12.1.12 shows the behavior in break-even points of BTO and Kanban types. From Fig. 12.1.12, it is seen that the Kanban type is better than the BTO type in the area over the respective lines for, $N = 5\,(5)\,20$.

12.1.5 Management Strategy

12.1.5.1 Two-stage design

The strategic management/design problem for lot/cell production is a simultaneous decision of traffic variables (Q, m) and buffer variables (r, N). A graphical method for this decision is shown in the two-stage design method in [7, 8], and the design procedure for lot/cell production is seen in Fig. 12.1.13.

Following Fig. 12.1.13, the economic traffic (Q^*, m^*) is given under the minimization of EC with respect to variables $(Q, m;\ r, N)$ at Stage 1. At Stage 2, the lead time, LT^*, is uniquely determined by $(Q^*, m^*;\ r^*, N^*)$ and is called the economic lead time.

Stage 1: Economic traffic (Q^*,m^*)
(Economics)

↓

Stage 2: Economic Buffer (r^*, N^*) and Lead time (LT^*)
(Reliability)

Fig. 12.1.13 Two-stage design procedure

For example, consider a case of sales leader (Q given). From (12.1.3), the optimal processing time, m_A^*, under given Q and $N = \infty$ is given at Stage 1 by

$$m_A{}^* = \frac{1}{D}\left[1 - \sqrt{\frac{\alpha_1 Q}{\alpha_3 - \alpha_2}}\right] - \frac{r}{Q}, \qquad N = \infty. \tag{12.1.6}$$

At Stage 2, the waiting time in the system is regarded as the lead time, and the economic lead time, LT_m^*, under m_A^* is from [3] as follows:

$$\begin{aligned} LT_m{}^* &= \frac{1}{\mu\left(1 - \rho^*\right)} \\ &= \frac{Q\left(r + m^* Q\right)}{Q - D\left(r + m^* Q\right)}. \end{aligned} \tag{12.1.7}$$

12.1.5.2 Production Matrix

By the two-stage design procedure in Fig. 12.1.13, the strategic management/design is summarized as the production matrix. The production matrix consists of batch size, Q, in row and processing time, m, in the column. Suppose that $N_{\max} = 30$ and the setup time are viable or optimized.

From the production matrix for $\alpha_0 > \alpha_1$ [9], it is seen that the BTO type is superior in the term of the expected operating cost, EC, while it is inferior in term of the economic lead time, LT. Also, the Kanban types is better than the Omote-Kanban type in the expected operating cost. This superiority is ascertained from Eq. (12.1.4) and (12.1.5) as follows:

$$\begin{aligned} EC_B - EC_C = \alpha_0 Q &\frac{\left[N\left(1 - \rho\right) + \rho^{N+1}\right]\rho^{N+1}}{1 - \rho N + 1} \\ &+ \alpha_1 Q\left[N - \frac{\rho\left(1 - \rho^N\right)}{1 - \rho}\right]\frac{\rho^{N+1}}{1 - \rho^{N+1}} \geq 0. \end{aligned} \tag{12.1.8}$$

However, the Omote-Kanban type is better than the Kanban type in the economic lead time. Thus, this type is superior to other types in terms of the economic lead time, and is an alternative type from the view of management speed.

From the production matrix for $\alpha_0 < \alpha_1$ [9], it is seen that the Kanban type is superior in terms of the expected operating cost, EC, except $Q = 100$, while it is inferior in terms of the economic leadtime, LT. Also, the Omote-Kanban type is superior to other types in terms of the economic leadtime, except $Q = 100$, while this type is inferior in terms of the expected operating cost.

Thus, it is concluded that the three types are alternative. Then, the production matrix proposed would suggest that the management strategy for trade-off, and an appropriate setup time, r^*, would exist under some environments. In particular, it is noted that the Kanban type operates usually under the limit of low inventory, and frequent backlogs occur, but would be a better strategy for continuous improvement in inventory.

References

1. Akturk, M.S. and Erhun, F., An Overview of Design and Operational Issues of Kanban Systems, *International Journal of Production Research*, 37(17), 3859–3881, 1999
2. Buzacott, J.A. and Shanthikumar, J.G., *Stochastic Models of Manufacturing Systems*, Prentice-Hall, New Jersey, 98–152, 1993
3. Cox, D.R. and Smith, W.L., *Queues*, Chapman & Hall, London, 1961
4. Huang, C. and Kusiak, A., Overview of Kanban Systems, *International Journal of Computer Integrated Manufacturing*, 9(3), 169–189, 1996
5. Karmarker, U.S. and Kekre, S., Banching Policy in Kanban System, *Journal of Manufacturing Systems*, 8(4), 317–328, 1989
6. Karmarker, D.S., Kekre, S. and Freeman, S., Lot-sizing and Leadtime Performance in a Manufacturing Cell, *Interfaces*, 15(2), 180–188, 1995
7. Matsui, M., Optimal Economic Design of Production and Queueing Systems, *Abstracts of APORS*, 194, Fukuoka, Japan, 266, 1994
8. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
9. Matsui, M., A Queueing/Management Consideration on Japanese Production System, *Production Planning and Control*, 13(8), 688–701, 2002
10. Ohno, T., *Toyota Production System: Beyond Large Scale Production*, Productivity Press, Cambridge, MA, 1988
11. Spearman, M.L. and Zazanis, M.A., Push and Pull Production Systems: Issues and Comparisons, *Operations Research*, 40(3), 521–532, 1992
12. Zhangwill, W.I., The Limits of Japanese Production Theory, *Interfaces*, 22(5), 14–25, 1992

12.2 Toyota Versus Dell Strategy

12.2.1 Introduction

In the SCM age, there is significant amount of demand-to-supply management of complex enterprise systems [2]. A main management concern is the inventory logic of connecting each enterprise in a dependent demand type.

Now, we know the two main inventory/lean logics of KANBAN and VMI types for SCM. The former is a closed-loop type, and the latter is an open-loop type. A recent study of the KANBAN versus VMI type is seen in Chapter 12 [4], for example.

In this chapter, the three models of production-type SCM are introduced and formularized under the form of M/M queus [1], and are considered through a balancing approach [5, 8]. The three models are Toyota type with Kanban, Dell type with vendor managed inventory (VMI), and Dell type with Kanban, and all of them are discussed comparatively.

Recently, a lean-extended comparison of the Toyota versus Dell type is seen in management [9]. We have been concerned with the two balancing problems in the economics (profit) and reliability (time) of Toyota versus Dell type since 2003 [7].

By a numerical example, each unit-optimization in profit gives the total optimization in sum. Similar to Chapter 11.1 [8], this integral optimization results in the noncooperative solution as would support the win-win-like strategy for Toyota versus Dell types.

12.2.2 SCM Balancing

12.2.2.1 SCM Models

The focused object of SCM is a two-chain MGM (Management Game Model) [3] outlined in Fig. 12.2.1. This type of SCM is a production-type SCM, and consists of assembly enterprise and parts enterprise. In this case, the JIT/VMI is introduced as the method of connecting both the enterprises.

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_23,

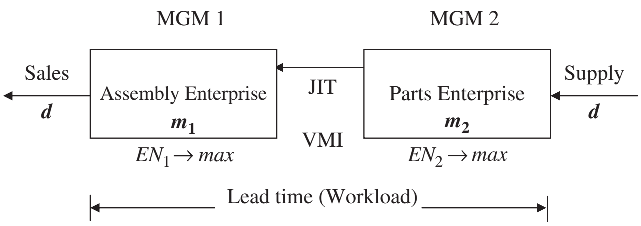


Fig. 12.2.1 Two-MGM SCM model

Then, the problem of SCM is to optimize the profit totally through the supply chain as shown in Fig. 12.2.1, and to speed up the management by the reduction of lead time/workload. This problem is considered here from the viewpoint of balancing each enterprise in SCM.

12.2.2.2 Balancing Problem

There is a balancing problem of assembly and parts enterprises in economics and reliability. For the balancing of the respective enterprises, several objective functions are as follows:

ER_1: Mean sales reward per unit time in assembly enterprise
ER_2: Mean sales reward per unit time in parts enterprise
EC_1: Mean operating cost per unit time in assembly enterprise
EC_2: Mean operating cost per unit time in parts enterprise
EN_1: Net reward in assembly enterprise
EN_2: Net reward in parts enterprise
EN: Profit of the whole SCM
BT_1: Workload in assembly enterprise
BT_2: Workload in parts assembly
BT: Workload of the whole SCM

As a SCM goal, two alternative criteria are presented as follows: One is a profit maximization in SCM (Main goal), and the other is the integral optimization of profit for the win-win strategy (Dual goal).

$$Main\ goal : MEN = (ER_1 + ER_2) - (EC_1 + EC_2) \rightarrow \max \tag{12.2.1}$$

$$Dual\ goal : DEN = (ER_1 - EC_1)^+ + (ER_2 - EC_2)^+ \rightarrow \max \tag{12.2.2}$$

where $(a)^+ = \max\ (a,\ 0)$.

Another goal for SCM is to pursue the workload (lead time) optimization in reliability as follows:

$$BT = BT_1 + BT_2 \rightarrow \min . \tag{12.2.3}$$

12.2.3 Toyota and Dell

12.2.3.1 Three Models

The three types of SCM models are introduced in Figs. 12.2.2–12.2.4 [7]. These are the Toyota, Dell-A, and Dell-B types. The used symbols are as follows:

T: Planning period
D: Total demand in period
Q: Batch size
N_1, N_2: Waiting capacity
m_1, m_2: Mean processing time
r: Fixed setup time
α_0: Coefficient of backlog cost
α_1: Coefficient of inventory- carrying cost
$\alpha_1{}'$: Coefficient of order-holding cost
α_2: Coefficient of busy cost
α_3: Coefficient of idle cost
$d = {}^{T}\!/_{D}$: Mean interarrival time
$d' = {}^{TQ}\!/_{D}$: Mean lot interarrival time
$\rho_1 = m_1 D/T$, $\rho_2 = (m_2 + r/Q)D/T$: Traffic intensity
p_1: Sales price of products (items) in assembly enterprise
p_2: Sales price of products (items) in parts enterprise
p_3: Sales price of products (items) in the outside market $\quad (p_2 < p_3 < p_1)$

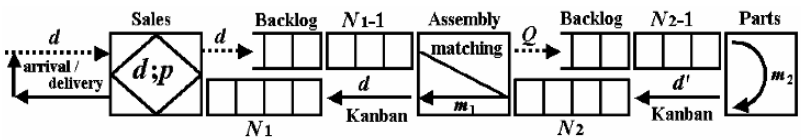


Fig. 12.2.2 Toyota model

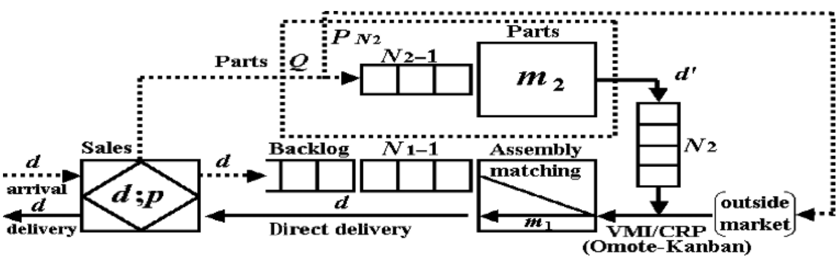


Fig. 12.2.3 Dell-A model

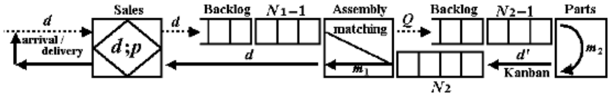


Fig. 12.2.4 Dell-B model

The Toyota and Dell-B types are a series system of assembly and parts enterprises, while the Dell-A type is a parallel system with by-passed parts enterprises. For the Toyota type, the Kanban system is introduced in both assembly and parts enterprises.

For the Dell type, the BTO (build-to-order) system is introduced in assembly enterprises. The parts enterprise has the VMI system in A type and the Kanban system in B type. In this case, the Kanban and VMI systems are an individual condition for SCM.

12.2.3.2 Queueing Results

The supply chain consisting of assembly and parts enterprises is here treated as the two-chain MGM model in Fig. 12.2.1. The MGMs (Management Game Models) in the respective enterprises are assumed to be an M/M/1 queueing type [3, 6].

For the three models, the objective functions in two goals are easily obtained from [4, 7] as follows:

<Case of Toyota type>

$$ER_1 = \frac{1}{d}(p_1 - p_2), \tag{12.2.4a}$$

$$EC_1 = \alpha_0\left(\frac{\rho_1^{N_1+1}}{1-\rho_1}\right) + \alpha_1\left[N_1 - \frac{\rho_1\left(1-\rho_1^{N_1}\right)}{1-\rho_1}\right] + \alpha_2\rho_1 + \alpha_3(1-\rho_1), \tag{12.2.4b}$$

$$ER_2 = \frac{1}{d}p_2, \tag{12.2.4c}$$

$$EC_2 = \alpha_0 Q\left(\frac{\rho_2^{N_2+1}}{1-\rho_2}\right) + \alpha_1 Q\left[N_2 - \frac{\rho_2\left(1-\rho_2^{N_2}\right)}{1-\rho_2}\right] + \alpha_2\rho_2 + \alpha_3(1-\rho_2), \tag{12.2.4d}$$

$$BT_1 = m_1\rho_1\frac{1-(N_1+1)\rho_1^{N_1} + N_1\rho_1^{N_1+1}}{(1-\rho_1)\left(1-\rho_2^{N_1+1}\right)}, \tag{12.2.4e}$$

$$BT_2 = m_2 Q\left[N_2 - \frac{\rho_2\left(1-\rho_2^{N_2}\right)}{1-\rho_2}\right]. \tag{12.2.4f}$$

<Case of Dell-A type>

$$ER_1 = \frac{1}{d} p_1 - ER_2 = \frac{1}{d} \left\{ p_1 - \rho_2^{N_2+1} p_2 - \left(1 - \rho_2^{N_2+1} \right) p_3 \right\}, \tag{12.2.5a}$$

$$EC_1 = \alpha_0 \frac{(N_1 + 1)\, \rho_1^{N_1+1}}{1 - \rho_1^{N_1+1}} + \alpha_1{}' \rho_1 \frac{1 - (N_1 + 1)\, \rho_1^{N_1} + N_1 \rho_1^{N_1+1}}{(1 - \rho_1) \left(1 - \rho_1^{N_1+1} \right)}$$
$$+ \alpha_2 \rho_1 + \alpha_3 (1 - \rho_1), \tag{12.2.5b}$$

$$ER_2 = \frac{1}{d} \left\{ \left(1 - P_{N_2} \right) p_2 + P_{N_2} \right\} = \frac{1}{d} \left\{ \rho_2^{N_2+1} p_2 + \left(1 - \rho_2^{N_2+1} \right) p_3 \right\}, \tag{12.2.5c}$$

$$EC_2{}^* = \alpha_1 Q \left[N_2 - \frac{\rho_2 \left(1 - \rho_2{}^{N_2} \right)}{1 - \rho_2} \right] \frac{1}{1 - \rho_2^{N_2+1}} + \alpha_2 \rho_2 + \alpha_3 \frac{1 - \rho_2}{1 - \rho_2^{N_2+1}}, \tag{12.2.5d}$$

$$BT_1 = m_1 \rho_1 \frac{1 - (N_1 + 1)\, \rho_1^{N_1} + N_1 \rho_2^{N_1+1}}{(1 - \rho_1) \left(1 - \rho_1^{N_1+1} \right)}, \tag{12.2.5e}$$

$$BT_2 = m_2 Q \left[N_2 - \frac{\rho_2 \left(1 - \rho_2^{N_2} \right)}{1 - \rho_2} \right] \frac{1}{1 - \rho_2^{N_2+1}}. \tag{12.2.5f}$$

<Case of Dell-B type>

$$ER_1 = \frac{1}{d} (p_1 - p_2), \tag{12.2.6a}$$

$$EC_1 = \alpha_0 \frac{(N_1 + 1)\, \rho_1^{N_1+1}}{1 - \rho_1^{N_1+1}} + \alpha_1{}' \rho_1 \frac{1 - (N_1 + 1)\, \rho_1^{N_1} + N_1 \rho_1^{N_1+1}}{(1 - \rho_1) \left(1 - \rho_1^{N_1+1} \right)}$$
$$+ \alpha_2 \rho_1 + \alpha_3 (1 - \rho_1), \; p_1 > p_3 > p_2 \tag{12.2.6b}$$

$$ER_2 = \frac{1}{d} p_2, \tag{12.2.6c}$$

$$EC_2 = \alpha_0 Q \left(\frac{\rho_2^{N_2+1}}{1 - \rho_2} \right) + \alpha_1 Q \left[N_2 - \frac{\rho_2 \left(1 - \rho_2^{N_2} \right)}{1 - \rho_2} \right] + \alpha_2 \rho_2 + \alpha_3 (1 - \rho_2) \tag{12.2.6d}$$

$$BT_1 = m_1 \rho_1 \left[N_1 - \frac{\rho_1 \left(1 - \rho_1^{N_1+1} \right)}{1 - \rho_1} \right], \tag{12.2.6e}$$

$$BT_2 = m_2 Q \left[N_2 - \frac{\rho_2 \left(1 - \rho_2^{N_2} \right)}{1 - \rho_2} \right]. \tag{12.2.6f}$$

12.2.4 Total versus Integral

12.2.4.1 Total Optimization

The three models are numerically compared with total or integral optimization. In the maximization, the integral optimization problem involves maximizing the DEN by cooperation, even if each MGM agent pursues the self-goal in non-cooperation.

The parameter settings are as follows:

$$\begin{aligned}&T = 1,\ Q = 5,\ r = 0.001;\\&\alpha_0 = 100,\ \alpha_1 = {\alpha_1}' = 1,\ \alpha_2 = 100,\\&\alpha_3 = 500,\ p_1 = 20,\ p_2 = 10,\ p_3 = 12;\\&N_1 = 5,\ N_2 = 5,\ a = 2,\ b = 0.005\end{aligned}$$

From Eqs. (12.2.4)–(12.2.6), Figs. 12.2.5–12.2.7 are given. Figures 12.2.5–12.2.7 show the behaviors of MEN under the mean interarrival time (demand speed), d. From these figures, the optimal d^* exists for price constraint ($d^{-1} \leq 2 - 0.005p$).

12.2.4.2 Integral Optimization

(a) Win-win condition

Figures 12.2.8–12.2.10 show the behaviors of DEN by the mean interarrival time (demand speed), d. From these figures, the profit maximization is attained at the optimal d^*, and then, both assembly and parts enterprises can obtain the even profit in the neighborhood of optimal, d^* (cycle time).

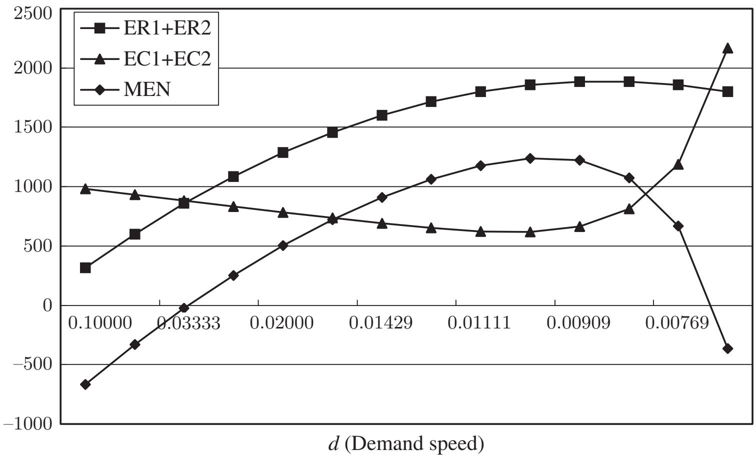


Fig. 12.2.5 Behaviors of main goal: Toyota type, $m_1 = m_2 = 0.006$ (production speed), price constraint

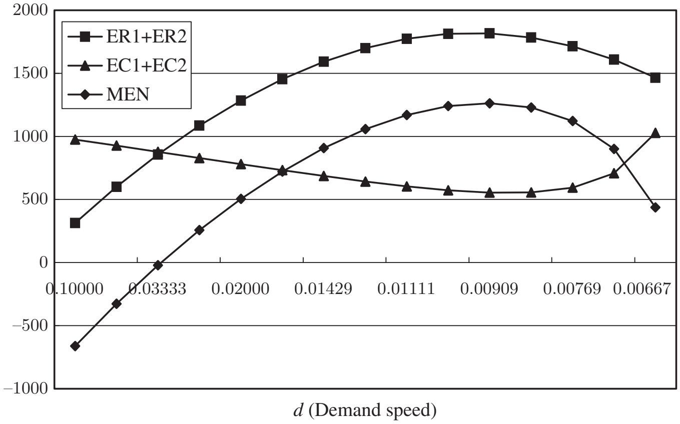


Fig. 12.2.6 Behaviors of main goal: Dell-A type, $m_1 = m_2 = 0.006$ (production speed), price constraint

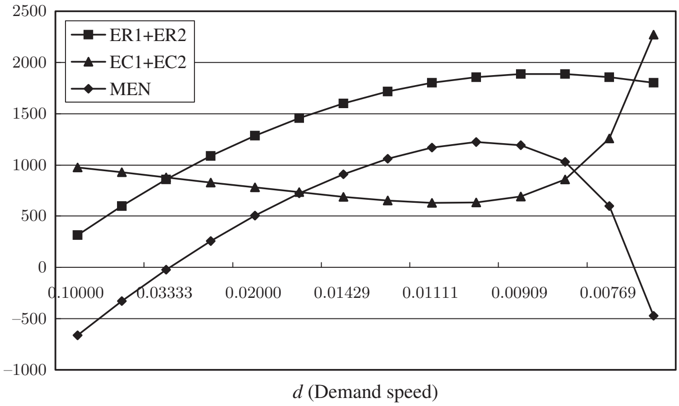


Fig. 12.2.7 Behaviors of main goal: Dell-B type, $m_1 = m_2 = 0.006$ (production speed), price constraint

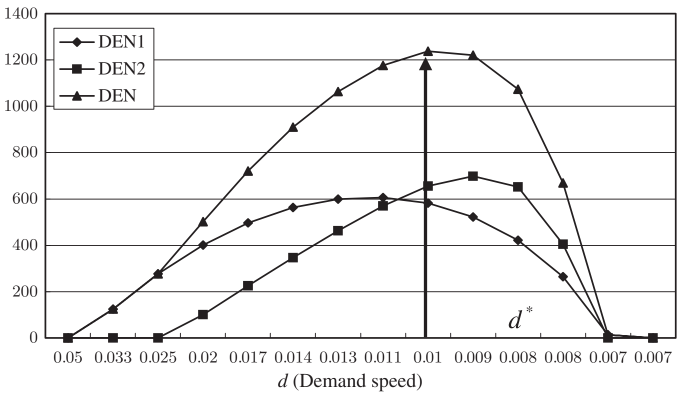


Fig. 12.2.8 Behaviors of dual goal: Toyota type, $m_1 = m_2 = 0.006$ (production speed), price constraint

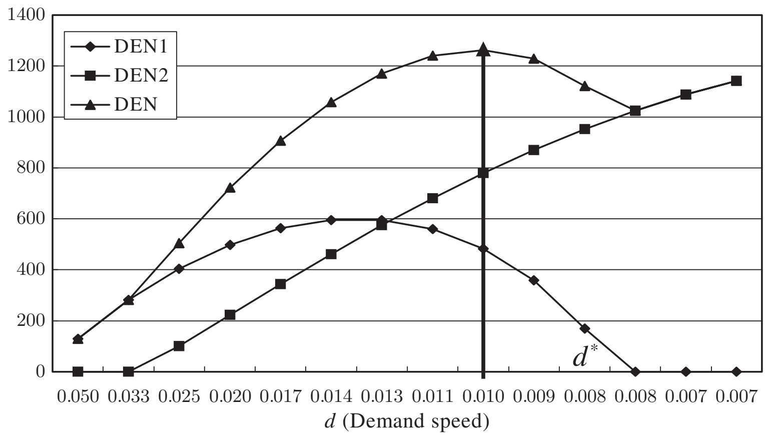


Fig. 12.2.9 Behaviors of dual goal: Dell-A type, $m_1 = m_2 = 0.006$ (production speed), price constraint

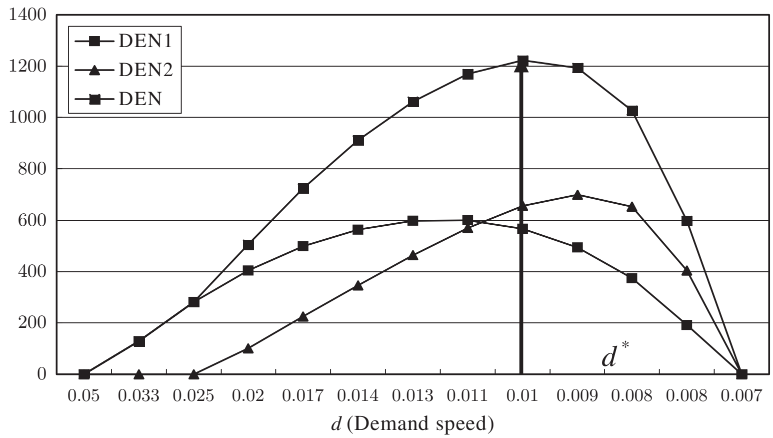


Fig. 12.2.10 Behaviors of dual goal: Dell-B type, $m_1 = m_2 = 0.006$ (production speed), price constraint

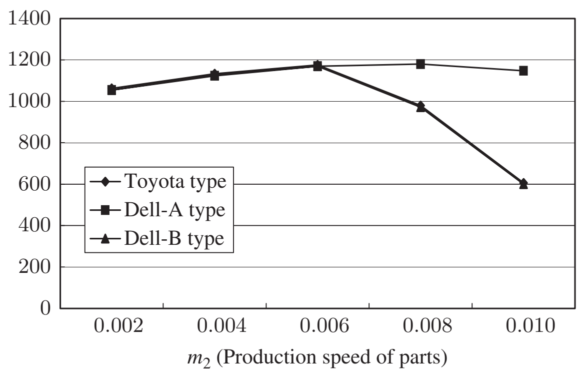


Fig. 12.2.11 Behaviors of dual goal: $d = 0.0111$, $m_1 = 0.006$, price constraint

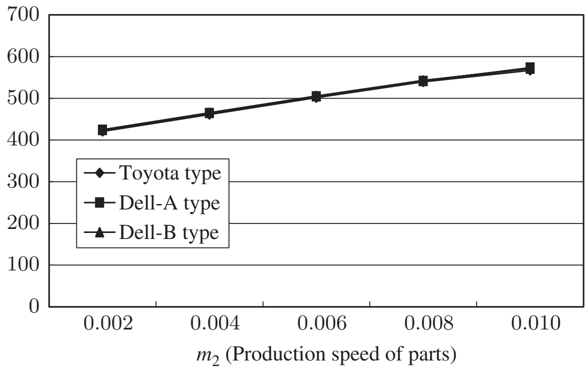


Fig. 12.2.12 Behaviors of dual goal: $d = 0.02$, $m_1 = 0.006$, price constraint

Table 12.2.1 Profit comparison of Toyota and Dell

$m_1 = 0.006$		Toyota			Dell-A			Dell-B		
	m_2	0.010	0.012	0.014	0.010	0.012	0.014	0.01	0.012	0.014
No price constraint (D = 70/d = 0.01429)	EN_1		362.8			363.8			364.0	
	EN_2	294.2	346.5	368.9	293.3	344.2	383.1	294.2	346.5	368.9
	DEN	657.0	709.2	731.7	657.1	707.0	743.2	658.2	710.5	732.9
Price constraint (D = 90/d = 0.01111)	m_2	0.004	0.006	0.008	0.004	0.006	0.008	0.004	0.006	0.008
	EN_1		606.7		598.9	595.3	587.4	599.7	599.7	598.0
	EN_2	526.9	570.0	372.9	523.9	574.5	591.7	526.9	570.0	429.9
	DEN	1133.6	1176.8	979.6	1122.8	1169.8	1179.1	1126.6	1169.7	1028.0

(b) Toyota Versus Dell

Figures 12.2.11 and 12.2.12 show the behaviors of DEN under the mean processing time (production speed) of parts, m_2. From these figures, it is found that the Dell-A type is stable in profit under the production speed, m_2, while the Toyota and Dell-B types are unstable in profit under $m_2 > m_1$. Thus, the Dell-A type would be better for stability in fluctuation.

A profit comparison of Toyota and Dell types is summarized in Table 12.2.1. From Table 12.2.1, it is seem that the Dell-A type is better under no price constraint and $d = m_2 = 0.014$. Under price constraint, it is seem that the Toyota type is better for $m_1 = m_2 = 0.006$.

References

1. Cox, D.R. and Smith, W.L., *Queues*, Chapman & Hall, London, 1961
2. de Kok, A.G. and Graves, S.C. (eds.), *Supply Chain Management: Design, Coordination and Operation*, Elsevier, Amsterdam, 2003
3. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002

4. Matsui, M., A Queueing/Management Consideration on Japanese Production Systems, *Production Planning and Control*, 13, 688–701, 2002
5. Matsui, M., MGM-Modeling and Balancing Problem in Supply Chain Management, *Proceedings of APIEMS2004*, Gold Coast, Australia, 2004 (on CD-ROM)
6. Matsui, M., Management Game Theory: Manufacturing vs. Service Enterprises Type, *International Journal of Productivity and Quality Management*, 1(1/2), 103–115, 2006
7. Matsui, M. and Ichihara, S., A Game Approach to SCM: Modeling, Formulation Example and Integral Optimization, *Journal of Japan Society of Logistics Systems*, 4(1), 67–80, 2003 (in Japanese)
8. Matsui, M. and Motohashi, M., A Basic Study for Strategic Supply Chain Balancing, *Journal of Japan Society of Logistics Systems*, 7(1), 21–23, 2007
9. Shonberger, R.J., Lean Extended, *Industrial Engineer*, December, 26–31, 2005

Part VII
Emerging Challenge

Chapter 13
Pair-Strategic Map Issues

13.1 Conflict of Business and Manufacturing

In a company, do business (sales) and manufacturing really coexist? How can one attempt not to measure the conflict but the effective coexistence? The conflict between these two functions is a classic, unsettled problem.

In 1933, a business administration researcher, Mary Parker Follet stated this problem in a lecture [3]. She discussed the functional relations between these sections in the form of "Separation of Planning Division," though about 100 years had passed since Frederic Taylor's scientific management was generated. It is said that Follet's problem was different, although there has been a significant amount of criticism of her organization theory according to this function for a long time.

Shapiro [10] and Davis [2] took up the interface problem of marketing and manufacturing in 1977, and contributed their ideas to *Harvard Business Review* magazine and *Interfaces* magazine. Recent issues are seen in [1, 6].

Generally, a marketing section is interested in the maximization of sales, and a manufacturing section is interested in minimization of costs. However, the difference between sales and cost is not maximized if there is no cooperation of labor between both sections, and thus, the collaboration tool is developed here [9].

13.2 Pair-Strategic Map

13.2.1 Tools for Collaboration

In reality, for manufacturing and sales collaboration, there is an intractable problem, and under the existing circumstance, based on the knowledge gap and the difference of culture in business sections and production sections, any collaboration with high continuation is not realized by management.

For instance, many people in charge of a business do not know the mechanisms of the manufacturing process, the inventory cost, and the production plan. Business sections that realize these factors are rare. Justifying this ignorance and pursuing to exaggerate the gross sales and market share, such kind of manufacturing and sales collaboration is not desirable.

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_24,

The business department should especially understand the production plan. The brokerage department usually passes on information in the order from the circulation to manufacturing management as is, ignores the demand forecasts, the production plans, and the inventory planning, and only requires the change in the production level. Because there is order, this condition is necessary.

Following actual demand this way, when order quantity is one sidedly indicated to the production section from the business section, one can image two choices in production as follows: modification of the production level or adjustment of the balance of the stock quantity.

However, without temporary modification of the production level, adjustment of the existing stocks and the defective items easily occur, and leveling the stock is assured by the fact that the production level is modified. Consequently, this process can force the kind of production, which deviates from the cost minimization or sales (revenue) maximization.

Demand and supply planning of the manufacturing industry is planned in order not to cause the defective item on the basis of past demand information of the respective company and competition, or in order for stock not to become excessive. In such a case, it is important how this balance points to production speed.

And, needless to say, the sales of the business departments and the costs of the manufacturing section are related and are not independent, and change while influencing each other. Therefore, the difference of the sales and cost is largely related to the cooperation during this trade off, and involves neither sales maximization nor cost minimization.

13.2.2 Pair Strategy Chart

The tool that achieves this collaboration is a pair-strategy chart. This aims to achieve management that values the supply and demand flow, while requiring business and manufacturing to be in the relation of non-cooperation and to transfer from the world at the cost center to the world at the profit center. The so-called spreadsheet, a usual tool for S&OP in a traditional ERP package, is not sufficient for effective collaboration.

The strategy that should be selected comes into view after the position of each company is clarified when this chart is used. Needless to say, each supply-demand relationship in "profit = sales − cost" can be calculated for a combination of production and demand speeds.

Data regarding sales and cost per time unit are then collected, and when the profit and lead-time in each combination are calculated, estimated, and arranged into one chart, the "pair-matrix chart" is complete. This chart is basically based on the traffic accounting in chapter 4.2.

This pair-matrix chart shows at which supply and demand speed, or at which production speed, the cost is minimized, and at which demand speed, the sales is maximized. In this case, the point that minimizes cost and maximizes the sales makes an elliptic shape (Fig. 13.1) [7]. Examples of major enterprises are seen in Part V.

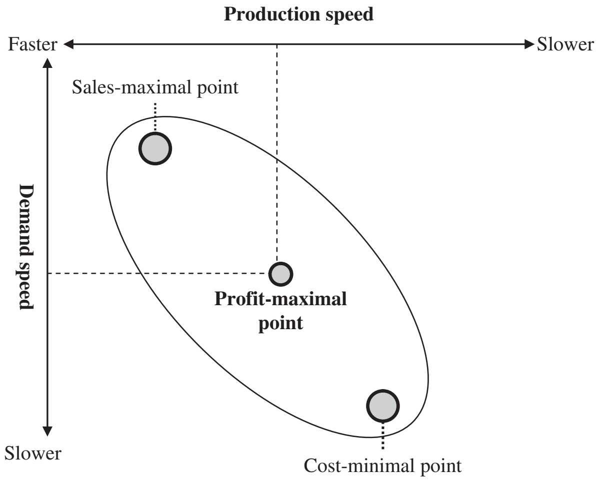


Fig. 13.1 A pattern for the problem of a two-center model

In this ellipse, when cost minimization and sales maximization show two counter electrodes, the particular commodity is presently located somewhere else. For example, the sales-maximal point shows the point that converts the maximum profit, and some kind of strategy is drawn and developed, and thus the scenario for this maximum profit can be induced.

13.3 Strategy for Profit Maximization

When the supply-demand situation of the commodity is actually shown according to this pair strategy chart, it is classified into three types (Fig. 13.2) as follows:

(i) Sales-initiated type

This type cancels the restrictions in the manufacturing section chiefly by the initiation of the business department, and aims at the maximization of the sales, which is equal to profit maximization, similar to those shown in Figs. 4.2.9 and 4.2.10 in Chapter 4.2.

Figure 13.2 (i) is the case of the Dell model. It becomes a scenario of shortening the lead time while improving the route shown by the dotted line in (i), that is, the production speed, and acceleration of the demand speed.

For instance, the Dell model is presented at point "a," where the cost is minimized. That is, the production facility is operating fully though demand is small, and cost minimization is maintained. However, the Dell assumes that it aims at "b," which is the location it assumes sales occur, and it attempts the maximization of the profit and achieves it.

It is possible to cancel the restriction on manufacturing as one of the scenarios for this growth target. The scenario is that the demand for its own

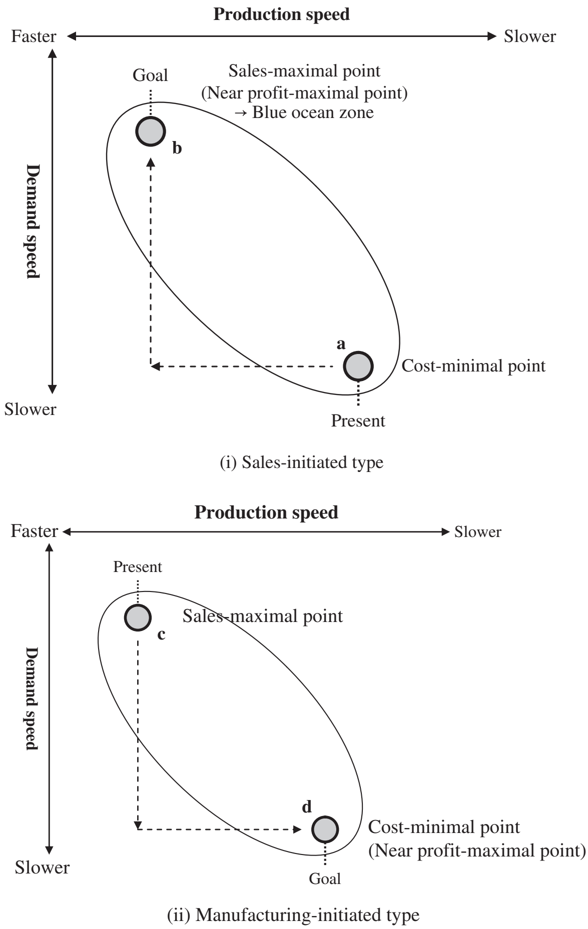


Fig. 13.2 Three approaches toward profit maximization

commodity is accelerated as shown in the route by the dotted line of (i), and these commodities can be brought to the market faster and cheaper than those of rivals by shortening the lead time and improving the production speed.

It can be said that the Dell has set up the BTO and the system of direct sales for this purpose. As a result, a great profit increase will be attained for Dell by raising the production speed even if it is only by a small amount.

(ii) Manufacturing-initiated type

In Japan, this type (ii) chiefly aims at the minimization of costs that are equal to maximization of the profit shown in Fig. 13.2 (ii). The improvement approach by the manufacturing initiation is used well for the cost minimization. In general, the minimization of the cost is at the point of certain sales but not maximizing profit.

If this occurs, the goal position is necessary in the next step to change/move the chart to the left, or the right, or diagonally, compared to the case of point

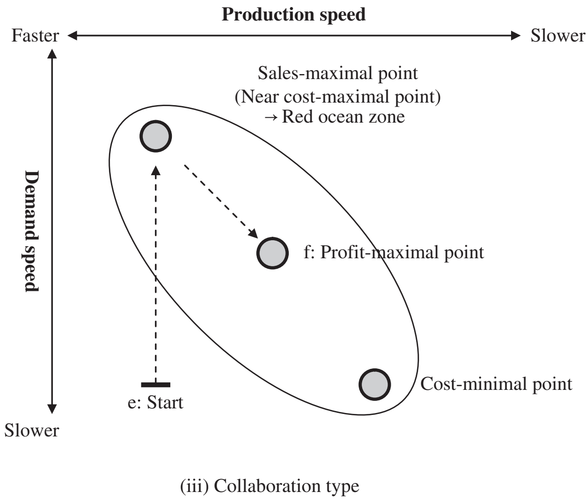


Fig. 13.2 (continued)

"d," where the cost is minimized so that the supply and demand may be in equilibrium.

(iii) Collaboration type

This type (iii) is integrated so that business and manufacturing may resolve the conflict, and the point that maximizes the profit by the collaboration is located at the oval center.

Let us consider Kirin Beverage as an example (iii). At the release time of a new product, it is assumed that this company is in the position "e" and that demand is still small and the production capacity is in excess. And, let us assume the route should reach point "f" where the profit is maximized. At this time, the strategy that increases the demand speed to cancel the restriction on demand is considered.

After the release, the new item assumes the responsibility of the authority concerning demand and the stock by the business headquarters, and it pursues the maximization of sales for Kirin Beverage for 5 weeks as mentioned above. And, these responsibilities and authorities will shift to the logistics headquarters in 5 weeks, and the minimization of the cost is pursued while reducing the excess of production capacity. If this scenario is achieved, forecasting a great profit increase becomes possible.

13.4 Strategy for Four Points

Furthermore, this pair strategic chart is classified into four parts. This is due not only to the fact that the specific strategy which it should select is ascertained, but also to the four points, namely "financial," "customer," "innovation and learning," "internal process" perspectives in the balanced scorecard (BSC, refer to Fig. 13.3 and [4, 5]).

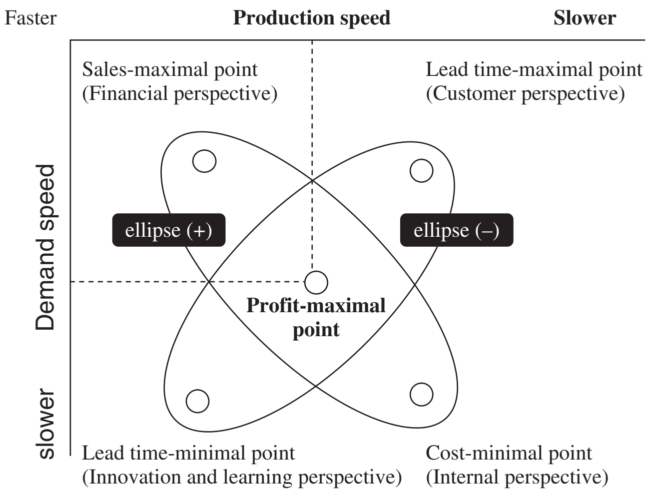


Fig. 13.3 Balance solution in enterprise

For this case, in addition to "the plus ellipse shape" shown in Fig. 13.1, "the minus elliptic shape," the counter electrode of the point that makes the lead time maximized, and the point that makes it minimized, are added [8]. The strategy to aim at the point of this profit maximization exists at each point as mentioned above.

(i) The point at which the lead time is maximized

Unnecessary time is lost in production because the production speed has fallen below the demand speed, and as a result, the lead time is maximized.

This is a result of the manufacturing section being able to catch up because the business department stimulates demand that improves the demand speed. It can be said that the state of the strategy is in the perspective of "customer" buys.

Therefore, the manufacturing section should improve the production speed and shorten the lead time. The perspective of "innovation and learning" is needed to execute this.

This strategy recommends a game with such a process that the customer works from the environment of "Outside" to the enterprise of "Inside." At this time, the enterprise should react so that the customer is satisfied. As a result, as demand increases, the lead time should be reduced. Therefore, a game strategy that plays these repeats is needed.

(ii) The point at which the lead time is minimized

The production speed exceeds the demand speed, and if the order comes, it is possible to ship it instantly. In other words, it is possible because the lead time has been converted maximally. This kind of ability is acquired by the strategy that stands in the perspective of "the innovation and learning." Therefore, the business department needs the strategy from the aspect of "customers."

(iii) The point at which sales is maximized

The enterprise that is located here seriously considers the sales that the shareholder seeks from the view of "financial perspective." The manufacturing (sales) section hastens the production (demand) speed, and both sections maximize the sales.

However, the manufacturing section should aim at the review of the manufacturing cost from the perspective of "internal process," and shift to the improvement of the profit, because it does not necessarily relate to the improvement of the profit even if sales are extended as understood from the pair strategy chart.

First of all, if the success factor is requested outside, the environment that can reach the goal becomes important for the enterprise. The location in the environment that maximizes sales is the so-called positioning strategy in competitive management.

(iv) The point at which costs are minimized

This point can aim at the continuous improvement of the manufacturing process based on the perspective of "internal process," and is a typical pattern of manufacturing that minimizes the cost. It is necessary to work on the improvement of the profit with the "financial" perspective, although it is common in Japanese enterprises.

References

1. Berry, W.L., Hill, T.J. and Mclaughlin, C.P. (eds.), Special Issue on Linking Strategy Formulation in Marketing and Operation: Empirical Research, *Journal of Operations Management*, 10, 3(special issue), 1991
2. Davis, K.R., The Process of Problem Finding: A Production-Marketing Example, *Interfaces*, 8(1), 82–86, 1977
3. Follet, M.P, *Freedom & Coordination-Lectures in Business Organization*, L.H. Urwick (ed.), Pitman Publishing, London, 1949
4. Kaplan, R.S. and Norton, D.P., The Balanced Scorecard: Measure that Drive Performance, *Harvard Business Review*, Jan–Feb, 71–79, 1992
5. Kato, T. and Aoshima, Y., Perspectives in Management Research: Competitive Strategy, *Hitotsubashi Business Review*, Sum–Aut, 102–114, 2000
6. Malhotra, M.K. and Sharma, S. (ed.), Spanning the Continuum between Marketing and Operations, *Journal of Operations management*, 20, 3(special issue), 2002
7. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
8. Matsui, M., Theory of Demand-to-supply Systems and Management, *KEST 2003*, Akita, Japan, 2003 (on CD-ROM)
9. Matsui, M. and Fujikawa, H., Selling and Manufacturing can Collaborate Profitably, *DIAMONO Harvard Business Review*, 30(1), 72–83, 2005 (in Japanese)
10. Shapiro, B.P., Can Marketing and Manufacturing Coexist? *Harvard Business Review*, Sep–Oct, 104–114, 1977

Chapter 14
Summary and Remarks

14.1 Introduction

This book is based on more than 30 years of research of production/queueing management, and is systematized from the viewpoint of stochastic management. Traditionally, this kind of research has focused on the production center; while in this book, we took the sales center into consideration and examined the profit maximization (total optimization) from the cost minimization.

In the final chapter, we would like to give some supplementary remarks for the further development of this research. Our goal is to theorize this research to the demand-to-supply system and process management in the SCM era. Also, we would like to rewrite a suggestion on ERP/SCM researches based on a cycle/game model.

14.2 Two-Center Issues

14.2.1 Two-Stage Design

Management designs are developed for each of the three types of production systems, namely, assembly line, jobbing production and lot/cell production. The characteristic of our management design is that it takes the sales center into consideration, and focuses on the throughput maximization (total optimization).

Concretely, the basic model, MGM in Chapter 4, and its general two-stage design method is generated, and its particular version is developed for the four production models based on the research of the three types. The outline is arranged in Table 14.1, together with the respective stochastic models. Thus, we can see that the two-stage design method is applicable anywhere.

14.2.2 Generalized MGM

Under MGM (Chapter 4), it is not assumed that arriving demands are lost. However, it is often the case that the market demand is above the production capacity or latent by maker price.

M. Matsui, *Manufacturing and Service Enterprise with Risks*,
DOI 10.1007/978-0-387-84804-4_25, © Springer Science+Business Media, LLC 2009

Table 14.1 A summary of Two-stage design method for manufacturing models

Production model		Type	Stochastic model	Stage 1	Stage 2
Lot model	Lot/Cell Production	Push(lot Q)	M/M(Q)/1(N)	(Q, m)	(r, N)
		Pull(lot Q)	$M/M(Q)/1 \langle N \rangle$		
Conveyor model	Assembly line	Moving line	D/G.CSPS/K	(d, K)	c_i
		Free flow	$D/G/1/ \langle N \rangle$		N_i
	Flexible assembly	Ordered-entry (OE)	M/G.CSPS/K		(c_i, N_i)
Job-shop model	Order-selection	Periodic/ Dynamic	$M/\langle G, G \rangle/1(N)$	(c_1, c_2)	N
	Selection and Switch-over	Periodic	$M/\langle G, G \rangle/1$	$(c_1, c_2; i_1, i_2)$	Due time
		Dynamic	$M/\langle G, M \rangle/1$		
Flexible model	Machining	Fixed/Dynamic routing	Closed network	(N,M)	B_i
	Assembly	Ordered-entry (OE)	Open network	(d, K)	N_i
	Machining/ Assembly	Ordered-entry (OE)	Closed network	(N,M)	B_i

For this case, the Generalized MGM may be developed, and is seen in Fig. 14.1. Then, the mean operating cost is given by

$$\mathrm{EC} = \text{queueing cost} + \text{busy cost} + \text{idle cost} + \text{loss cost} \tag{14.1}$$

$$= \boldsymbol{\alpha}_1 L + \boldsymbol{\alpha}_2 \boldsymbol{\rho}_0 + \boldsymbol{\alpha}_3 (1 - \boldsymbol{\rho}_0) + \boldsymbol{\alpha}_4 \boldsymbol{\eta}, \tag{14.2}$$

where $\boldsymbol{\rho}_0 = \boldsymbol{\rho} P(< 1)$ and $\boldsymbol{\eta} = \boldsymbol{\rho} B$. This traffic accounting would be also useful as a material flow cost accounting (MFCA) under resource environment(recycle) issues.

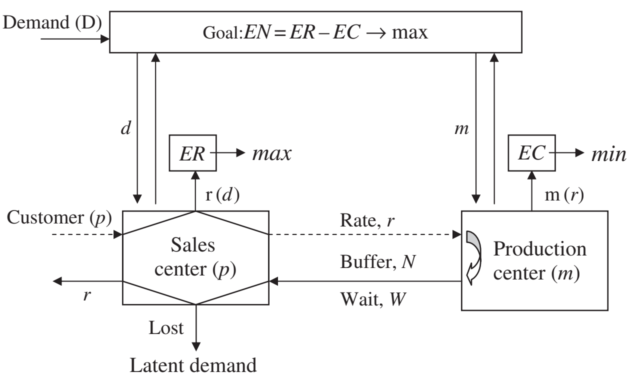


Fig. 14.1 Generalized MGM: A MGM with lost customers

14.3 Balancing Issues

14.3.1 Balancing Principle

The balancing issues of SCM-like processes is generally shown in Fig. 14.2. Then, the balancing problem by the cycle-time $\boldsymbol{Z}$ may be formulated as follows:

$$TH = \frac{1}{\mathbf{Z}} \prod_{i=1}^{n} (1 - R_i) \to \max_{Z}, \tag{14.3}$$

subject to

$$W = ZL, \tag{14.4}$$

where $R_{\mathrm{i}} = \Pr(T_{\mathrm{i}} \leq Z)$. (Note an alternative cost approach [10].)

The pursuit of balancing is better, but is followed by integration risk (Fig. 14.3). This would increase the disruption risk of business continuity in the institution/social risk. Thus, the autonomous balancing with redundancy would probably be better, and the processes toward equilibrium would face a wave of unbalancing in negative/positive feedback.

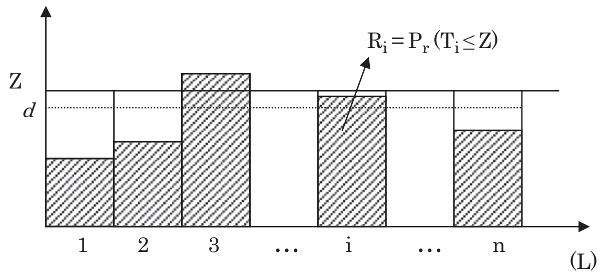


Fig. 14.2 Balancing problem: W = ZL

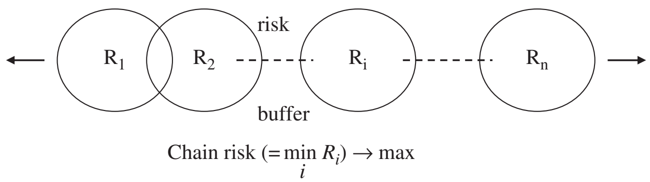


Fig. 14.3 Chain risk in balancing

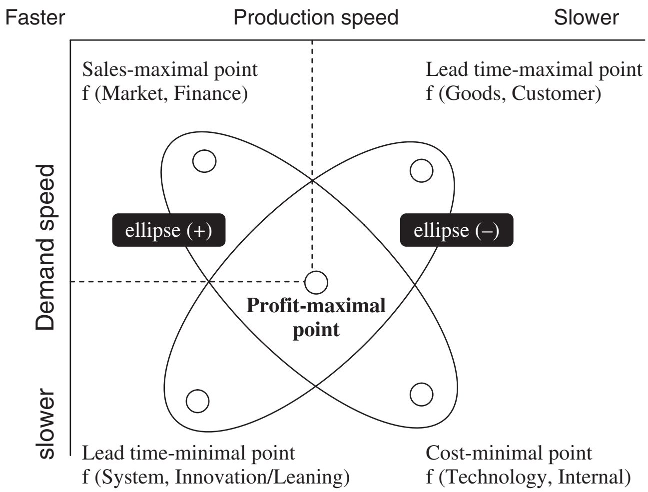


Fig. 14.4 Balance strategy

14.3.2 Enterprise Balancing

From Part **V**, the pair-matrix table by MGM is referred to as an ellipse-cross shape consisting of four centers (poles) in economics/reliability, and is discussed from a strategic view in chapter 13 [8]. The profit maximization would usually lie between the sales maximization pole and cost minimization pole (p. 266).
Thus, the enterprise balancing may be managed by a combination of four poles (strategies), and would be better in term of profit maximization and economic reliability.

The further strategies, f, seen in Fig. 14.4, and would correspond to the function of the four element in the business concept and the four perspectives in the Balanced Scorecard (BSC) [4], respectively. That is, strategy f: (Product) $\times$ (Enterprise) $\rightarrow$ Sustainability. The structure of this function should be further developed in future.

14.4 Balancing of Limited-Cycle

14.4.1 Limited-Cycle Problem

An example of the single limited-cycle model is shown in Fig. 14.5. If the production time of one period were T and due time were Z, then the risks due to the length of the production time would occur, which are the risks by $T \leq Z$ and the risks by $T > Z$. From Fig. 14.5, it can be noted that there is a trade-off problem for the two risks.

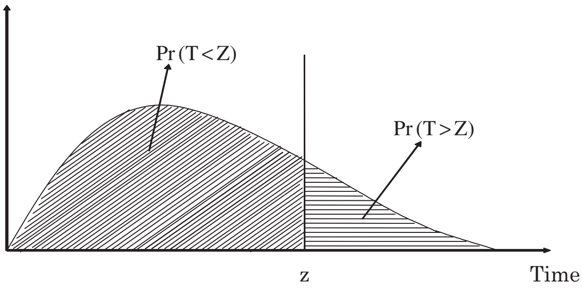


Fig. 14.5 A limited-cycle model: two kinds of risks

This problem is shown as the following expression:

$$\min_{z} \{\beta_1(Z)P_r(T \le Z) + \beta_2(Z)P_r(T > Z)\},$$

where, $\beta_1(Z)$ is the risk by $T \le Z$, $\beta_2(Z)$ is the risk by $T > Z$. This kind of problem is known as various problems of the reliability field, the problem of due time restriction and the class of newsboy problem [9]. A detailed model of a single limited-cycle recently appears in [7].

14.4.2 Multi-limited Cycle Problem

Now, the cases are considered in which the above two risks not only occur in the single period, but also in multiple periods repeatedly. This problem of minimizing the expected risk in such a situation is called a "limited-cycle problem with multiple periods." The multi-period problem could be classified according to whether the periods are independent or not (Fig. 14.6).

For this problem, one result is the general form of production rate and waiting time by a station-centered approach as discussed in Chapter 2.2 [6]. The explicit form is obvious and consists of the product form in the period-independent case, such as a single line, but it is untraceable in the period-dependent case such as with a mixed or tandem line. The mixed line has an absorbing barrier, but the tandem line has a reflective barrier at the end.

We give a cost approaches to the latter, which is another approach [10] to the bowl phenomenon in a tandem system [1, 2, etc.]. It is also noted that the bowl phenomenon is seen not only in the consecutive 2-out-of-n: F-system for a reliability

Line
- Period-independent – Simple Line
- Period-dependent
  - Without Terminal Condition – Mixed line
  - With Terminal Condition – Tandem line

Fig. 14.6 Classification of multi limited-cycle problems problem [5] and Johnson rule for a scheduling problem [3], but also in the profit world such as the so called smile curve at SCM. The details are omitted here.

Further station-centered approaches should be directed to not only serial (line) but also to parallel (or complex) systems.

References

1. Hillier, F.S. and Boling, R.W., The Effects of Some Design Factors on the Efficiency of Production Lines with Variable Operation Times, *Journal of Industrial Engineering*, 17, 651–658, 1966
2. Hillier, M.S. and Hillier, F.S., Simultaneous Optimization of Work and Buffer Space in Unpaced Production Lines with Random Processing Times, *IIE Transactions*, 38, 39–51, 2006
3. Johnson, S.M., Optimal Two-and Three-stage Production Schedules with Set-up Times Included, *Naval Research Logistics Quarterly*, 1(1), 61–68, 1954
4. Kaplan, R.S. and Norton, D.P., The Balanced Scorecard: Measure that Drive Performance, *Harvard Business Review*, Jan–Feb, 71–79, 1992
5. Malon, D.M., Optimal Consecuive-2-Out-of-n: F Component Sequencing, *IEEE Transaction on Reliability*, R-33, 414–418, 1984
6. Matsui, M., MGM-Modeling and Balancing Problem in Supply Chain Management, *Proceedings of APIEMS 2004*, Gold Cost, Australia, 2004 (on CD-ROM)
7. Matsui, M., A Management Cycle Model: Switching Control Under Lot Processing and Time Span, *Journal of Japan Industrial Management Association*, 56(4), 256–264, 2005
8. Matsui, M. and Fujikawa, H., Selling and Manufacturing can Collaborate Profitably, *DIAMOND Harvard Business Review*, 30(1), 72–83, 2005 (in Japanese)
9. Week, J.K., Optimizing Planned Lead Times and Delivery Dates, *21st Annual Conference Proceedings*, APICS, 177–188, 1979
10. Yamamoto, H., Matsui, M. and Liu, J., A Basic Study on a Limit-Cycle Problem with Multi Periods and the Optimal Assignment Problem, *Journal of Japan Industrial Management Association*, 57(1), 23–31, 2006 (in Japanese)

Appendix A
A Theory of Demanded-to-Supply Economics

The demand (customer) and supply (production) system is considered in queueing form. Then, a general or relative theory of demand and supply system is obtained by queueing formulas in Matsui et al. [3]

A.1 Introduction

In the SCM age, a foundation for demand-to-supply management is desired [4]. This appendix presents the relative theory of demand (customer) and supply (production) by queueing formulas. In this case, a relative relationship of demand and supply is used and corresponds to that of customers and service/processing in queueing theory.

We have already given a general relationship of average criteria in queueing systems. This result appears in [1–5,7,8] on the basis of the new formula in [9], and is applied here to a demand and supply system. Then, a system of efficiencies and the demand and supply formulas, etc. are given in quening form.

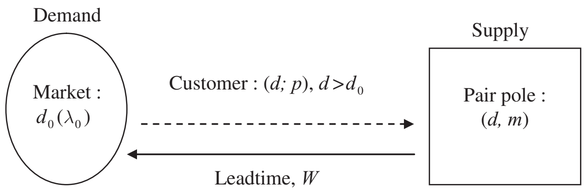
A.2 Demand-and-Supply System

The demand and supply system in queueing form is shown in Fig. A.1. In Fig. A.1, the market has a latent demand, while the supply has a pair pole in Chapter 4.1 [6].

The following notations are seen in Fig. A.1 and later.

λ: Demand (arrival) rate
λ_0: Virtual demand rate
$d(= 1/\lambda)$: Demand speed (Mean interarrival time)
$d_0(= 1/\lambda_0)$: Virtual demand speed
m: Production speed (Mean processing time)
$\rho(= m/d)$: Traffic intensity
P: probability of processing
$B(= 1 - P)$: Probability of loss
η: Mean number of overflows per unit produced

Fig. A.1 A demand and supply system



Z: productive cycle time (Mean work-time per unit produced)
L: stock (Mean number of customers in system)
W: lead time (Mean waiting time in system)
p: Selling price
V: Economic value (profit in system)
α_i, $i = 1, 2, 3,$: Coefficients of cost

A.3 A System of Efficiencies

The relation of demand and supply is regarded as relative. The relative efficiencies for production are distinguished from the demand and supply sides shown in Table A.1.

Table A.1 Efficiencies for demand and supply sides

	Demand (customer) side		Supply (facility) side	
Transformation	P (= 1–B)	Probability of processing	P	Resource/ availability
	B (= 1–P)	Probability of loss	B	Restability
Output	r (= λP)	Production rate	ρP	Busy rate (utilization)
	υ (= λB)	Overflow rate	1–ρP	Idle rate

In Table A.1, the probabilities P and B are from [1,2,7,8] as follows:

$$P = 1/(1+\eta), \qquad 0 \leqq \eta < \infty \tag{A.1}$$

$$B = \eta/(1+\eta), \quad 0 \leqq \eta < \infty \tag{A.2}$$

Especially, $\eta = \rho = m/d$ for the $GI/GI/1$ system.

The right side in Table A.1 is important to the make-to-stock type, and is related to customer risks. On the other hand, the left side is important to the make-to-order type, and is related to facility risks.

A.4 Demand-to-Supply Formulas

As an equilibrium solution, the demand-to-supply system is formed by the following queueing formulas:

$$\text{Queueing formula I} : \lambda Z = M = 1 + \eta \tag{A.3}$$

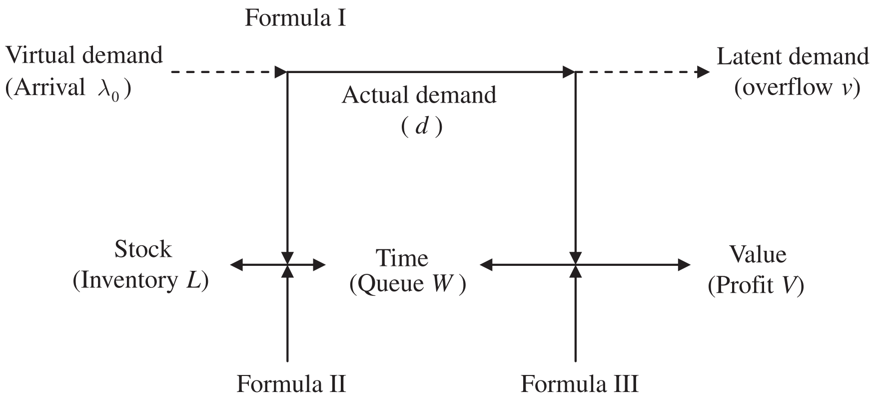


Fig. A.2 Demand-to-supply formulas

$$\text{Queueing formula II}: W = ZL \tag{A.4}$$

$$\text{Queueing formula III}: VZ = p - \alpha_1 W - CZ \tag{A.5}$$

where the busy and idle cost, C, is given by

$$C = \alpha_2 \rho P + \alpha_3(1 - \rho P) \tag{A.6}$$

From formulas (A.3)–(A.5), a general relationship of stock (L), time (W) and value (V) is obtained in Fig. A.2.

A.5 Further Formulas

In the *ROA* (return on asset), the asset is regarded here as L or W in Fig. A.2. Then, the *ROL* and *ROW* are defined, respectively, by

$$ROL = V/L, \tag{A.7}$$

$$ROW = V/W \tag{A.8}$$

From (A.7) and (A.8), the following relation is × easily obtained:

$$ROL = Z \times ROW \tag{A.9}$$

Also, the ROW is decomposed into the two efficiencies as follows:

$$\begin{aligned} ROW &= (\text{Production efficiency}) \times (\text{Management efficiency}) \\ &= (m/W)(V/m) \end{aligned} \tag{A.10}$$

In addition to Fig. A.2 and Eqs. (A.3) and (A.5), the two formulas of Little ($\lambda W = L$) and input-output ($\lambda Z = M$) are here unified as follows:

$$\lambda W = ML \tag{A.11}$$

This formula is easily obtained from the input-output formula (A.3): $\lambda Z = M$. That is, the result is obvious from producing by Z and exchanging ZL by W. Thus, it is noted that Little's formula is also a special case of an input-output relation.

References

1. Matsui, M., *A Study on Optical Operating Polices in Conveyer-Serviced Production System*, Doctral Dissertation, Tokyo Institute of Technology, Japan, 1981 (in Japanese)
2. Matsui, M., Conveyor-Serviced Production System: Queueing Formulas, CSPS Analysis and 2-Level Mathematical Formulation, unpublished paper, 1982
3. Matsui, M., A Relationship of Average Criteria for Queueing System with Lost Units, *Symposium on Performance Model for Information Communication Networks*, Numazu, Japan, 371–378, 1993
4. Matsui, M., New Demand and Supply Theory: Pair-Pole, Relativity and 2-Level, *Preprints of Japan Industrial Management Association*, Autumn, 44–45, 2000 (in Japanese)
5. Matsui, M., Queueing Formulas "$W = ZL$" and its Circumference, *Monthly Meeting of Special Interest Group on Queueing Theory*, 162, ORSJ, Japan, 2002 (in Japanese)
6. Matsui, M., A Management Game Model: Economic Traffic, Leadtime and Pricing Setting, *Journal of Japan Industrial Management Association*, 53(1), 1–9, 2002
7. Matsui, M., CSPS Model: Look-Ahead Controls and Physics, *International Journal of Production Research*, 43(10), 2001–2025, 2005
8. Matsui, M., Shingu, T. and Makabe, H., Conveyor-Serviced Production System: An Analytic Framework for Station-Centered Approach by Some Queueing Formulas, *Preliminary Report of the Operations Research Society of Japan*, Autumn, 104–107, 1977 (in Japanese)
9. Matsui, M., Shingu, T. and Makabe, H., An Analysis of Conveyor-Serviced Production Station by Queueing Theory, *Journal of Japan Industrial Management Association*, 28(4), 375–386, 1978 (in Japanese)

Index

NOTE: The letters '*f*' and '*t*' following the locators refer to figures and tables respectively.

Early titles in the
INTERNATIONAL SERIES IN OPERATIONS RESEARCH & MANAGEMENT SCIENCE
(Continued from page ii)

Wierenga/*HANDBOOK OF MARKETING DECISION MODELS*
Agrawal & Smith/*RETAIL SUPPLY CHAIN MANAGEMENT: Quantitative Models and Empirical Studies*
Brill/*LEVEL CROSSING METHODS IN STOCHASTIC MODELS*
Zsidisin & Ritchie/*SUPPLY CHAIN RISK: A Handbook of Assessment, Management & Performance*
Saigal/ *A MODERN APPROACH TO LINEAR PROGRAMMING*
Nagurney/ *PROJECTED DYNAMICAL SYSTEMS & VARIATIONAL INEQUALITIES WITH APPLICATIONS*
Padberg & Rijal/ *LOCATION, SCHEDULING, DESIGN AND INTEGER PROGRAMMING*
Vanderbei/ *LINEAR PROGRAMMING*
Jaiswal/ *MILITARY OPERATIONS RESEARCH*
Gal & Greenberg/ *ADVANCES IN SENSITIVITY ANALYSIS & PARAMETRIC PROGRAMMING*
Prabhu/ *FOUNDATIONS OF QUEUEING THEORY*
Fang, Rajasekera & Tsao/ *ENTROPY OPTIMIZATION & MATHEMATICAL PROGRAMMING*
Yu/ *OR IN THE AIRLINE INDUSTRY*
Ho & Tang/ *PRODUCT VARIETY MANAGEMENT*
El-Taha & Stidham/ *SAMPLE-PATH ANALYSIS OF QUEUEING SYSTEMS*
Miettinen/ *NONLINEAR MULTIOBJECTIVE OPTIMIZATION*
Chao & Huntington/ *DESIGNING COMPETITIVE ELECTRICITY MARKETS*
Weglarz/ *PROJECT SCHEDULING: RECENT TRENDS & RESULTS*
Sahin & Polatoglu/ *QUALITY, WARRANTY AND PREVENTIVE MAINTENANCE*
Tavares/ *ADVANCES MODELS FOR PROJECT MANAGEMENT*
Tayur, Ganeshan & Magazine/ *QUANTITATIVE MODELS FOR SUPPLY CHAIN MANAGEMENT*
Weyant, J./ *ENERGY AND ENVIRONMENTAL POLICY MODELING*
Shanthikumar, J.G. & Sumita, U./ *APPLIED PROBABILITY AND STOCHASTIC PROCESSES*
Liu, B. & Esogbue, A.O./ *DECISION CRITERIA AND OPTIMAL INVENTORY PROCESSES*
Gal, T., Stewart, T.J., Hanne, T. / *MULTICRITERIA DECISION MAKING: Advances in MCDM Models, Algorithms, Theory, and Applications*
Fox, B.L. / *STRATEGIES FOR QUASI-MONTE CARLO*
Hall, R.W. / *HANDBOOK OF TRANSPORTATION SCIENCE*
Grassman, W.K. / *COMPUTATIONAL PROBABILITY*
Pomerol, J-C. & Barba-Romero, S. / *MULTICRITERION DECISION IN MANAGEMENT*
Axsäter, S. / *INVENTORY CONTROL*
Wolkowicz, H., Saigal, R., & Vandenberghe, L. / *HANDBOOK OF SEMI-DEFINITE PROGRAMMING: Theory, Algorithms, and Applications*
Hobbs, B.F. & Meier, P. / *ENERGY DECISIONS AND THE ENVIRONMENT: A Guide to the Use of Multicriteria Methods*
Dar-El, E. / *HUMAN LEARNING: From Learning Curves to Learning Organizations*
Armstrong, J.S. / *PRINCIPLES OF FORECASTING: A Handbook for Researchers and Practitioners*
Balsamo, S., Personé, V., & Onvural, R./ *ANALYSIS OF QUEUEING NETWORKS WITH BLOCKING*
Bouyssou, D. et al. / *EVALUATION AND DECISION MODELS: A Critical Perspective*
Hanne, T. / *INTELLIGENT STRATEGIES FOR META MULTIPLE CRITERIA DECISION MAKING*
Saaty, T. & Vargas, L. / *MODELS, METHODS, CONCEPTS and APPLICATIONS OF THE ANALYTIC HIERARCHY PROCESS*
Chatterjee, K. & Samuelson, W. / *GAME THEORY AND BUSINESS APPLICATIONS*
Hobbs, B. et al. / *THE NEXT GENERATION OF ELECTRIC POWER UNIT COMMITMENT MODELS*
Vanderbei, R.J. / *LINEAR PROGRAMMING: Foundations and Extensions, 2nd Ed.*

Kimms, A. / *MATHEMATICAL PROGRAMMING AND FINANCIAL OBJECTIVES FOR SCHEDULING PROJECTS*
Baptiste, P., Le Pape, C. & Nuijten, W. / *CONSTRAINT-BASED SCHEDULING*
Feinberg, E. & Shwartz, A. / *HANDBOOK OF MARKOV DECISION PROCESSES: Methods and Applications*
Ramík, J. & Vlach, M. / *GENERALIZED CONCAVITY IN FUZZY OPTIMIZATION AND DECISION ANALYSIS*
Song, J. & Yao, D. / *SUPPLY CHAIN STRUCTURES: Coordination, Information and Optimization*
Kozan, E. & Ohuchi, A. / *OPERATIONS RESEARCH/ MANAGEMENT SCIENCE AT WORK*
Bouyssou et al. / *AIDING DECISIONS WITH MULTIPLE CRITERIA: Essays in Honor of Bernard Roy*
Cox, Louis Anthony, Jr. / *RISK ANALYSIS: Foundations, Models and Methods*
Dror, M., L'Ecuyer, P. & Szidarovszky, F. / *MODELING UNCERTAINTY: An Examination of Stochastic Theory, Methods, and Applications*
Dokuchaev, N. / *DYNAMIC PORTFOLIO STRATEGIES: Quantitative Methods and Empirical Rules for Incomplete Information*
Sarker, R., Mohammadian, M. & Yao, X. / *EVOLUTIONARY OPTIMIZATION*
Demeulemeester, R. & Herroelen, W. / *PROJECT SCHEDULING: A Research Handbook*
Gazis, D.C. / *TRAFFIC THEORY*
Zhu/ *QUANTITATIVE MODELS FOR PERFORMANCE EVALUATION AND BENCHMARKING*
Ehrgott & Gandibleux / *MULTIPLE CRITERIA OPTIMIZATION: State of the Art Annotated Bibliographical Surveys*
Bienstock/ *Potential Function Methods for Approx. Solving Linear Programming Problems*
Matsatsinis & Siskos / *INTELLIGENT SUPPORT SYSTEMS FOR MARKETING DECISIONS*
Alpern & Gal / *THE THEORY OF SEARCH GAMES AND RENDEZVOUS*
Hall/ *HANDBOOK OF TRANSPORTATION SCIENCE-*2^{nd} *Ed.*
Glover & Kochenberger / *HANDBOOK OF METAHEURISTICS*
Graves & Ringuest/ *MODELS AND METHODS FOR PROJECT SELECTION: Concepts from Management Science, Finance and Information Technology*
Hassin & Haviv/ *TO QUEUE OR NOT TO QUEUE: Equilibrium Behavior in Queueing Systems*
Gershwin et al/ *ANALYSIS & MODELING OF MANUFACTURING SYSTEMS*
Maros/ *COMPUTATIONAL TECHNIQUES OF THE SIMPLEX METHOD*
Harrison, Lee & Neale/ *THE PRACTICE OF SUPPLY CHAIN MANAGEMENT: Where Theory and Application Converge*
Shanthikumar, Yao & Zijm/ *STOCHASTIC MODELING AND OPTIMIZATION OF MANUFACTURING SYSTEMS AND SUPPLY CHAINS*
Nabrzyski, Schopf & Weglarz/ *GRID RESOURCE MANAGEMENT: State of the Art and Future Trends*
Thissen & Herder/ *CRITICAL INFRASTRUCTURES: State of the Art in Research and Application*
Carlsson, Fedrizzi, & Fullér/ *FUZZY LOGIC IN MANAGEMENT*
Soyer, Mazzuchi & Singpurwalla/ *MATHEMATICAL RELIABILITY: An Expository Perspective*
Chakravarty & Eliashberg/ *MANAGING BUSINESS INTERFACES: Marketing, Engineering, and Manufacturing Perspectives*
Talluri & van Ryzin/ *THE THEORY AND PRACTICE OF REVENUE MANAGEMENT*
Kavadias & Loch/ *PROJECT SELECTION UNDER UNCERTAINTY: Dynamically Allocating Resources to Maximize Value*
Brandeau, Sainfort & Pierskalla/ *OPERATIONS RESEARCH AND HEALTH CARE: A Handbook of Methods and Applications*
Cooper, Seiford & Zhu/ *HANDBOOK OF DATA ENVELOPMENT ANALYSIS: Models and Methods*
Luenberger/ *LINEAR AND NONLINEAR PROGRAMMING,* 2^{nd} *Ed.*
Sherbrooke/ *OPTIMAL INVENTORY MODELING OF SYSTEMS: Multi-Echelon Techniques, Second Edition*
Chu, Leung, Hui & Cheung/ *4th PARTY CYBER LOGISTICS FOR AIR CARGO*
Simchi-Levi, Wu & Shen/ *HANDBOOK OF QUANTITATIVE SUPPLY CHAIN ANALYSIS: Modeling in the E-Business Era*
Gass & Assad/ *AN ANNOTATED TIMELINE OF OPERATIONS RESEARCH: An Informal History*

Greenberg/ *TUTORIALS ON EMERGING METHODOLOGIES AND APPLICATIONS IN OPERATIONS RESEARCH*
Weber/ *UNCERTAINTY IN THE ELECTRIC POWER INDUSTRY: Methods and Models for Decision Support*
Figueira, Greco & Ehrgott/ *MULTIPLE CRITERIA DECISION ANALYSIS: State of the Art Surveys*
Reveliotis/ *REAL-TIME MANAGEMENT OF RESOURCE ALLOCATIONS SYSTEMS: A Discrete Event Systems Approach*
Kall & Mayer/ *STOCHASTIC LINEAR PROGRAMMING: Models, Theory, and Computation*
Sethi, Yan & Zhang/ *INVENTORY AND SUPPLY CHAIN MANAGEMENT WITH FORECAST UPDATES*
Cox/ *QUANTITATIVE HEALTH RISK ANALYSIS METHODS: Modeling the Human Health Impacts of Antibiotics Used in Food Animals*
Ching & Ng/ *MARKOV CHAINS: Models, Algorithms and Applications*
Li & Sun/ *NONLINEAR INTEGER PROGRAMMING*
Kaliszewski/ *SOFT COMPUTING FOR COMPLEX MULTIPLE CRITERIA DECISION MAKING*
Bouyssou et al/ *EVALUATION AND DECISION MODELS WITH MULTIPLE CRITERIA: Stepping stones for the analyst*
Blecker & Friedrich/ *MASS CUSTOMIZATION: Challenges and Solutions*
Appa, Pitsoulis & Williams/ *HANDBOOK ON MODELLING FOR DISCRETE OPTIMIZATION*
Herrmann/ *HANDBOOK OF PRODUCTION SCHEDULING*
Matsui/ *MANUFACTURING AND SERVICE ENTERPRISE WITH RISKS*

**A list of the more recent publications in the series is found at the front of the book **