Supply Chain Risk Management : Approaches for Functional Business Processes

by

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Abstract

A supply chain is a set of individual and cross-functional business processes from upstream to downstream, which can also be thought of as a combined value chain for the whole optimization of the processes. It usually involves R&D, procurement, production, distribution and retail, and offers various opportunities to optimize the organically combined business processes. For the optimization to be possible, a supply chain management(SCM) has a key step for a risk control. It is a fact that the supply chain cannot be optimized unless the risk is controllable, so that supply chain risk management(SCRM) is attracting significant attention in the study of business management. However, in recent years, the types of risk have been extremely diversifying due to the complicated SCM and rapidly changing business environment, such as the diversity of customer needs, the shortened product life-cycle, globalization, the complexity of a production system, and so forth. Furthermore, such as derivative risks, it is not easy to recognize when and which risks occur. Exactly, the risk defined as generally possible loss or a likelihood of threat comes from not knowing what the main causes are. For this reason, the SCRM is getting difficult, and also requires more practical responses from the various viewpoints.

The objective of this dissertation is to propose models for the SCRM focusing on individual and cross-functional processes in a supply chain. We first extract and analyze core risk drivers leading to direct and indirect risks in Chapter 2. Total 10,181 articles from 68 international journals published during the past four decades has been reviewed for the work. We extracted 133 supply chain risk drivers, and analyzed types of the risk and the associated impacts, as well as the trends. In Chapter 3, we developed an economic make-or-buy decision model in multistage production processes. We proposed a solution procedure that can specify an economic making or buying area based on the break-even analysis. In Chapter 4, we examined an optimal replacement time of a production equipment under failure uncertainties. And we designed flexible supply contract models using options in Chapter 5. In details, we formulated a single-period two-stage decision-making model for analyzing four types of supply contracts. Moreover, by numerical examples, we showed the optimal option contracts and comparative advantages and risks between the contracts. In Chapter 6, we designed a prediction market using multi-agent system(MAS), and analyzed a price convergence. We also discussed the results related to parameter dependency of various types of agents. Then in Chapter 7, we proposed a dynamic cubic neural network(DCNN) with demand momentum for demand forecasting. In our model, an output scope of an activation function of hidden layer is modified for every period, according to a demand momentum which is defined by a demand inertia and a price acceleration plays a key role in adjustment of the output in iterative learning processes. We finally provided a brief summary of our conclusions in Chapter 8, in addition to discussion for the future of a supply chain.

Keywords; Supply chain risk driver, Make-or-buy decision, Production equipment replacement, Flexible supply contract, Prediction market, Dynamic cubic neural network.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background and goal

Supply chain management(SCM), in order to control information, materials and cash flow across the entire supply chain, has been a major component for strategic operation in the rapidly changing business environment. The dynamic business environment usually leads to a high uncertainty so that it is not surprising that the SCM has been attracting much attention as a collaborative logistics management technology to respond efficiently against the uncertainty. First of all, fundamentally, the SCM offers an opportunity to mitigate internal and external uncertainties from a market dynamics, a diversity of customer needs, a rapid progress of globalization and technology innovation. A survey of Deloitte & Touche(1999) suggested that many firms in North America had benefited through the SCM; the biggest plus was an accuracy of demand forecasting which was improved from 35 to 90 percent. The next was a reduction of inventory level that was cut down from 35 to 70 percent of total inventory in a supply chain, as well as a reduction of an operating cost and order cycle time. Furthermore, a perfect order fulfillment ratio and total productivity had also improved [1].

Although a SCM is obviously one of the most advanced management methodologies for optimization of a supply chain, it is always necessary for us to consider questions of what makes the SCM hard and how to overcome the difficulty from many uncertainties, for more effective management or to encourage further business activities, in details. A source of the uncertainties inherent in a supply chain is an unbalance of a supply and demand that focuses on how to timely meet an unpredictable customer demand based on a stable supply reliability. And a lot of potential factors, called risk drivers, have forced the supply chain to be out of the balance. As one of the uncontrollable and inherent risk drivers, a fluctuating customer demand can never be exactly forecasted which not only causes an oversupply or shortage in supply, but also interrupts an optimal and stable operation of the supply chain. Moreover, since a strike, a natural disaster and war can temporarily disrupt the supply chain, it is sure that they are also risks to be certainly avoided even though they do not occur as frequently as other risks. To give an example, due to a fire caused by a lightning at a local plant owned by Royal Philips Electronics in 2000, a major customer, Nokia, changed their suppliers to supply microchips smoothly based on a multiple-supplier strategy, and had suffered little during the crisis, thanks to an exhaustive risk management strategy [2]. This is an essential reason why the risks have to be strategically managed.

Discussions on a risk and its management in a supply chain often fail to recognize completely both sides of those: a possibility of danger and a golden opportunity. The literal meaning of word of 'Risk' actually calls our attention to a something that has to avoid unconsciously. However, unless the risk is considered, there are no additional benefits as well as opportunities to strengthen core capabilities in the supply chain, whereas a strategic risk management is what gives us a competitive advantage comparing with other supply chains. That is, a supply chain risk management(SCRM) is to reinforce a vulnerability of the supply chain and to obtain more opportunities by mitigating of uncertainties. The main issues of the SCRM are derived and structured in accordance with a three conceptual level of 'philosophy', 'principles' and 'processes' [3].

The first, philosophy-related issues of a SCRM are mainly dealt with inevitable aspects for the importance, a strategic classification, a risk driver and trend of the SCRM, which can be a basic approach of what risk is, and what to do for a sustainable growth and riskless improvement of the supply chain, and may also be related to how to balance risks and benefits of the supply chain in a broad perspective. Sunil Chopra and ManMohan S. Sodhi(2004) presented categorized supply chain risks and their drivers as well as mitigation strategies on what managers should do, not only to help better understanding of the variety and interconnectedness of supply chain risks but also to assess the impact of the various mitigation strategies. Besides, they also presented a concept of balancing between the level of risk management and reward relationship such as a cost of reserve and benefit of polling reserve, etc., and emphasize an establishment of the optimal level of risk management by the balance of the risk and benefit [2]. Roshan S. Gaonkar and N. Viswanadham(2007) developed an analytic framework to classify problems of the SCRM, and structured supply chain risks that need to be handled in four levels: organizational level-related risk, network-related risk, environmental-related risk and industrial level-related risk [4]. Similarly, Paulsson, U. and Norrman, A.(2003) identified three points on categorized supply chain risks along a particular continuum as an operational disturbance, a tactical disruption and strategic uncertainty. In essence, since the risk types can be divided into those of three levels, it is required different approaches to an efficient management [6]. On the other hand, Christopher S. Tang(2006) reviewed various quantitative models for managing supply chain risks with classifying SCRM papers, and presented six potential ideas for future studies in the fields of the SCRM [5].

The second, principles-related issues of a SCRM are extensively discussed about risk management techniques, logics, tools and performance measures. To identify and assess risks, the first step to do is the performance measurement that leads to a better SCM. By making a standard of judgment of whether a supply chain runs effectively or not, unspecified approaches of risk management can be a visualization and quantification. Many authors address how to measure the performance of the supply chain from various viewpoints. One of the well-known models is a supply chain operations reference(SCOR) model of Supply Chain Council, Inc.(SCC). The SCOR model provides an unique cross-functional framework which links business activities, business processes, a best practice and technology for the better supply chain. It also can help a strategic management, a supply chain optimization, a successful benchmarking and new business start-up, etc. [7]. A balanced scorecard(BSC) has also been widely used as an another standard pattern for both the supply chain performance and general business process measurement. The BSC is composed of 4 perspectives related to financial, customer, international business and learning and growth. And each of those initiatives, targets, measures and objectives have closely linked, through a cause and effect relation. Therefore, the BSC can be used an outstanding risk-related performance measurement tool within how to be linked to management effectiveness. Turn our attention to scientific researches, A. Gunasekaran et al.,(2004) proposed a metrics framework to promote a better understanding of an importance of the supply chain performance measurement, by a strategic, a tactical and operational [8]. Similarly, as the latest study, Dominique Estampe et al.,(2010) also presented a framework for analyzing and evaluation of the supply chain performance [9]. On the other hand, for risk management tools and techniques, Tobias Schoenherr et al.,(2008) reported an approach for assessing and managing of supply chain risks by an analytic hierarchy process(AHP), which supports a decision-making under uncertainties and serves a practical methodology for manufacturing firms [10]. The white paper of PWC(2009) proposed a new analysis on how firms can remove risks in their supply chains: a collaborative risk management. It concludes that a sharing risk information and strengthening of collaborative responsibilities between players across the supply chain help in optimizing a whole supply chain and in improving business performances [11]. And there are some studies using more practical and specified tools and techniques for the risk management. As representative studies in the filed of the SCRM, for instance, it comes under papers using financial options and portfolio strategies, etc. By using a cooperative game theory, Yingxue Zhao et al.,(2010) developed an option contract model, and tried to coordinate a supply chain which is closely related to a wholesale price mechanism and channel coordination based on a negotiation power [12]. Similarly, Xiaolong Wang and Liwen Liu(2007), as a risk management approach, discussed a coordination in a retailer-led supply chain by option contracts, too [13].

The last issue of related SCRM is a business process. A supply chain is a set of the business processes and activities that are organically connected. This suggests that making those of the set visible across the supply chain is the first step for SCM and it also linked to an efficient risk management. As the same time, most of core business decisions in the supply chain are based in part on results of the risk identification and assessment from the viewpoint of an individual or an integrated business process. It functionally includes R&D, sourcing, manufacturing, distribution and sale, and requires an innovative product development, a strategic outsourcing, a flexible manufacturing and inventory management, an optimal distribution network configuration and efficient demand forecasting, by each process. Therefore discussing about the business processes is quite available for a practical risk management.

There are number of researches and discussions on a supply chain risk management. However, there is a lack of practical analysises and detailed studies on the risk management dealing with key issues of an individual or a cross-functional business process, while much attention has been focused on the business process integration and collaborative management with a information sharing in a supply chain. The collaborative management is obviously necessary and a sufficient condition for a SCRM, but can not cover all of the relevant problems in depth, at an operational level. At the same time, there is a considerable gap between a strategic and the operational level, so that practical approaches by each process or cross-functional aspects of the supply chain are extremely required, especially for managers who have to consider about exactly what relevant risks are. Furthermore, it also needs to be simultaneously discussed about detailed risk drivers and a linking to a design of mathematical models with respect to the risks, which has never been mentioned in any research materials so far; for instance, a fluctuating demand or a market dynamics as a risk driver has a big influence on a decision of an optimal production volume for a manufacturer, which can be described by mathematical models of flexible supply contracts using various financial options as one of the practical approaches to mitigate the risks.

We will therefore discuss in this dissertation key issues by each business process or a cross-functional aspect, collectively. This dissertation makes several contributions to a filed of a SCRM. First, a supply chain risk drivers(SCRD) leading to many types of uncertainties are systematically clarified, based on a lot of research materials; by general business attributes and the business processes of a supply chain, we derive various types of risks and analyze frequency of listed on articles, after categorizing those types. Second, we provides a set of process-focusing approaches of the risk management which needs to be considered in a supply chain for both an individual business process and cross-functional business processes, such as an economic make-or-buy decision, an optimal production equipment replacement, a flexible supply contract and dynamic demand forecasting, as well as an identifying of risk drivers, etc. Finally, we shows how our approaches can be used to support a decision-making under many uncertainties at an operational level; with mathematical models, numerical experiments are also presented which could lead to a better understanding for the SCRM.

1.2 The scope of research directions

A research scope of this dissertation is limited to an individual and cross-functional business processes in a supply chain, as shown in Figure 1.1. The individual process can simply be described by a single player, whereas the cross-functional processes can be described by two or more collaborative players in the supply chain.

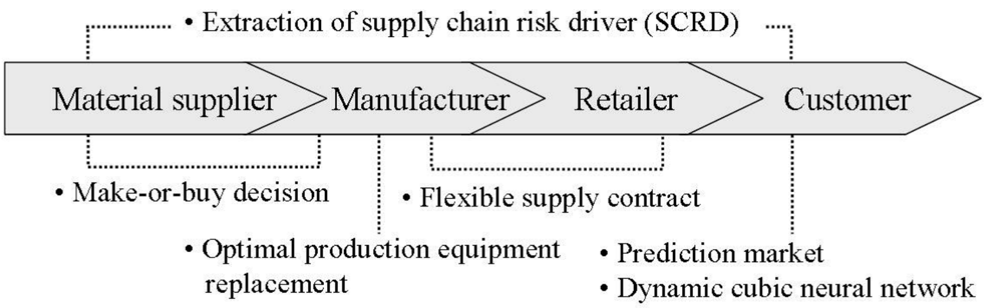


Figure 1.1: The scope of research directions

We deal with in this dissertation the total six practical approaches with respect to a supply chain risk driver(SCRD), sourcing risk, manufacturing risk, supply and purchase risk, and prediction risk, to help building a flexible supply chain by reducing the potential risks. Based on a definition and structure of the supply chain risk in Chapter 1, we first extract and analyze the SCRD in Chapter 2. And then, by chapters, we design concrete models connected with some of key risks out of the extracted SCRDs. To design a risk management model for a procurement process, we deal with an economic make-or-buy decision problem referred to the SCRD such as 'a level of financial resource', 'allocation of scarce resource', and 'resource substitutionality'. The SCRDs such as 'a level of accident cover-ups' and 'dangerous conditions on the production line' refer to a model for an economic replacement of a production equipment considering failure uncertainties in Chapter 4, and 'a production flexibility' and 'responsiveness to changing market/customer requirements' as SCRDs refer to a flexible option contract model in Chapter 5, respectively. Finally, 'a value(accuracy) of forecast' and 'market unmeasurely uncertain' refer to a prediction risk for Chapter 6 and 7.

1.3 Supply chain risk and its structure

According to Hugh Courtney et al. of Harbard Business Review(July 2009), the uncertainty that remains after the best possible anaysis facing strategic decison-making has been under taken is what we call residual uncertainty. Based on the extent to which it is possible to understand of or know an aspect of the future, it is indispensable to differentiate the levels of the uncertainty. They have classified risks from the uncertainties by four levels, and proposed strategic analysises of how to overcome them [14].

Level 1: A clear enough future
The residual uncertainty is irrelevant to making strategic decisions at level one, so managers can develop a single forecast that is a sufficiently precise basis for their strategies. To help generate this usefully precise prediction of the future, managers can use the standard strategy tool kit: market research, analyses of competitors' costs and capacity, value chain analysis, Michael Porter's fiveforces framework, and so on. A DCF model that incorporates those predictions can then be used to determine the value of alternative strategies.

Level 2: Alternative futures
The future can be described as one of a few discrete scenarios at level two. Analysis can't identify which outcome will actually come to pass, though it may help establish probabilities. Most important, some, if not all, elements of the strategy would change if the outcome were predictable.

Level 3: A range of futures
A range of potential futures can be identified at level three. A limited number of key variables define that range, but the actual outcome may lie anywhere within it. There are no natural discrete scenarios. As in level two, some, and possibly all, elements of the strategy would change if the outcome were predictable.

Level 4: True ambiguity

A number of dimensions of uncertainty interact to create an environment that is virtually impossible to predict at level four. In contrast to level three situations, it is impossible to identify a range of potential outcomes, let alone scenarios within a range. It might not even be possible to identify, much less predict, all the relevant variables that will define the future.

Based on the four levels of uncertainty, we will discuss a supply chain risk and its structure by classifying them into the following two clear viewpoints: (1) a deterministic approach for from the level one to three, and (2) a stochastic approach for the level 4 . As shown in Figure 1.2, as a risk, the (1) represents a gap (a quantitative deviation) between an alternative and an optimal solution satisfying an objective function, while the (2) stands for an uncertainty in the result of presented strategy. For the deterministic approach, the uncertainty is not involved in the risk, unless it is converted into the quantitative deviation. And in case of the stochastic approach, if the uncertainty becomes a zero in spite of a huge loss, the risk becomes a zero. For example, there is a game in which an investor has a probability of 0 to win the game. This obviously looks a very risky, but it is not a risk for the second case. Because a defeat in the game is sure, that is, the uncertainty is a zero.

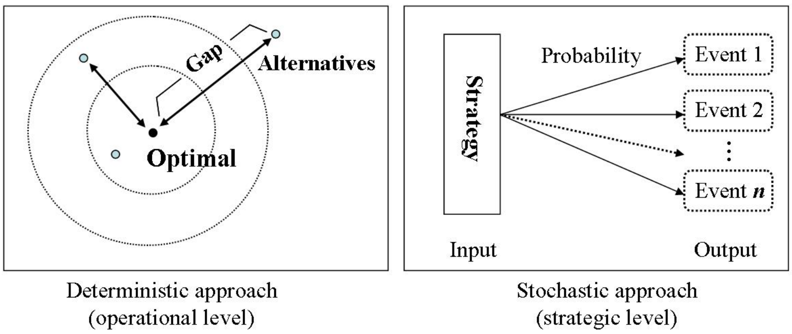


Figure 1.2: Two viewpoints for a supply chain risk

A risk management maximizes an opportunity and focuses attention where it is needed. By putting resources where they belong and taking an economical and capacious chance, a goal of enterprise is decided at operational and strategic level. To maximize the opportunity and to avoid inefficient resource allocation by a removal of uncertainty, our approaches are referred to :

- Deterministic approach (a selecting an optimal plan to avoid a comparative risk): an economic make-or-buy decision, economic production equipment replacement, and flexible supply contract design using options.
- Stochastic approach (a model design to reduce a future uncertainty): a prediction market as a collective intelligent technology and dynamic cubic neural network for a demand forecasting.

Chapter 2

Extraction and analysis of SCRD

2.1 Overview of a supply chain risk

The types of risk in a supply chain have been excessively diversifying in a rapidly changing business environment in these days. Specifically, new risks requiring unique skills and knowledge to manage effectively are introduced from a diversity of customer needs, a complexity of production, a short life-cycle product, and globalization, so that a supply chain management(SCM) is getting hard. Furthermore, since a supply chain is an organically combined set of different businesses and related activities, even though a very trifling incident can be a huge risk which makes a serious problem in the supply chain. However, most of the risks, except in case of non-controllable risks such as a natural disaster, can usually be removed or mitigated, if the cause is cleared. It is a fact that the risk mostly comes from not knowing what the main causes are. This is the principal reason why a risk driver leading to the direct and indirect risks has been attracting much attention for the effective SCM.

Then, why not simply avoid a risk in a supply chain? Is there any reason that we feel difficult to avoid? It principally is originated from unique characteristics of the risk. First, since the risk can be widely defined as a possible loss or damage, a deviation from the expected value, a less-then-expected returns, and an undesirable outcome, etc, sometimes it is easy to confuse an opportunity and a crisis. Actually, the risk has two sides; always, great opportunities and risks go hand in hand, not come alone. Greater risk brings obviously greater reward. The risk involves potential uncertainties and threats to a great loss, but it often accompanies good opportunities. For instance, an advent of Internet helped to enable us to create a lot of new businesses, such as an E-commerce, an online business, etc., but it required a new paradigm to survive in the new business environment at the same time. Second, the risk with many uncertainties is fundamentally unpredictable. This is one of the main reasons that we generally adopt a possibility or scenario to describe the risk. Finally, this is a business environmental problem. As the supply chain is structurally complicated more and more, various derivative risks are appeared. In practice, the supply chain is becoming more complex with the dynamically changing business environment. This complexity leads to new derivative risks in the result. Therefore, we always need to consider a question of what kind of risks occur in the supply chain and how to mitigate or remove them. It is not too much to say that a clear recognition and identification of the supply chain risk drivers(SCRDs) should be the first step for a successful supply chain risk management(SCRM).

In Chapter 2, we extract and analyze SCRDs with a text mining and multivariate analysis, according to a proposed framework by De-bi Cao and Bong-sung Chu [15]. Total 10,181 articles from 68 journals published during the past four decades on a business management, a SCM and SCRM in five categories(Management, Business, Business Finance, Engineering Manufacturing, and Engineering Industrial) have been reviewed.

2.2 Literature review

A supply chain risk management has been becoming one of the most popular research themes in a field for a business management and industrial engineering. In these days, the numerous papers with different focuses and approaches have been published. In this section, briefly, We review some papers relevant to the supply chain risk and its management strategies, by classifying them into two categories.

2.2.1 The types of supply chain risks and their classifications

By an operational level, a strategic level and tactical level, there exist different types of supply chain risk, according to how its realization impacts on a supply chain. And a criteria for classifying risks is also diverse, extremely. Sunil Chopra and ManMohan S. Sodhi(2004) categorized the supply chain risks into nine types: disruptions, delays, systems, forecast, intellectual property, procurement, receivables, inventory, and capacity [2]. From a holistic approach to the risk assessment and management, Christine Harland et al.(2003) summarized and combined various authors' works related to the supply chain risk, including a classifying type of the risk. According to their works, the risks of the supply chain could be classified into twelve types: strategic risk, operations risk, supply risk, customer risk, asset, impairment risk, competitive risk, reputation risk, financial risk, fiscal risk, regulatory risk, and legal risk [16]. Similarly, George A. Zsidisin(2003) provided a combined classification of the supply chain risk from case study data of various authors. He categorized the supply chain risk into twenty-three types under four main areas(Individual supplier failures, Market characteristics, Inability to meet customer requirements, and Threats to customer life and safety) [17]. And Christopher S. Tang(2006) developed an unified framework which consists of four basic approaches for classifying SCRM articles [5]. We can also find many articles dealing with the supply chain risk classification and types, for example, Jukka Hallikas et al.(2004), Juttner U. et al.(2003) [5].

2.2.2 Strategy of a supply chain risk management

The strategies of a SCRM can be normally included activities for identifying risk drivers, a risk measurement, an establishment of framework, an evaluation and analysis of effect on a supply chain performance, and a feedback refers to the results of analysis. There are many discussions about the issues from different perspectives. We review here several papers focusing on various risk management strategies, processes, and frameworks. The general approaches and specific tailored strategies for removing or mitigating the supply chain risks were proposed by Sunil Chopra and ManMohan S. Sodhi(2004). Their arguments concern a balancing supply chain risk and reward relationship; the highest possible profits can be achieved by attempting to trade off reward against the risks because a removing or mitigating the risks without eroding profits is extremely hard. For constructing strategies of the supply chain risk, they emphasized (1)organization-wide understanding of the supply chain risk, and (2)strategic decision on how to adapt general risk-mitigation approaches to circumstances of their particular companies [2]. Jukka Hallikas et al.(2004) presented a general structure for the supply chain risk management process of which empirical evidence is offered based on case studies. Based on four typical risk management strategies and processes, they discussed a risk diagram for a risk identification and assessment [18]. Christopher S. Tang(2006) proposed various strategies and basic approaches for the SCRM, and addressed issues of the SCRM along two dimensions: a supply chain risk and its mitigation approach [5]. As a more practical approach, Gonca Tuncel et al. showed how a timed Petri Nets(PN) framework can be used effectively to manage the supply chain under various risks [19].

2.3 Structural framework and a creating D/B

For more logical and reliable results, we propose a structure framework and create a database for classifying and extracting supply chain risk drivers(SCRDs). The framework involves following two points. In most case, the SCRDs can be classified by them.

- A supply chain can be thought of as a set of individual processes from upstream to downstream in a supply chain; R&D, procurement, production, distribution, retail, customer, and whole supply chain.
- Most business decisions and business problems are closely related to quality, cost, delivery, environment, flexibility, assessment, and strategy.

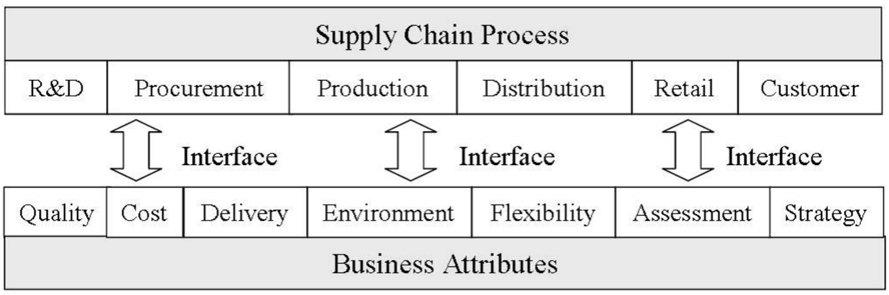


Figure 2.1: Structural framework for SCRD extraction

We here decide, based on the proposed framework, 62 keywords as raw drivers leading to potential risks in a supply chain. By two dimensions of (1) supply chain processes and (2) general business attributes, the detailed raw drivers appeared in Table 2.1 and Table 2.2.

Table 2.1: Supply chain processes and 22 raw drivers

R&D	Procurement	Production	Distribution	Retail	Customer	Whole SC
Research Development Technology	Resource Lead-time	Cycle-time Quality	Inventory Network	Demand Order	Relationship Partnership Service	Capacity Delay Disruption Disaster Information Flexibility Globalization Financial

Table 2.2: Business attributes and 40 raw drivers

Quality	Cost	Delivery	Environment	Flexibility	Assessment	Strategy
Availability Quality ability Relationship Customer Disaster	Disruption Market Fluctuation Receivable Exchange rate Service Financial Disaster	Delay Availability Information System Network Transportation Inaccuracy Flow	Fiscal Regulatory Legal Hazardous Substances Recycle	Inventory Monopoly Oligopoly Fluctuation Cycle-time Reputation	Performance Design	Intellectual property New product dev. Change Decision constraint Asset strategy

On the other hand, it is necessary to review many articles which have been published not only in a business management field but also in other fields, to extract reliable and objective risk drivers from different viewpoints. Therefore, we created a database containing five categories of Management, Business, Business finance, Manufacturing engineering, and Industrial engineering with 68 journals, 10,181 papers, indexed by SCI(E) and SSCI, published during the past four decades(from 1970 to 2010) on a SC(R)M and related science fields. The literature search was done using various electronic databases: Cambridge, Science Direct, EBSCOhost, Interscience, Oxford journals, Informaworld, Emeraldinsight, and Springerlink. The created database was used for a text mining, after it was saved in a format satisfying conditions required by IBM COGNOS CONTENT ANALYTICS, a text mining software. The journal list examined by the 5 categories are summarized in Appendix A.

2.4 Extraction of SCRD using text mining

A text mining is a process to derive unknown knowledge and information from a large-scale group of text, based on a non-structure database, whereas a data mining is based on a structured database. Generally, a high quality in the text mining refers to a specific relevance for discovering useful information and interesting patterns that no one yet knows, which it supports a decision of what should be considered to obtain useful information. In this chapter, we consider an association rule mining for the extraction of SCRDs.

2.4.1 Extraction process for an association rule mining

We use a proposed 62 raw drivers(RDs) as keywords to find out articles, called hit articles, involving compound nouns, based on a correlation coefficient which can be obtained as: $\frac{EF^{hit-articles}}{TF^{total-articles}}$ where $EF^{hit-articles}$ means 'a frequency of each RD in the hit articles / the number of hit articles', and $TF^{total-articles}$ means'a total frequency of each RD in all articles / the total number of articles'.

To get more reliable results, we adopt more than 1.5 correlation coefficients, which can be thought of as keywords that appear more significantly in the fit articles than in all target articles. The articles containing extracted main compounds were finally selected for a target of analysis.

Table 2.3: Main compound nouns and correlation coefficients for a supply chain process

SC Process	Compound noun	correlation coefficient	Number of hit articles
R&D	technology transfer R&D project research focus	1.7 1.6 1.6	23
Procurement	resource management resource constraint	7.5 5.8	17
Production	product quality time period	2.0 1.8	18
Distribution	distribution system distribution network	11.3 8.8	10
Retail	retail channel retail store retail assortment	17.1 17.1 17.1	6
Customer	customer satisfaction customer service customer relationship	7.6 7.3 4.9	12
Whole SC	information flow capacity constraint communication technology	2.2 2.1 2.1	9

Table 2.4: Main compound nouns and correlation coefficients for a business attribute

Business attribute	Compound noun	correlation coefficient	Number of hit articles
	quality management	2.6	
	TQM	30.9	
	TQM practice	22.9	
	quality orientation	5.9	
Quality	quality management system	4.5	7
	transaction cost	3.1	
	inventory cost	2.9	
	production cost	2.8	
	on–transaction cost	27.4	
Cost	of–transaction cost	27.4	8
	distribution system	1.8	
	of–distribution system	112.2	
	for–distribution system	53.6	
Delivery	of–channel	8.1	10
	business environment	3.6	
	change	2.1	
Environment	in–business environment	61	14
	inventory management	4.5	
	mix flexibility	3.6	
Flexibility	market requirement	2.2	17
	product design	2.4	
	supply chain performance	1.7	
	product	1.6	
	of–product design	55.1	
Assessment	into–product development	4.2	7
	operation strategy	3.5	
	management strategy	3.4	
	of–operation strategy	50.8	
Strategy	of–management strategy	14.5	7

Table 2.3 and Table 2.4 present main compounds and correlation coefficients, by supply chain processes and business attributes, respectively. As a result, total 165 articles satisfying a given condition, more than 1.5 coefficient, were ultimately prepared for extracting and analyzing SCRDs.

2.4.2 Extraction results

Based on a proposed framework and results from objective data by a text mining software, we decided carefully final SCRDs after discussion on what factors force fundamentally a supply chain vulnerable by SCM specialists (See Appendix B).

2.5 Analysis on SCRD

In a supply chain, a risk management strategy refers basically to identifying supply chain risk, a risk measurement, a risk classification by an impact level affecting stable supply chain operations, and the last step for developing action plans to mitigate or remove the risks. It normally involves assessing possibilities of the risks for a long-term, a middle-term and short-term plan, prioritizing the risk through a classification and analysis of an impact on a supply chain flexibility. We here analyze SCRDs and RDs using multivariate statistics. A high correlation among themselves, and the most frequently appeared risk drivers in these days, are clarified, from a three different perspectives: K-mean clustering, GRI(Generalized Rule Induction), Time series analysis.

2.5.1 Risk driver classification: K-means clustering

Generally, a clustering technique focuses on identifying specific groups of similar records and labeling the records according to the group to which they belong. This is done without any benefits of prior information or knowledge about the groups and their characteristics, which are often referred to as unsupervised learning models, because there is no external criterions by which to judge the models' classification performance. The techniques are used to find out useful information through an iterative process assigning each record to defined clusters to which it is most similar, based on a similarity defined by Euclidean distance of values for a set of input fields. Repeatedly, the records are checked to identify whether they should be reassigned to an updated different cluster. And a parameter of the maximum interactions controls how long an algorithm will search continuously for a stable cluster solution. The algorithm repeats a classification-updating cycle no more than the number of times specified, initially.

At first, by a K-means clustering technique, we classified obtained 133 SCRDs to identify similar independent entities by groups. The SCRDs can be essentially classified through a correlation matrix, as shown below, which can be defined as a value of i^{th} row for the j^{th} column.

$$Correlation\ x_{ij} = \begin{cases} if \quad i \text{ and } j \text{ have no relation, } then\ 0 \\ if \quad i \text{ causes } j, \ then\ 1 \\ if \quad j \text{ causes } i, \ then\ -1 \end{cases} \tag{2.1}$$

where i is a risk driver of a row, and j is a risk driver of a column.

We set initially 8 cluster centers, and used 133 SCRDs obtained by a proposed framework in Chapter 2.3 for clustering, excluding redundant risk drivers appeared in both areas of business attributes and supply chain processes. As a result, we can identify the grouped SCRDs, for example, a concerning globalization for second group, an environment for third group, a supply chain design for fifth group, and so forth. The results are presented in Appendix C.

2.5.2 Generalized rule induction(GRI)

Our analysis here concerns a GRI(generalized rule induction) which aims at finding out some association rules among extracted risk drivers. The GRI is well known as an useful technique to generate several rules to summarize specific patterns in a given data, using a quantitative measure. This measure provides a method for ranking competing rules and allows a system to constrain a search space for useful rules, as well as identifying the best or most interesting rules describing a database. It is fundamentally based on the association rules which associate a particular conclusion with a set of conditions.

We begin our analysis in consideration of a creating database. In detail, the following approaches were employed for this analysis.

- We first created a revised TF-matrix of which components had only ‘True’ or ‘False’. we set that ‘T is equivalent to 1 or -1’ while ‘F is equivalent to 0’ in the matrix.
- Second, Confidence ’for an accuracy of rule and ‘Support’ for a frequency of rule are given as ‘$C = N_a/N'$ and ‘$S = N_r/N'_a$ where N presents a total number of records, N_a presents the number of records for which the antecedent is true, and N_r presents the number of records for which the entire rule is true, respectively.

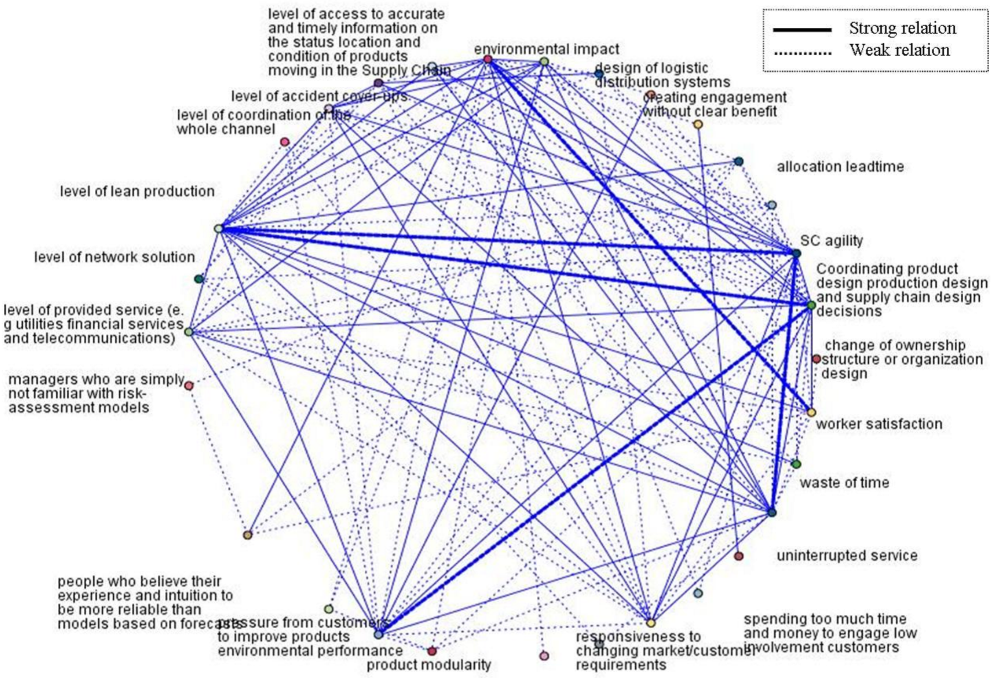


Figure 2.2: Web graph of supply chain risk drivers with the strength of link(≥ 34)

A strength of links between risk drivers is presented in Figure 2.2, by Sara M. et al.. A web graph includes 29 raw drivers which had constituted rules imposing a ‘Support’ of more than 15.00. In addition, as one of the results, as shown in Figure 2.3 by the Sara M. et al., we can identify that a supply chain agility closely related with some risk drivers, such as a level of access to accurate and timely information, a level of accident cover-up, a level of lean production, an uninterrupted service, a responsiveness to the market and customer requirements, and a product line design for a distribution channel. And they are also effected by a design of logistic distribution systems, a competence of risk managers, a coordinating of product, a production and SC design, an immediate order, en environmental impact, a waste of time, a level of provided services, and a globalization of business.

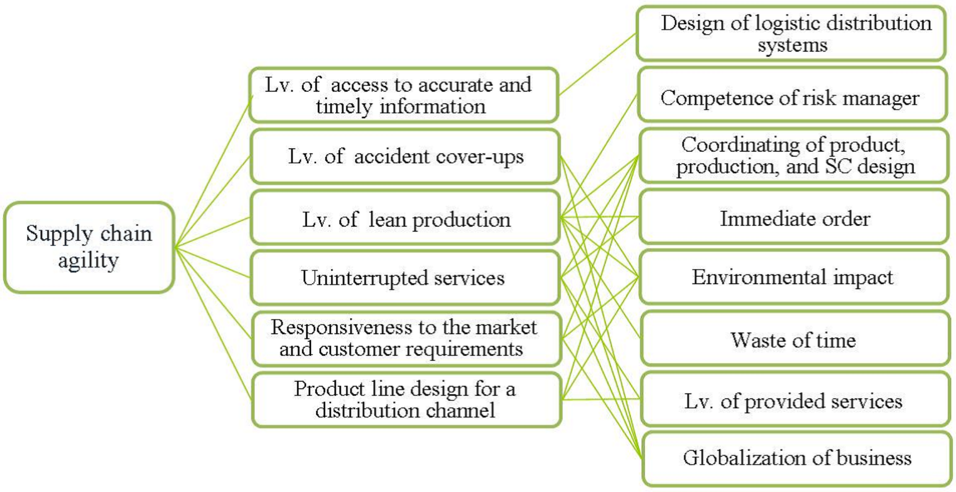


Figure 2.3: Relation structure for a supply chain agility

2.5.3 Time series analysis

A frequency of appearance from 1970 to 2010 for RDs leading to direct or indirect risk is presented here. To identify which driver has frequently been an issue in a field of a SCM nowadays, we analyze the RDs, using a time series analysis providing an extremely accurate information on a trend of certain type of time series data. The time series analysis provides effects of a historical change in which data are collected for a single entity. And it has two main goals of (1) continuous observations of the data and (2) identifying the nature of the phenomenon and forecasting the future events.

Because a rapid changing business environment causes new risks that we have never seen before, we need to recognize them to cope with a crisis in a supply chain. This is absolute the truth that specific plans to mitigate or remove the risks can be established only if the causes are cleared with a transformation. That is, what is the most significant in an argument about the supply chain risk management is that if the cause is cleared then it is possible to know how the risks can be removed or mitigated. This suggests that the first step for the supply chain risk management should be to identify the risk drivers with their transformations.

First, we set a database with 35 raw drivers appeared in more than 100 articles out of 10,181 articles. And then we separated six groups by periodical tendencies for more effective observations and analysises. Table 2.5 shows a summarized result of analysises. In group

6, several raw drivers, such as a development, a performance, a strategy and system, shows a high frequency in these days, whereas an asset strategy shows a low frequency for an appearence. And Figure 2.4 presents a time series graph during last four decades (from 1970 to 2010).

Table 2.5: Grouped periodical tendency of raw drivers

Group	Frequency of appearence	Raw driver
1	Decrease	Asset strategy
2	Basic (low level but stable)	Assessment, Availability, Capacity, Delivery, Disruption, Financial, R&D, Flexibility, Flow, Globalization, Lead-time, Transportation
3	Constant (in normal level)	Demand, Production, Environemnt, Resource, Change, Cost, Information, Relationship
4	Constant (in high level)	Market, Research
5	Slow increase	Customer, Design, Service, Inventory, Network, Order, Quality, Technology
6	Rapid increase	Development, Performance, Strategy, System

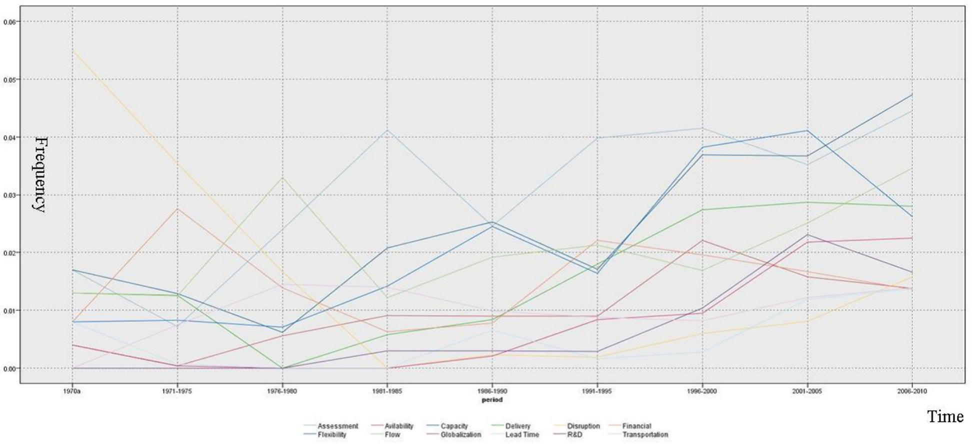


Figure 2.4: Frequency analysis of a raw driver

2.6 Brief summary and discussion

An introduction of a SCM into a modern business environment brought many advantages such as a creation of new value-added of manufacturing and consumption through a collaboration, an integrated management of information and material as well as a cash flow from a global and holistic view, and a possibility of quick response to customer needs. Furthermore, to response new needs from a rapid progress of information technology, it becomes more and more complicated in various transformation processes in which new concepts are introduced; e-SCM, global SCM, Green SCM, and intelligent SCM. However, companies have been facing a new operating crisis due to the complicated SCM. An advent of the SCM causes new types of risks which we have never experienced before. For more effective collaboration, one of the key concepts of the SCM, for instance, secrets of business or technology can unavoidably be exposed to a business connection in the same supply chain. That is, an information sharing to achievement of the ultimate collaboration can conversely lead to the worst results, as an unpredictable new risk. Therefore, for an establishment of a reliable supply chain and effective management, identifying and assessing the risks are core.

In this chapter, ‘SCRD(supply chain risk driver)’, which is a source factor of risks in a supply chain, has been discussed. We suggested a framework focusing on two dimensions of supply chain processes and general business attributes, and also extracted and analyzed 133 SCRDs from 10,181 articles published during the past four decades, using a text mining and multivariate statistics. It is a very useful work, because it is clear that a risk cannot be managed if the cases are not clarified. Although we acknowledge that new risks may appear according to a rapidly changing business environment, it is not removed or mitigated if a direct or even for indirect causes are not cleared. Our work can give a correct answer to this agony. However, we also have many things to be discussed and studied, later. First, it can be different that which is a real risk driver or not, because of a difference of viewpoint of specialists. And since it doesn’t have any logical causes and effect relations, excluding several cases, we can guess from the previous cases and related studies. Furthermore, this problem can be originated from not only the difference of viewpoints, but also a fundamental limit of text mining technology. Second point to discuss is that we need to consider seriously an unpredictable and invisible derivative risks as possible. Actually, it is a fact that it is a quite difficult to know how transformed risks are derived from raw risks. Finally, for the future study, methodologies to manage risks are needed to discuss and should be proved those by an experimental studies. The ultimate objective of identifying the SCRDs is an efficient management of the risks. We shouldn’t overlook this point.

Chapter 3

Economic make-or-buy decision

3.1 Economic outsourcing and a risk

Recently, with a rapidly changing business environment, an outsourcing to external suppliers can be a great way to reduce operating costs. In practice, most of the manufacturers try to reduce the operating costs through a strategic outsourcing leading to a flexible organization. An economic make-or-buy decision, also known as an outsourcing option, is one of the main business decisions focusing on an avoidance of sourcing risks. It is not to say that an economical choice is often the first priority of the decision making because the manufacturer focuses fully on profit activities. The make-or-buy decision is conducted at strategic level, which includes a current production environment and potentiality of the future.

We reviewed pertinent studies that discussed on a make-or-buy decision. Henrik Brandes et al.(1997) argued that three kinds of reasons for the decision regarding an outsourcing; Cost efficiency, Financial problem and Core competence. They indicated, especially, a combination of focus on cost efficiency reasons and core competences tends to lead a greatest probability of success [20]. Gardiner and Blackstone(1991) introduced a CPCM(Contribution per Constraint Minute) method of make-or-buy analysis, which makes the decision using a traditional costing method to decide whether to make or buy. They showed that a standard cost method for making the outsourcing decision was inferior to the CPCM approach, which follows a TOC(Theory of Constraints) principle (Jaydeep Balakrishnan and Chun Hung Cheng) from a cost perspective [21]. Edward and Geoffrey(2002) developed an engineering-based model of the outsourcing, and showed relations between optimal outsourcing fraction and cost structures, as well as a technological change [22]. In addition, there were lots of researches for outsourcing options, it had been approached from the cost viewpoint. According to Thamrong et al., Balakrishnan(1994) investigated make-or-buy decision that compared the cost of administering transactions inside a firm and across markets, and Basset(1991) and Poppo et al.(1995) studied on the make-or-buy decision related to an economics and accounting, respectively [23]. To decide making or buying, Lynn and James(2002) studied from a cost system approach. They analyzed cost accounting systems, such as ABC(Activity-based costing), DC(Direct costing), TCA(Traditional cost accounting) and TOC(Theory of constraints), and showed significant differences between obtained solutions by the TOC/LP and other three accounting systems [24]. And Gordon and David focused on a transaction and production cost for the make-or-buy decision, based on a structural equation model(SEM). The result showed that a production and transaction cost had a great influence [25].

It has been shown in most studies on this subject that a make-or-buy decision mainly focuses on a cost and capacity. The LP, TOC, and traditional accounting methods were usually used to solve this problem, but they did not discuss and guarantee the best solution for multi-stage production processes which can give us an outsourcing flexibility related to a production stage at which more profits can be obtained under a demand change. Furthermore, even though the production capacity is strongly affected by production volume, little research has focused on it with the cost into the decision. That is, a question of how to establish an optimal formula of this problem with the cost efficiency and outsourcing flexibility is still open. In this point, we have two points to remember with respect to the decision-making from an economic viewpoint. First, a point of scale of economy associated with a fixed cost has been invested or going to be invested. A manufacturing cost for an unit product depends strongly on the total volume of production under a given fixed cost. Second, it is necessary to consider a break-even point of production volume to obtain the outsourcing flexibility with cost. Thus, in this chapter, we formulate, in multistage production system, an economic make-or-buy decision model, and show optimal solutions and comparative risks. The major effect of the proposed model is that the optimal solution dealing with both a cost-based capacity and outsourcing flexibility can be obtained, efficiently.

3.2 Theoretical background

3.2.1 General make-or-buy decision process

The aim of a make-or-buy decision is to make a strategic choice between assembling a product internally or buying it externally at operational level. Today's global competition forces manufacturers with resource limits to concentrate their core competences, strategically. Obviously, they may not be able to afford to have all businesses and related activities internally, although a complicated business environment requires many things from them. What kind of standards can we solve this problem? Generally, the make-or-buy decision concerns many factors: cost considerations(less expensive to make a product internally), a quality and productivity control, an efficient and stable workforce assignment, a diversification of reliable suppliers (multi-source policy or strategic partnership), a technical limits, a control of distribution costs, a desire to maintain core competences, small-volume requirements, and other social or business environmental reasons.

There is a framework proposed by Laura canez et al.(2001) for a process of make-or-buy decision [26]. The process based on a multiattribute decision-making consists of the following four steps .

Step 1. It is referred to a preparation phase which requires creating a multi-disciplinary team, selecting the part, assembly or family of parts for analysis and briefing the team.

Step 2. This stage is concerned with data collection. Three workshops are organized to collect information required to carry out analysises. First, workshop 1 consists of prioritizing make-or-buy areas and factors. And workshop 2 is concerned with an assessment of internal and external capabilities using a set of ProFormas, which cover four relevant areas. Finally, workshop 3 consists of capturing costs incurred in both producing internally and externally.

Step 3. This stage consists of data analysis using a spreadsheet which provides final scores for in-house and for the supplier, weighted gaps for each factor area, highlighting the strengths and weaknesses of this option, and a sensitivity analysis which tests the robustness of the final outcome.

Step 4. Final stage consists of feeding back the results to the team.

A framework is summarized in Figure 3.1.

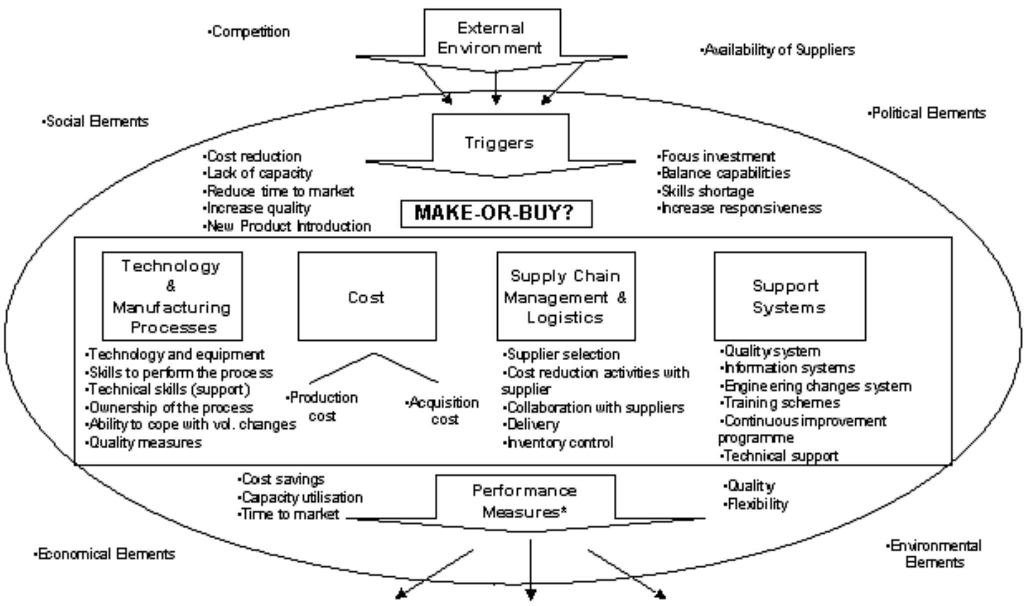


Figure 3.1: Framework for a strategic make-or-buy decision (by Laura et al.)

3.2.2 Cost factors and analysis

A cost and available productivity are the most important factors in a make-or-buy decision. Among them, the cost is the first priority. David burt et al.(2003) present an analysis with rules for a strategic make-or-buy decision [27]. Their analysises describe principally major elements focusing on costs for making and buying. For making analysis includes:

- Incremental inventory-carrying costs
- Direct labor costs
- Incremental factory overhead costs

- Delivered purchased material costs
- Incremental managerial costs
- Any follow-on cost stemming from quality and related problems
- Incremental purchasing cost
- incremental capital costs

On the other hand, their buying analysises include:

- Purchase price of the part
- Transportation costs
- Receiving and inspection costs
- Incremental purchasing costs
- Any follow-on costs related to quality or service

Whereas an available productivity should be considered from various factors, a cost analysis can simply be carried out through a break-even point which provides a standard to evaluate economic areas. We will discuss next section about a model design in details.

3.3 Model setup and a solution procedure

3.3.1 Problem description for multistage production processes

Before formulating a model focusing on a cost, we assume that:

- First, production stages are serial, and each stage has an input(material or intermediate component) and output(product).
- Second, there are various intermediate components which can be fabricated or assembled internally, or are purchased from outside suppliers.
- Third, total production volume is depended on market conditions.

In case of an internal assembly, we consider a fixed cost and variable cost in each production stage, and a purchasing cost of original materials. On the other hand, in the case of a purchasing, a buying(sourcing) cost at each production stage is considered, only if the intermediate components are supplied from the outside. In other words, some intermediate components are externally purchased from outside suppliers, or it can be assembled internally, from the original materials into a complete unit of final product. Each production stage i has a fixed cost F_i ($i \in 1, 2,...,n$) and unit variable cost v_i, respectively. Also, there exists an unit purchasing cost p_i, if the intermediate parts is procured from the outside suppliers. All materials and intermediate components flow the right side from the left in sequence. And a finished product is obtained at the end of right.

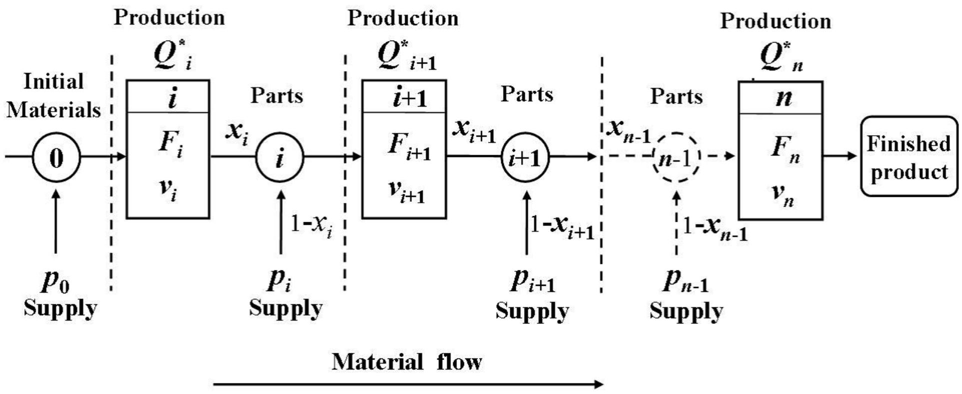


Figure 3.2: Multistage production processes

3.3.2 Formulation

Our concern in this section is an optimal solution and solution process of a make-or-buy decision. We use the following notation throughout this approach:

Table 3.1: A summary of notation

Variable	Definition
p_0	Material cost
p_i	Purchasing price of intermediate parts or components at production stage i
F_i	Fixed cost at stage i
W_i	Composed unit variable cost at stage i
v_i	Unit variable (fabrication) cost at stage i
$\overline{F}$	Consolidated total fixed cost
$\overline{V}$	Consolidated unit variable cost
Q	Total production volume
Q_i^*	Break-even point for single stage i
$\overline{Q^*}$	Consolidated break-even point
x_i	Allocation ratio of cost at stage i
C_i^M	Making cost of stage i
C_i^B	Buying cost of stage i
TC_M	Total making cost
TC_B	Total buying cost
TC	Total cost for manufacturing

The critical point of this problem is a break-event point between making and buying which essentially is affected by a total production volume. We introduce here a decision variable x_i

representing an allocation ratio of a production cost at stage i, which implies allocating the x_i of total cost to internal assembly, while allocating $1 - x_i$ of the total cost to an outside purchasing. The break-even point of production volume can be derived from a total production cost minimizing sum of an internal assembly and a purchasing cost at each production stage associated with the allocation ratio of the production cost.

A total manufacturing cost in a single production stage consists of making cost $C_i^M = (F_i + v_i Q)x_i$ and buying cost $C_i^B = p_i Q(1 - x_i)$ where a decision variable x_i satisfies $0 \leq x_i \leq$ representing an allocation ratio of a cost related to a making quantity and buying quantity. Here, if the x_i is a binary variable that only has o or 1, then, in a serial manufacturing system, a total internal making cost TC_M can be written as $TC_M = \sum_{i=1}^{n} C_i^M + p_0 Q$ where p_o represents a purchasing cost for original materials easily. Similarly, a total purchasing cost TC_B can be given by $TC_B = \sum_{i=1}^{n} C_i^B$. Therefore, an objective function to minimize the total manufacturing cost TC, can be written as

$$
\begin{aligned}
&Minimize \;\; TC = \sum_{i=1}^{n} \Big\{ x_i(F_i + v_i Q) + (1 - x_i) p_i Q \Big\} + p_o Q x_0 \\
&Sub. \;\; \sum_{i=1}^{n} x_i \geq 1, \;\; where \;\; x_i = 0, 1 \\
&\qquad F_i, v_i, p_i, Q \geq 0
\end{aligned}
\tag{3.1}
$$

We introduce a new concept, ‘break-even point’, to find an optimal solution for above cost function. The break-even point in a single production stage i, Q_i^* is given by a production volume Q which makes an internal making cost and a buying cost from outside equal, without considering costs at previous production stage. That is, the Q_i^* satisfies $F_i + (v_i + p_{i-1})Q = p_i Q$, hence, it can simply be written as

$$
Q_i^* = \frac{F_i}{p_i - (v_i + p_{i-1})} \tag{3.2}
$$

From below proposition 1, we can identify that make-or-buy can be decided by a production volume Q and a break-even point Q_i^*. For instance, if the production volume Q exceeds the break-even point, i.e., $Q > Q_i^*$, then an internal assembly is an optimal solution which has smaller cost, whereas if $Q < Q_i^*$, then it leads to an outsourcing at production stage i.

Proposition 1. The make-or-buy is decided by a production volume Q, if a break-even point Q_i^* and the production volume Q satisfy the following conditions:

$$
Q_i^* > Q > Q_{i+1}^*, \;\; \text{where} \;\; Q^* > 0, \forall i = (1, 2, ..., n) \tag{3.3}
$$

Proof of proposition 1. The making cost i, C_i^M and buying cost from outside suppliers at production stage i can be written as follows, respectively.

$$
C_i^M = F_i + \{v_i + x_{i-1} C_{i-1}^M + (1 - x_{i-1}) p_{i-1}\} Q, \;\; C_i^B = p_i Q \tag{3.4}
$$

From equation (3.4), we can obtain an inequality as follows.

When $Q_i^* > Q$,

$$= \frac{F_i}{p_i v_i + x_{i-1} C_{i-1}^M + (1 - x_{i-1}) p_{i-1}} > Q$$

$$= F_i + \left\{ v_i + x_{i-1} C_{i-1}^M + (1 - x_{i-1}) p_{i-1} \right\} Q > p_i Q \tag{3.5}$$

On the other hand, we can describe a cost function y for a production stage $i - 1$ from equation (3.1).

$$y = (F_{i-1} + v_{i-1} Q - p_{i-1} Q + p_{i-2} Q) \vec{x}_{i-1} + p_{i-1} Q \tag{3.6}$$

Here, above equation (3.6) can be written simply as $y = a\vec{x} + b$, since all parameters F_i, v_i, p_i and a production volume Q are integers. As a result, to minimize the cost function y, we can obtain following conditions.

$$Decision\ variable\ x_{i-1} = \begin{cases} If\ \ F_{i-1} + (v_{i-1} + p_{i-2})Q > p_{i-1},\ \ then\ \ 0 \\ If\ \ F_{i-1} + (v_{i-1} + p_{i-2})Q < p_{i-1},\ \ then\ \ 1 \end{cases} \tag{3.7}$$

If we substitute $x_{i-1} = 0$ for equation (3.5) here, a make-or-buy decision problem has the following structure:

- $If \quad Q_i^* > Q, \quad F_i + (v_i + p_{i-1})Q > p_i Q$ (i.e., $F + vQ > pQ$)

Therefore, it is clear that an economic make-or-buy decision problem is decided by the production volume Q.

The serial break-even points have a characteristic which gets generally smaller toward a finished product, i.e., $Q_i^* > Q_{i+1}^*, > ..., > Q_{i+n}^*$. However, the characteristic is not always valid. We found that disqualified plans existed in case of $Q_i^* < Q_{i+1}^*$, and production stages could be consolidated due to the disqualified plans, as shown in proposition 2.

Proposition 2. The production stages can be consolidated, if some serial break-even points $Q_i^*, Q_{i+1}^*, .., Q_{i+n}^*$ satisfy the following conditions:

$$\forall i : Q_i^* < Q_{i+1}^*, \ \ where\ Q^* > 0, \ \ \forall i = (1, 2, ..., n) \tag{3.8}$$

Proof of proposition 2. It is clear that there exists a disqualified plan between two or more production stages, if each break-even point of the production stages Q_i, Q_{i+1} satisfies $Q_i^* < Q_{i+1}^*, (Q^* > 0)$. And there exist three plans, (a), (b) and (c), which can be evaluated in case of the serial two break-even points, as follows.

(a) Qp_{i+1}
(b) $F_{i+1} + Q(p_i + v_{i+1})$
(c) $F_i + F_{i+1} + Q(v_i + v_{i+1} + p_{i-1})$

We consider here above plans one by one. First, a plan (b) is inferior as compared with the rest two plans at all occasions. That is, we can identify here that the plan (b),i.e., $F_{i+1} + Q(p_i + v_{i+1})$ is a disqualified plan, as follows:

$$Qp_{i+1} > F_{i+1} + Q(p_i + v_{i+1}) \tag{3.9}$$

and

$$F_{i+1} + Q(p_i + v_{i+1}) < F_i + F_{i+1} + Q(v_i + v_{i+1} + p_{i-1}) \tag{3.10}$$

In case of $Q_i^* < Q_{i+1}^*$, ($Q^* > 0$), a plan (a) is better than the plan (b), and a plan (c) is also better than the plan (b), economically. Therefore, it is clear that the production stages can be consolidated, since there exists the disqualified plan(b) between two production stages.

3.3.3 Solution procedure with a break-even analysis

In this section, we propose a simple solution procedure using a break-even analysis to find an optimal solution. We first begin by considering of 'disqualified plan(D.P)' which is known as the worst solution among feasible solutions. To obtain an economic plan, the first point to be discussed is whether disqualified plans exist in the problem. The second is to calculate the break-even points after deleting the discovered disqualified plans. And the next discussion concerns a consolidation of production stages. Actually, production stages can be consolidated as shown in proposition 2. It should be accomplished before comparing of feasible solutions. The optimal solution is given, according to the below steps.

Step 1. Find out all of disqualified plans(D.Ps) through comparing of two variables, v_i, p_i, $i \in \{1, 2, ..., n\}$.
Step 2. If the disqualified plans(D.P) satisfying $p_i < v_i$ exist, delete all of the D.Ps.
Step 3. Calculate the break-even point Q_i^*, $i \in \{1, 2, ..., n\}$ at each production stage, if $p_i > v_i$.
Step 4. Compare each break-even point Q_i^*, Q_{i+1}^*, .., Q_{i+n}^*, $i \in \{1, 2, ..., n\}$. If the break-even points satisfy $Q_i^* > Q_{i+1}^*$, go to step 5, otherwise go to step 3 and calculate a new break-even points $\overline{Q^*}$ after a consolidation of production stages.
Step 5. Compare a production volume Q with the break-even points Q_i^* by production stages. If $Q > Q_i^*$, the making plan $x_i = 1$ is better, otherwise the buying plan $x_i = 0$ from outside suppliers is better, economically.

We need to compare, first, a variable cost v_i of each production stage with a buying cost p_i for evaluating whether disqualified plans exist. For example, if $p_i < v_i$ at production stage

i, a buying plan is more economical than a making plan representing a disqualified plan. However, if $Q_i^* < Q_{i+1}^*$, it is necessary to change the form of a framework, because of the disqualified plans. We used the following equations to consolidate. Therefore, we adopt $F_i + F_{i+1} = \overline{F}$ and $v_i + v_{i+1} = \overline{V}$. Using those, a new break-even point $\overline{Q^*}$ can here be obtained such as below.

$$\overline{Q_{i,\ i+1}^*} = \frac{\overline{F}}{p_{i+1} - (\overline{V} + p_{i-1})} \tag{3.11}$$

The most important part of this argument is that an economic plan is given by a break-even analysis. It is clearly shown in our model that: (1) $if\, Q > Q_i^*, x_i = 1$ and (2) otherwise, $x_i = 0$. The summarized solving process for this problem is shown in Figure 3.3.

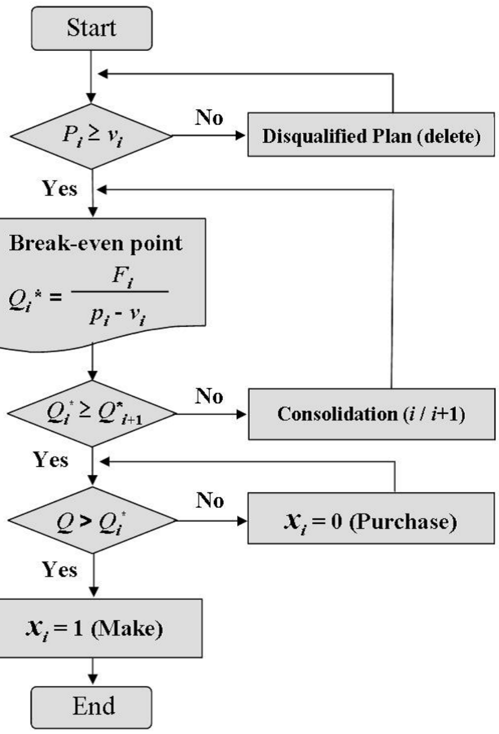


Figure 3.3: The solving process

3.4 Numerical example

We examine in this section a simple example with 4 serial production stages. The parameter set to be used is shown in Table 3.2, and an initial material cost p_o is to be set \$8.9.

Table 3.2: Initial parameter set(unit, $)

Production stage i	Break-even point Q_i^*	Fixed cost F_i	Unit variable cost v_i	Cost for intermediate part p_i
1	2,333	7,000	30	41.9
2	2,222	4,000	10	53.7
3	2,250	4,500	30	85.7
4	2,143	6,000	10	98.5

Table 3.2 can be shown as below Figure 3.4. In this problem, there is no D.Ps, but a production stage 2 and 3 can be consolidated due to $Q_2^* < Q_3^*$. And a new break-even point, $\overline{Q_{2,3}^*}$, is obtained.

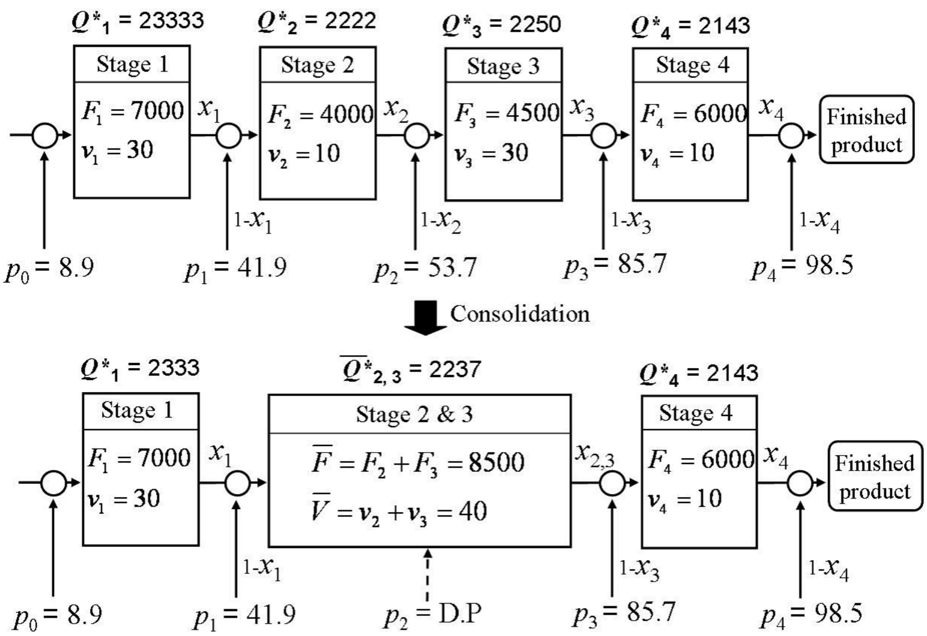


Figure 3.4: An example with 4 production stages

Generally, serial break-even points are in a row from the left to the right in sequence. If production stages are consolidated, the break-even point of the right side is less than the left side, as shown in the bottom of Figure 3.4 In this problem, it is possible for the production stage 2 and 3 to be consolidated, which leads to an optimal solution, efficiently. Therefore, for instance, if a predicted production volume Q is 2,230 units, a making plan will be selected at production stage 4, which means $x_i \in \{0, 0, 0, 1\}$.

The bottom of Figure 3.4 can be shown as Table 3.3 with modified parameters. And Figure 3.5 shows a comparison of economic areas when Q is given as 2,230 units.

Table 3.3: Modified parameter set(unit, $)

Production stage i	Break-even point Q_i^*	Fixed cost F_i	Unit variable cost v_i	Cost for intermediate part p_i
1	2,333	7,000	30	41.9
2,3(consolidated)	2,237	8,500	40	85.7
4	2,143	6,000	10	98.5

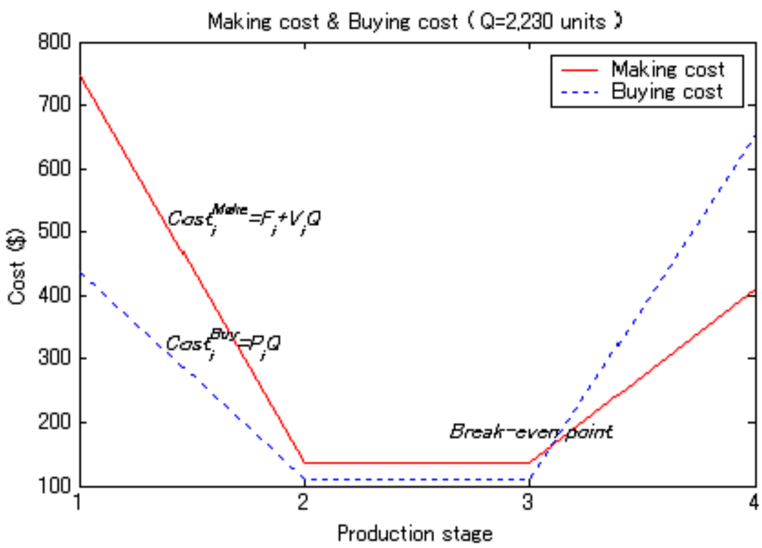


Figure 3.5: Economical area when Q=2,230 units

On the hand, in case of $Q = 2,280 units$, an optimal solution is $x_i \in \{0, 1, 1, 1\}$. This suggests that a making in-house from a production stage 2 is economical because a break-even point is appeared between the production stage 1 and 2. Figure 3.6 shows economic areas when Q i given as 2,280 units. In other wards, for this case, if an intermediate components should be assembled at the production stage 2 according to a rule $Q > Q_i$, all the intermediate components for the finished products should be assembled in-house from the production stage 2. Therefore, the best plan is to assemble all the components in an organization from the production stage 2 to the final production stage for this case. As a result, the optimal solutions and minimized total cost by them are given as follows.

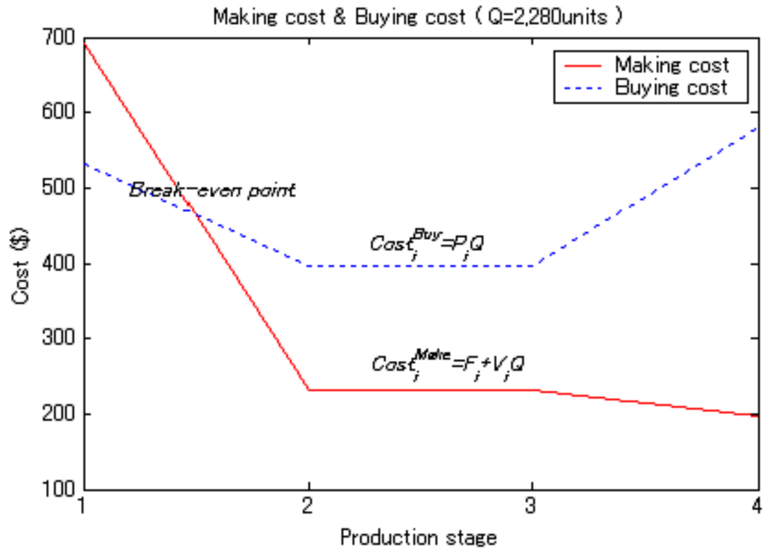


Figure 3.6: Economical area when Q=2,280 units

$$Optimal = \begin{cases} If \;\; Q = 2,230, \;\; then \;\; x_i \in (0,0,0,1) \;\; and \;\; TC_{Min} = \$219.411 \\ \\ If \;\; Q = 2,280, \;\; then \;\; x_i \in (0,1,1,1) \;\; and \;\; TC_{Min} = \$224,032 \end{cases} \tag{3.12}$$

In case of a production in an organization, the comparative risk is summarized in Table 3.4. First of all, in case of $Q = 2,230$, if a making internally from a production stage 1 to the final stage, total 336 dollars in lost production, while only 26 dollars in lost production for the second case of from a production stage 2 to the final production stage. And, in case of $Q = 2,280$, about 160 dollars in lost production for both cases, compare to an optimal production cost.

Table 3.4: Risk as a comparative loss

Production volume	Production stage(in organization)	Total production cost	Comparative loss($)
Q=2,230	From 1 stage	219,747	336
	From 2 stage	219,437	26
Q=2,280	From 1 stage	224,192	160
	From 4 stage	224,196	164

3.5 Brief summary and discussion

Usually, a quality of a decision-making heavily depends on an experience and knowledge of a manager. And most of the business problems, as well as a production optimization, are strongly affected by demand changes. We have outlined in this chapter the way to minimize a production cost for a make-or-buy decision in multistage production processes. We formulated a model based on a break-even analysis reflecting the demand changes, and demonstrated an applicability of analysis from numerical examples. It is an effective supporting tool for the manager, to respond, and to adapt to the demand changes leading to a controlling production volume. It was discussed a fixed cost and variable cost, and a cost analysis related to predicted production volume and the break-even points. To sum up the major characteristics of our model, a full understanding of the break-even analysis, comparative advantage of cost, a condition of consolidation and disqualified plan(D.P) are of most significance.

Chapter 4

Production equipment replacement

In this chapter, we examine an economical production equipment replacement in consideration of a failure uncertainty [1]. It mainly involves a discussion on an opportunity of maintenance, a cash flow based on an economic life, EOS(End of Service), and value at risk(VaR).

4.1 Failure uncertainty of a production equipment

For stable and economical operation of a production equipment, one of the most considerable things is to remove a failure uncertainty. The production equipment has many risks from unpredictable events, such as the equipment failure and expected loss by a shutdown, after maintenance service providing an opportunity to be repaired within a given period is expired(called EOS: End-of-Service), even if it can be used more. The maintenance service affecting an equipment replacement schedule, therefore, is a crucial component of strategic equipment replacement to avoid the risks which can be thought of as a certain price that users have to pay due to the services expiration date.

To examine an optimal time of a production equipment replacement, we here deal with a possibility of an application of failure uncertainty to the replacement problem, in addition to an economic life representing a point to be minimized total LCC(Life Cycle Cost) which can be a good standard to solve the problem. It refers to a period that is cheaper to replace an equipment which to continue maintaining it. Actually, an economical use of the equipment considering its life-cycle has been attracting significant attention in the field of a corporate strategy in these days, due to an increase of operating cost by the variety and complexity of product development and supply to satisfy sophisticated customers in modern operational environments. The corresponding strategies are actively developed, and their applications are mainly focused on removing failure uncertainties. For this reason, EOS(End of Service) as a standard for a decision on an optimal replacement, is often considered for an economical use. Specifically, because of a short life-cycle and characteristic as a main business infrastructure, a high-tech production equipment is exceedingly sensitive to the EOS. The business efficiency and extension in the high-tech industry are generally under a control of rapid up-

[1]A partial content described in this chapter has been accepted for publication in INFORMATION-An International Journal, in July 2011

grade and adaptive equipment replacement, so that the EOS is often thought of as the first priority for the decision making about the equipment replacement and upgrade.

Many attempts have been made to construct models of equipment replacement in an engineering economy. From a viewpoint of product life-cycle management, we reviewed the related studies which mainly discussed on the equipment replacement decision, as it relates to an economical use and manufacturing. A typical MAPI model for the economic replacement problems is presented by Terborgh.G.[28],[29]. What is shown in his study is that a basic tradeoff in the equipment management lies between a capital cost and operating inferiority where latter is defined to include both the direct cost of repair and a consequential cost arising from a failure, which is a quite useful guide to solve the equipment replacement problems. To some extent, Zentaro Nakamura applied a cost of extending the life to his study based on the above MAPI model. He argued that the cost consists of an additional operation cost and opportunity loss of disposal income caused by one year extension of an equipment utilization [30]. The argument presented in Qing-Guo Meng and Zentaro Nakamura was an economic replacement model using the Index Rate of Return. They especially focused on a value of capital interest rate and analyzed the effect of value of the interest rate upon the economic life, can be obtained by a simple cash flow pattern [31]. David G. Woodward provided some pointers that are interested in pursuing LCC(Life Cycle Costing) approach to an asset acquisition by examining trade-offs between different cost areas, which the LCC attempts to ensure an optimum selection, a use and replacement of physical assets [32]. And it is clearly shown in William G. Sullivan et al. that how VSM(Value Stream Mapping) can provide necessary information for an analysis of equipment replacement decision problem in a cost-oriented strategy perspective [33].

These studies only investigate with the priority given to a cost, and also do not take into account any uncertainties caused by the PLM strategies such as EOS. However, in practice, equipment suppliers impose restrictions related to a maintenance service period on users because of some difficulties about supplying components and available capacity limits. A further important point is that the EOS leads to a failure uncertainty, which may give rise to serious troubles, such as an expenditure for repair, a loss by shutdown and modification of production schedule. Nevertheless, a question of how to conduct the optimal formula of this problem is still open. From the user's perspective, in this section, we discuss the problem about a determination of the timing from the current production equipment to the new one economically. A main approach for this problem is based on the EOS, an economic life, a cost variable for accepting risks of the failure.

4.2 Maintenance opportunity and a risk in operation

4.2.1 EOS(End-of-Service) and VaR(Value at Risk)

A EOS presenting maintenance service expiration date is one of the critical operational issues for life-cycle management. If an equipment reaches its end of life date, it will no longer be supported for a maintenance or repair. This is a strategy of the equipment suppliers to get additional profits after selling, and also to manage their product-mix with respect to a decision on a time of new product release. For example, a supplier can induce a buyer to extend a contract of the maintenance service or to purchase new one, through a reminding of failure leading to huge loss. From the buyer's perspective, the EOS can strategically be used, too. Especially, in order for the equipment replacement to be smooth, the EOS can play an important role between levels of the failure risks and cost effects.

On the other hand, we consider a bathtub curve and VaR(Value at Risk) for a risk. In details, we use the bathtub curve for each component failure rate of a production equipment, which is widely used to deal with a reliability of the components. The bathtub failure rate curve is generally regarded as a typical rate curve which is simply modeled using three different Weibull distributions by a piecewise set of three hazard rate functions, especially when representing the failure behavior of an equipment or its components [34]. For the failure rate function of production equipment, we mainly consider a probability distribution function for a degradation and fatigue period of the bathtub curve, known as a wear-out failure that is a failure rate increased continuously and time dependently, because we deal with a replacement problem for old equipments. And for loss by a shutdown from the equipment failure, we consider a VaR(Value at Risk) as a risk measure of the shutdown, which means a forecast of the maximal probable loss over a specified horizon and stated probability level [35].

4.2.2 Problem description with an economic life and a cash flow

Notice that we make a number of assumptions here to decide which parameters to consider throughout this study.

1. Let C be an initial purchase price of a production equipment.
2. Let $E_t(t = 1, 2, ...)$ be a maintenance cost for the t^{th} year. $E_t \leq E_{t+1}$.
3. Note that EOS is a point to be expired maintenance.
4. We assume that a production equipment can be continually used, even if the maintenance service is expired. In this case, users(decision makers) should be accepted some risks due to the service expiration. Here, note that a $R_t(EOS < t \leq EOS + l)$ is cost for the risk acceptance when the equipment is used for l years, after the service is expired(EOS). $R_t \leq R_{t+1}$.
5. We assume that a new production equipment is used in the manner of like-for-like replacement.
6. We assume that the production equipment has two types of risk after the maintenance service is expired: failure risk and its derivative risk.
7. Let i be an annual capital interest rate.

An economic life would certainly be a correct tool for an equipment replacement problem described in Figure 4.1 if we were interested in a cost-oriented operation. On the theoretical side based on above assumption (5), it is necessary to find a point to be minimized annual LCC(Life Cycle Cost) of a cash flow cycle in Figure 4.1. Hence, a basic objective function to find the optimal replacement time $M(T)$ can be written as

$$M(T) = \left(C + \sum_{t=1}^{T} \frac{E_t}{(1+i)^t} \right) \times \frac{i(1+i)^T}{(1+i)^T - 1} \tag{4.1}$$

where $T(= EOS + l)$ is an optimal replacement time.

Figure 4.1 illustrates a cash flow based on above assumptions in consideration of a failure uncertainty when a maintenance service is expired.

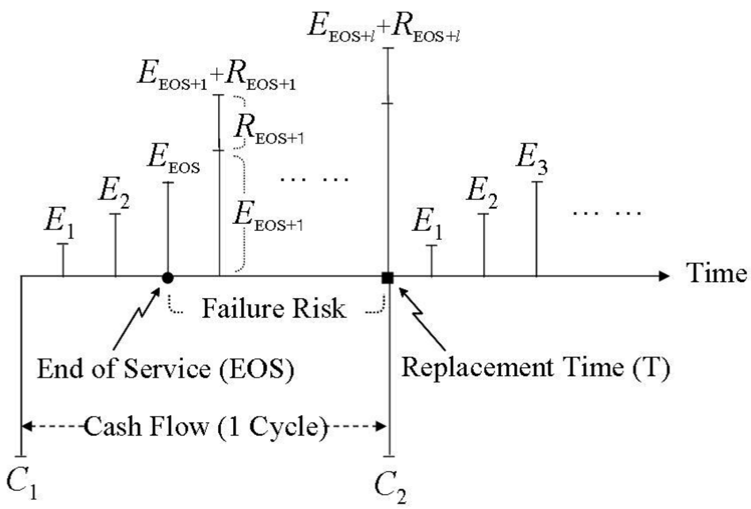


Figure 4.1: Cash flow for an equipment replacement considering a failure uncertainty

4.3 Model design

4.3.1 Model under consideration of a failure uncertainty

We will look at economic life to solve a replacement problem with EOS leading to a failure uncertainty. What we are concerned here is whether the EOS is earlier than a replacement time or not. Let us first begin our analysis by examining the following three options: (1) replacement from a current equipment to new one before EOS, (2) replacement from the current equipment to new one at EOS, and (3) replacement from the current equipment to new one after the EOS. Here, we can describe an optimal replacement time $M(T)$ for the three options to be minimized the LCC of each cash flow as shown in equation (4.2). The option (1) and (2) are applicable to the Case 1 of equation (4.2), and the option (3) can be presented Case 2 of equation (4.2), respectively.

$$
Minimize\ \ M(T) = \begin{cases} Case\,1: \ \text{If } T \leq EOS, & \left(C + \sum_{t=1}^{T} \frac{E_t}{(1+i)^t}\right) \times \frac{i(1+i)^T}{(1+i)^T-1} \\ Case\,2: \ \text{If } T > EOS, & \left(C + \sum_{t=1}^{T} \frac{E_t}{(1+i)^t} + \sum_{t=EOS+1}^{T} \frac{R_t}{(1+i)^t}\right) \times \frac{i(1+i)^T}{(1+i)^T-1} \end{cases} \tag{4.2}
$$

$Sub.\ \ E_t \leq E_{t+1},\ \ R_t \leq R_{t+1},\ \ i > 0,\ \ (t = 1, 2, ...T)$

We first discuss a Case 2 in this section. It is necessary to consider a cost for risk acceptance R_t to remove a failure uncertainty. We may see that an optimal replacement time from the below proposition 1.

Proposition 1. An optimal replacement time ORT_T refers to $\sum_{t=1}^{T} \frac{E_T - E_t}{(1+i)^t} + \sum_{t=1}^{T} \frac{R_T - R_t}{(1+i)^t}$ which has a positive number(cost) just before an initial purchase cost C.

Proof of proposition 1. While an average annual cost of the initial purchase cost C in equation (4.1) is gradually reduced by making constant use of an equipment, an annual maintenance cost E_t is increased according to the assumption (2) $E_t \leq E_{t+1}$. It is therefore obvious that M(T) of the equation (4.1) is a convex function when a horizontal and vertical axis of a two-dimensional graph represents using a time and the average annual cost, respectively. For an optimal replacement time T^*, therefore, we here have

$$
T^* = \begin{cases} M(T^* - 1) \geq M(T^*) \\ and \\ M(T^*) \leq M(T^* + 1) \end{cases} \tag{4.3}
$$

In addition to above equation (4.3), the below formula is also obtained in regard to the M(T) of equation (4.1) using a relation of capital recovery factors, where the factors represent average annual costs for several years, which are converted from total NPV(Net Present Value) of cash flow (See Appendix D-1).

$$
M(T) - M(T-1) = \left(-C + \sum_{t=1}^{T} \frac{E_T - E_t}{(1+i)^t} + \sum_{t=1}^{T} \frac{R_T - R_t}{(1+i)^t}\right) \times \frac{i(1+i)^{T-1}}{(1+i)^{T-1} - 1} \times \frac{i}{(1+i)^T - 1} \tag{4.4}
$$

where a capital recovery factor $\frac{i(1+i)^{T-1}}{(1+i)^{T-1}-1}$ and $\frac{i(1+i)^T}{(1+i)^T-1}$ have the following relation (See Appendix D-2.).

$$
\frac{i(1+i)^T}{(1+i)^T - 1} = \frac{i(1+i)^{T-1}}{(1+i)^{T-1} - 1} \times \left(1 - \frac{i}{(1+i)^T - 1}\right) \tag{4.5}
$$

From the equation (4.3), $M(T) - M(T-1)$ should be a negative while $M(T+1) - M(T)$

should be a positive, because the $M(T)$ is a convex function as mentioned above. Moreover, the second and third term of the equation (4.4) should also be positive numbers all, under $i > 0$. Therefore we also get

$$M(T) - M(T-1) = \left(-C + \sum_{t=1}^{T} \frac{E_T - E_t}{(1+i)^t} + \sum_{t=1}^{T} \frac{R_T - R_t}{(1+i)^t} \right) < 0 \tag{4.6}$$

and

$$M(T+1) - M(T) = \left(-C + \sum_{t=1}^{T} \frac{E_T - E_t}{(1+i)^t} + \sum_{t=1}^{T} \frac{R_T - R_t}{(1+i)^t} \right) > 0 \tag{4.7}$$

Using the equation (4.6) and equation (4.7), a new economic life is therefore given by

$$New\ economic\ life\,(T^*) = \begin{cases} C \geq \sum_{t=1}^{T^*} \frac{E_{T^*} - E_t}{(1+i)^t} + \sum_{t=1}^{T^*} \frac{R_{T^*} - R_t}{(1+i)^t} \\ and \\ C \leq \sum_{t=1}^{T^*+1} \frac{E_{T^*+1} - E_t}{(1+i)^t} + \sum_{t=1}^{T^*+1} \frac{R_{T^*+1} - R_t}{(1+i)^t} \end{cases} \tag{4.8}$$

Based on the equation (4.8), we have finally

$$ORT_T = \sum_{t=1}^{T} \frac{E_T - E_t}{(1+i)^t} + \sum_{t=1}^{T} \frac{R_T - R_t}{(1+i)^t} \tag{4.9}$$

where a ORT_T represents a simple discriminant to find an optimal replacement time, and if $t = 1, 2, ..EOS$, $R_t = 0$, when $T > EOS$.

Here we define a cost for risk acceptance R_t of production equipment as the sum of two costs: a total expenditures for repair TC_m^t and expected loss VaR_{EOS}^t by a shutdown that correspond to a failure risk and its derivative risk respectively, which can be formulated as

$$TC_m^t = \sum_{j=1}^{n} C_j^m \cdot \int_{EOS}^{t} x_j(t)dt \tag{4.10}$$

$$VaR_{EOS}^t = \lambda(e, \alpha)_{EOS}^t \tag{4.11}$$

$$R_t = TC_m^t + VaR_{EOS}^t = \sum_{j=1}^{n} C_j^m \cdot \int_{EOS}^{t} x_j(t)dt + \lambda(e, \alpha)_{EOS}^t \tag{4.12}$$

where $t \geq EOS$, and if $t \leq EOS$, $TC_m^t = 0$, and (See Table 4.1)

Table 4.1: Additional notation

Variable	Definition
TC_m^t	Total expenditures for repair for t years
VaR_{EOS}^t	Value at risk as expected loss of production equipment by shutdown e under a confidence level α for t years after EOS
n	Number of components in production equipment
j	Component(j=1,2,...,n)
C_j^t	Repair cost of component j for t years
$x_j(t)$	Characteristic function=1 if component j under repair for t years and =0 if component j is operational for t years, and a failure rate is behaved, according to a probability distribution function.

The VaR with respect to $L(e)$ which is a loss rate of some event e, can be defined by the following formula.

$$inf\,(\lambda|Pr(L(e) \leq \lambda) \geq \alpha) \tag{4.13}$$

where $Pr(L(e) \leq \lambda)$ is a probability that will not be larger that λ, and α is a confidence level.
Therefore, we denote the VaR of some event e that is represented as a shutdown by an equipment failure after a maintenance service is expired(EOS), at confidence level α by $\lambda(e, \alpha)$, which may be written as below

$$\lambda(e, \alpha)_{EOS}^t = inf(\lambda|Pr(L(e) \leq \lambda) \geq \alpha) \tag{4.14}$$

4.3.2 Model without a failure uncertainty

In this section, we formulate a model without a failure uncertainty. As a realistic approach to cope with the uncertainty, we consider a renewal of the maintenance contract as a solution. We here use the following assumption 4' with respect to a contract renewal S_l instead of an assumption 4 in section 4.2.2.

- 4'. Note that a user of equipment can renew a maintenance contract for l years at a point to be EOS, which refers to $S_l(l$=1,2,...$), S_l < S_{l+1}$.

We derive the optimal solution considering the maintenance contract renewal based on the above assumption 4', which is described in the proposition 2.

Proposition 2. An optimal replacement time ORT_T refers to $\sum_{t=1}^{T} \frac{E_T - E_t}{(1+i)^t} - \frac{S_l}{(1+i)^{EOS}} + \frac{S_l - S_{l-1}}{(1+i)^{EOS}} \times \frac{(1+i)^T - 1}{i}$ which has a positive number(cost) just before an initial purchase cost C.

Proof of proposition 2. A formula to calculate the optimal replacement time $T(= EOS + l)$ in consideration of a renewal of maintenance contract can be written as

$$M(T) = \left(C + \sum_{t=1}^{T} \frac{E_t}{(1+i)^t} + \frac{S_l}{(1+i)^{EOS}} \right) \times \frac{i(1+i)^T}{(1+i)^T - 1}, \ (T > EOS) \tag{4.15}$$

As the same way to the equation (4.4) in previous chapter, it can be shown that the $M(T) - M(T-1)$ is given by (See Appendix D-3.)

$$M(T) - M(T-1) = \left(-C + \sum_{t=1}^{T} \frac{E_T - E_t}{(1+i)^t} - \frac{S_l}{(1+i)^{EOS}} + \frac{S_l - S_{l-1}}{(1+i)^{EOS}} \times \frac{(1+i)^T - 1}{i} \right)$$
$$\times \frac{i(i+i)^{T-1}}{(1+i)^{T-1} - 1} \times \frac{i}{(1+i)^T - 1}, \ (T > EOS) \tag{4.16}$$

Based on the equation (4.16), we have the optimal replacement time.

$$New\ economic\ life(T^*) = \begin{cases} C \geq \sum_{t=1}^{T^*} \frac{E_{T^*} - E_t}{(1+i)^t} - \frac{S_l}{(1+i)^{EOS}} + \frac{S_l - S_{l-1}}{(1+i)^{EOS}} \times \frac{(1+i)^{T^*} - 1}{i} \\ and \\ C \leq \sum_{t=1}^{T^*+1} \frac{E_{T^*+1} - E_t}{(1+i)^t} - \frac{S_{l+1}}{(1+i)^{EOS}} + \frac{S_{l+1} - S_l}{(1+i)^{EOS}} \times \frac{(1+i)^{T^*+1} - 1}{i} \end{cases} \tag{4.17}$$

Therefore, we have

$$ORT_T = \sum_{t=1}^{T^*} \frac{E_{T^*} - E_t}{(1+i)^t} - \frac{S_l}{(1+i)^{EOS}} + \frac{S_l - S_{l-1}}{(1+i)^{EOS}} \times \frac{(1+i)^{T^*} - 1}{i} \tag{4.18}$$

4.4 Analysis on optimal replacement with examples

4.4.1 A case for accepting failure risks

We assume that each of production equipments has two types of probability function: a normal distribution(PDF: probability density function) for annual profit and loss which means sales records that are produced and sold by each production equipment, and a cumulative normal distribution(CDF: cumulative distribution function) refers to an annual failure rate of each component which depends on a time. Let's consider that the sum of all annual repair cost of components and their failure distributions to be the same as 5000$ and CDF($\mu = 6, \sigma = 1.5^2$) respectively just for the sake of convenience. In the Table 4.2, CDF(%) and PDF(z) mean a cumulative probability for failure and z value of normal distribution($\mu = 0, \sigma = 3\%$) respectively, where μ and σ are the same for every year. And a maintenance service is expired in 3^{rd} year(EOS=3). Table 4.2 presents a parameter R_t that is based on the given parameters when an initial purchase cost(C=50,000$) is considered as a value of the production equipment.

Table 4.2: Parameters for a cost of risk acceptance R_t, i=5(%)

$t\,(year)$	CDF(%)	TC^t_m($)	PDF(z: %)	Var^t_{EOS}($)	R_t($)
4	6.9	345	90	1,920	2,265
5	23.18	1,159	95	2,475	3,634
6	47.72	2,386	99	3,495	5,881
7	72.26	3,613	99	3,495	7,108

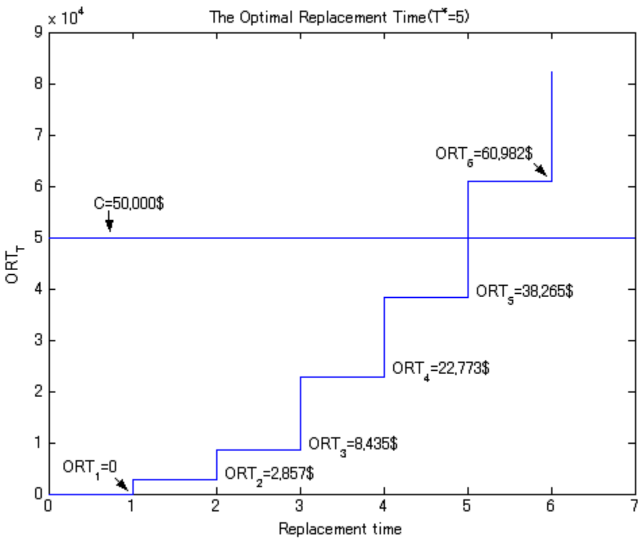


Figure 4.2: An optimal replacement time 1 ($T^* = 5$)

It is necessary that an equation (4.9) is first calculated in sequence according to $T = 1, 2, ..,$ and is then compared whether each ORT_T is exceeded an initial purchase cost C or not. Given that the ORT_T is illustrated as shown in Figure 4.2, we can simply identify an optimal replacement time, which refers to the ORT_T that has a positive number just before the initial purchase cost C. The Figure 4.2 shows that the optimal replacement time is 5($T = 5$) because of $ORT_5 < C < ORT_6$. That is, we can see from the Figure 4.2 that the $ORT_5(= 38,265\$)$ is not exceeded the initial purchase cost $C(= 50,000\$)$, while the next step $ORT_6(= 60,982\$)$, by contrast, exceeded.

4.4.2 A case for a renewal of a maintenance contract

This section concerns a renewal of maintenance contract not only to avoid a failure risk, but also to help a stable operation. For this case, in addition to the given parameters in Table 4.2, we use a renewal cost S_l : S_1=1,500, S_2=3,200, S_3=5,000, and S_4=7,000. As shown in Figure 4.3, we can identify an optimal replacement time ORT_T, which has a positive number just before an initial purchase cost C. An optimal replacement time is 6($T = 6$) in this case because of $ORT_6(46,488\$) < C(= 50,000\$) < ORT_7(63,487\$)$.

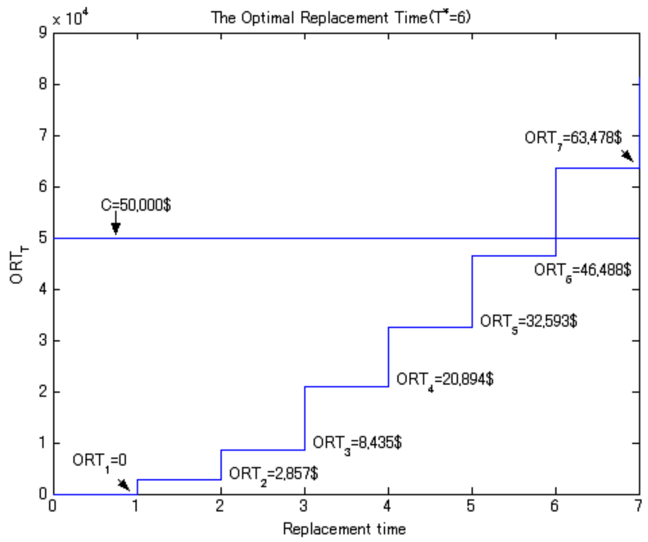


Figure 4.3: An optimal replacement time 2 ($T^* = 6$)

Consider for a moment whether there existed some uncertainties with respect to a replacement of production equipment. On the practical side, a decision making with lots of uncertainties from a current equipment to a new one should be particularly considered with related risks such as cost risks by unexpected failures, not to given the environments or predicted situations. From the standpoint of application of some uncertainties to the replacement problems, it is therefore clear that the defined method using a discriminant ORT_T is helpful many decision makers who weigh a cost advantage and disadvantage under uncertainties, because it gives us a certain simple standard. That is, to calculate each ORT_T from the expected maximum and minimum scope of annual maintenance costs is supportable for wise decisions under the given initial purchase cost. Because we can identify a change of scope of two lines, i.e., C and ORT shown as cost uncertainties.

4.5 Brief summary and discussion

A failure risk is one of the most notable threats for an economical manufacturing due to some possibilities of interruption of production activities by a shutdown which may interfere with a stable operation, by just one unpredicted failure, even if it is not a frequent occurrence. We dealt with an equipment replacement problem considering the risk, from a viewpoint of parameter uncertainty. In the concrete, we formulated two cases with a simple solution procedure: (1)a case for accepting failure risks without a renewal of contract, and (2)a case for coping with the failure risks through the renewal of maintenance contract. To sum up the major characteristics of our model, in addition to a convenience for searching optimal solution through a comparison with an initial purchase cost C and a cost as given by ORT_T , it may be useful for a determining of the replacement time and contract renewal for a decision-maker who always try to minimize a total operational cost.

Chapter 5

Flexible supply contract

The major risks in a supply chain mostly come from a mismatch of supply and demand when a demand is uncertainly changed. In this chapter, we deal with supply and purchase risks by the demand change. It mainly focuses on a flexibility of adjusting order quantity[1].

5.1 Order flexibility in a supply chain

The supply contracts using various types of financial options can give a holder the right and opportunity to guarantee a certain trading quantity without a stockout or opportunity loss in a dynamic market. In practice, there are many attempts to cope with the risks from a mismatch of supply and demand, using flexible supply contracts. An apparel business is the typical example. The apparel business is chiefly driven by customers because of a strong dependence on the customer preference that is awfully sensitive to a change of fashion, design and seasonal characteristics. In addition, in spite of a short selling season, the apparel is a representative business that can be freely returnable for an exchange and refund within a given period. From these unique characteristics, suppliers and buyers for the business often have troubles in a production, an order and inventory management. It extremely requires flexible supply contracts as well as strong partnerships between the suppliers and buyers. Especially, in these days, the supply contracts using various financial options are greatly attracting much attention in the study of the apparel supply chain, which give both the suppliers and buyers an appropriate flexibility. Because of its excellent flexibility for the risk management such as an insurance, it has been evaluated as one of the most suitable and practical methods to consider the unique and complicated characteristics of the apparel business.

As far as we know, there have been many studies reported on a supply contract and its mechanism. Andy A. Tsay(1996) models the Quantity Flexibility(QF) contract for identifying incentives of two independent agents(a supplier and its customer) in a supply chain and characterize implications of the QF contract for the behavior and performance of both the agents and the supply chain as a whole [36]. They point out inefficiency by different behav-

[1]A partial content described in this chapter has been accepted in International Journal of Production Economics, Available Online 1 February, 2011

iors of both the agents who pursue only their profits, and clarify their causes based on the proposed QF contract model. Karen L. Donohue(2000) develops the supply contract models for fashion goods which encourage a suitable coordination of production decisions as well as a close cooperation for an information sharing, even a demand forecasting between a manufacturer and a distributor in two production modes [37]. They show that efficient supply contracts lead to a strategic coordination of the manufacturer and distributor to act in the best interest of the supply chain. Gérard P. Cachon and Martin A. Larviviere(2005) consider the revenue-sharing contracts to solve an uncooperative problem in a supply chain consisting of a single supplier and a retailer from a viewpoint of strengths and limitations of the contracts. Particularly, they emphasize that the revenue sharing coordinates a supply chain, and demonstrate that the strategic revenue sharing allocates the profit of the supply chain which leads to an improvement of performance of the supply chain. However, they also add that the revenue sharing may not be attractive in some cases where if retailer's actions influence a demand [38]. Gray D. Eppen and Ananth. V. Iyer(1997) examine a backup agreement which provides an upstream sourcing flexibility for a fashion merchandise between a catalog company and manufacturers, in which buyer's initial reservation for an order quantity can be canceled by imposing penalty costs, according to demand changes. With some constraints and penalties, they show that the backup agreement as a buyback contract can have a positive impact on profits of both the manufacturer and retailer [39]. Dawn Barnes-Schuster et al.(2002) investigate a two-period problem using options and their roles in a buyer-supplier system. They show that a channel coordination can generally be achieved only if an exercise price is allowed to be a piecewise linear [40]. Xiaolong Wang and Liwen Liu(2007) study about a channel coordination and risk sharing based on the option contracts with two parameters(option price and exercise price of the option) in a retailer-led supply chain where a dominant and powerful retailer aims to coordinate a production quantity of a manufacturer. They note two conditions for successful channel coordination in the study; the first condition is to make the exercise price and option price negatively correlated, the second condition is that a firm commitment should be less than the optimal production quantity in a centralized system [41]. On the other hand, there is an attempt to investigate the possible solutions by non-cooperative bargaining theoretic approach for supply contracts and coordinations of a supply chain. Kadir Ertogral and S. David Wu(2001) show that both a supplier and a buyer can derive the cooperative optimal solution to maximize their expected profits in subgame perfect equilibrium. They not only formulate a model to identify the optimal negotiation sequence for the supply chain contracting and coordination, but clarify the subset of suppliers for the negotiation with buyers [42].

The subjects on a price problem and its roles as well as advantages of supply contracts have been already discussed sufficiently. Actually, most of the previous studies have been focused on the price conditions and optimal policies for a channel coordination as mentioned above. However, there is no practical comparative study dealing with both bright and seamy side(advantages and risks) of the supply contracts using options at the same time, which is related to how a better result(expected profit) than a newsvendor model can be derived, and is also related to how the worse result(risk) than other supply contracts can be derived when a customer demand is changed, uncertainly. In this chapter, from a new and extensive angle on the supply contract problem, we formulate various supply contract models for both a supplier(manufacturer) and a buyer(retailer) under the given different demand scenarios, through a full understanding of characteristics of the options. To describe a mathematical optimization problem, we consider the problem with two decision-making points in a single-period two-stage supply chain consisting of a supplier and a buyer. We introduce a fixed order quantity between the supplier(manufacturer) and the buyer(retailer), and examine cases where both the agents come to an agreement about some conditions of each of the order and production in the single-period two-stage supply chain. Our study contributes two points to the research areas.

- We propose four types of supply contracts using options from a new and extensive angle on a supply contract problem.
- Furthermore, we deal with both bright (expected profits) and seamy side (potential risks) of the supply contracts, at the same time.

5.2 Design of flexible supply contracts

We begin this section with a discussion of formulation of option contracts, in which the expected profit function and optimal solution are obtained under the given various demand scenarios. To describe mathematical models, we employ the following notation of Table 5.1.

Figure 5.1 presents a framework of a single-period two-stages supply chain; after a buyer places an initial order at the beginning of the planning horizon(t_1, the first decision-making point), the buyer can adjust the order at the beginning of selling season(t_2, the second decision-making point) based on updated demand information during a production lead-time from t_1 to t_2. And after the selling season(after t_3), the buyer salvages the unsold products if a supplied quantity is more than an actual demand. In such a decision structure, by purchasing options, the buyer can improve the expected profits at the beginning of the planning horizon with an obtaining the flexibility of adjusting the order quantity.

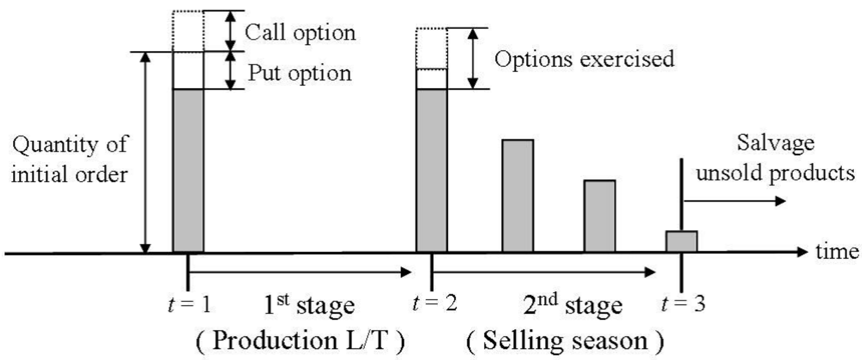


Figure 5.1: The model framework : single-period two-stage supply chain

Table 5.1: A summary of notation

Variable	Definition
Q	quantity of initial order
q_o	quantity of options purchased
q_e	quantity of options exercised(or quantity of buy-back for buy-back contract)
p_w	unit wholesale price
p_r	unit retail price
p_o	units option price
p_e	unit buy-back price
p_{ec}	unit exercise price of call option
p_{ep}	unit exercise price of put option
v_o	unit cost of opportunity loss for buyer
v_s	unit salvage value for buyer
v_b	unit salvage value for supplier
D	demand during a selling season
L	average demand of D
K	average demand of l
$\phi(L)$	probability density function of L
$f(D \mid l)$	conditional probability density function for $L = l$

In our model, a demand forecasting for a buyer is carried out in twice, to raise a forecast accuracy. The buyer first forecasts the demand which is expected to be occurred at t_2, and then, by using the demand information, makes again demand distribution for t_1 to decide an initial firm order. We assume that the demand D during in the selling season is uniformly distributed over the interval $[L - m, L + m]$ of an uniform distribution, where the average demand L is also expected to be distributed uniformly over the interval $[K - n, K + n]$ of the uniform distribution. The L value is specified by the buyer, $L = l$, at the beginning of the selling season(t_2) based on the latest forecasting information.

(1) Objective function for buyer

The purpose of buyer who has a right to get additional order opportunity or to return purchased goods to supplier by options is to maximize the total expected profit function during the planning horizon. It can be formulated as

$$\begin{aligned} Maximize\ \ G_{buyer}(Q, q) = {} & p_r E[D \wedge (Q \pm q)] + v_b E[Q - D]^+ - wE[(D - Q)^+ \wedge q] \\ & -v_o E[D - (Q \pm q)]^+ - p_w Q - c_o q \end{aligned}$$

$$Sub.\ \ Q > 0,\ \ q \geq 0 \tag{5.1}$$

where $E[a \wedge b]$ is equal to expected $Min\,[a, b]$, $c_o q$ is a total option price, and w is an unit purchasing price of option after the buyer confimed a predictive value for demand.

(2) Objective function for supplier

The purpose of supplier is to maximize the total expected profit function, which can be formulated as

$$\begin{aligned} &Maximize\ \ G_{supplier}(c_o,\ w) = p_w Q + c_o q + wE[(D-Q)^+ \wedge q] + v_s E[q-(D-Q)^+]^+ \\ &\qquad\qquad -p_{sc}(Q+q) \\ &Sub.\ \ c_o,\ w > 0 \end{aligned} \tag{5.2}$$

where p_{sc} is an unit supplying cost.

5.2.1 Buy-back contract

We provide a buy-back contract model with a theoretical analysis for an optimal order quantity, where a buyer has the right to return products ordered at t_1 to a supplier at t_2. In this model, the optimal buy-back quantity q_e^* for second stage is firstly obtained, and then, using the obtained q_e, an initial order quantity Q at the first stage is decided. For the buyer, we here consider four cases related to the q_e and derive maximum profit functions E_1^*-E_4^* by the cases. We assume that:

1. $p_r > p_w \geq p_e > v_s > 0$.
2. All costs for the first stage are not considered in this contract.

Case 1. A case where the possible minimum demand D exceeds the final order quantity(Q) ($Q < l - m$): $q_e^* = 0$.

In this case, obviously, an optimal buy-back quantity is $q_e^* = 0$. Because an initial order quantity Q is less than a demand D, it is not necessary to exercise in order to maximize the expected profits of a buyer. By a difference between an income and opportunity loss, we can formulate the expected profit based on the $D \in [l-m, l+m]$ and $f(D \mid l) = \frac{1}{2m}$, as follows.

$$E_1^* = p_r Q - v_o \int_{l-m}^{l+m} (D-Q) f(D \mid l) dD = p_r Q - v_o \int_{l-m}^{l+m} (D-Q) \frac{1}{2m} dD = p_r Q - v_o (l-Q)$$

(5.3)

where l can be decided by $Q+m<l\leq K+n$ which comes from $Q+m<l$ and an interval $[K-n, K+n]$ for the l.

Case 2. A case where the final order quantity(Q) exceeds the possible minimum demand($l-m$) a little ($Q\leq l-m$): $q_e^*=0$.

A different point with Case 1 is that Q satisfies ($l-m\leq Q$). For this case, since two optimal solutions can be considered according to an interval of l: $q_e^*=0$ or $q_e^*>0$, we consider both Case 2 and 3 to formulate the expected profit function. We first deal with in this case the maximum expected profit for the $q_e^*=0$, and another solution($q_e^*>0$) will be considered in Case 3 in details. An equation (5.4) shows a formulation of the expected profit function which can be referred to both Case 2 and 3.

$$E_{2-3}^*=p_eq_e+\frac{1}{2m}\int_{l-m}^{Q-q_e}p_rD+v_s(Q-q_e-D)dD+\frac{1}{2m}\int_{Q-q_e}^{l+m}p_r(Q-q_e)-v_o(D-(Q-q_e))dD \tag{5.4}$$

First, by $\frac{dE_2^*(q_e|l)}{dq_e}=0$, the optimal option quantity q_e^* to maximize E_{2-3}^* can be calculated as

$$q_e^*=Q-\Big(l+m-\frac{2m(p_e-v_s)}{p_r+v_s-v_s}\Big) \tag{5.5}$$

Here, if $q_e^*=Q-\Big(l+m-\frac{2m(p_e-v_s)}{p_r+v_s-v_s}\Big)<0$, the $q_e^*=0$, while if the $q_e^*>0$, the $q_e^*=Q-\Big(l+m-\frac{2m(p_e-v_s)}{p_r+v_s-v_s}\Big)$.

On the other hand, let us consider the expected profit function $E_2^*(0\mid l)$ when $q_e^*=0$ seriously. Due to $l>Q-\Big(l+m-\frac{2m(p_e-v_s)}{p_r+v_s-v_s}\Big)$ in case of the $q_e^*=0$, the l can be decided by $Q-z<l\leq Q+m$ where $z=m-\frac{2m(p_e-v_s)}{(p_r+v_o-v_s)}$. And we can obtain the expected profit function satisfying the l as

$$E_2^*=\frac{1}{2m}\int_{l-m}^{Q}p_rD+v_s(Q-D)dD+\frac{1}{2m}\int_{Q}^{l+m}p_rQ-v_o(D-Q)dD \tag{5.6}$$

Case 3. A case where the possible demand D contains $[Q - q_e, Q]$: $q_e^* = Q - (l + z)$.

This case is corresponded to $q_e^* > 0$ in Case 2. It is clear that an optimal buy-back quantity is $q_e^* = Q - (l + m - \frac{2m(p_c - v_s)}{p_r + v_o - v_s})$ from the Case 2. Therefore, when the l is given by $Q - m < l \leq Q - z$, the expected profit function can be written as

$$E_3^* = p_e q_e + \int_{l-m}^{Q-q_e} \frac{p_r D + v_s(Q - q_e - D)}{2m} dD + \int_{Q-q_e}^{l+m} \frac{p_r(Q - q_e) - v_o\Big(D - (Q - q_e)\Big)}{2m} dD \quad (5.7)$$

Case 4. A case where the possible maximum demand D is less than the final order quantity(Q) ($Q > l + m$): $q_e^* = Q - (l + z)$.

To remove a risk of overage inventory, a buyer exercises a buy-back option in this case. Therefore, this case has the same optimal buy-back quantity and expected profit function, which are given in Case 3, where l is decided by $K - n < l < Q - m$. The optimal solution for the buy-back contract is to exercise q_e^*. When $z = m - \frac{2m(p_e - v_s)}{(p_r + v_o - v_s)}$, the q_e^* is given by

$$q_e^* = \begin{cases} 0, & if \quad Q + m < l \leq K + n \\ 0, & if \quad Q - z < l \leq Q + m \\ Q - (l + z), & if \quad Q - m < l \leq Q - z \\ Q - (l + z), & if \quad K - n < l \leq Q - m \end{cases} \quad (5.8)$$

As a result, by substituting the obtained optimal buy-back quantity $q_e^* = Q - (l + z)$, we can obtain a total expected profit of the buy-back contract, as shown in equation (5.9).

$$\begin{aligned} G_{buy-back}(Q) = & -p_w Q + \frac{1}{2n} \int_{K-n}^{Q-z} \Big(p_e\Big(Q - (l + z)\Big) + \frac{1}{2m} \int_{l-m}^{l+z} (p_r - v_s)D + v_s(l + z) dD \\ & + \frac{1}{2m} \int_{l+z}^{l+m} (p_r + v_o)(l + z) - v_o D \, dD\Big) dl + \frac{1}{2n} \int_{Q-z}^{Q+m} \Big(\frac{1}{2m} \int_{l-m}^{Q} (p_r - v_s)D + v_s Q \, dD \\ & + \frac{1}{2m} \int_{Q}^{l+m} (P_r + v_o)Q - v_o D \, dD\Big) dl + \frac{1}{2n} \int_{Q+m}^{K+n} \Big((p_r + v_o)Q - v_o l\Big) dl \end{aligned} \quad (5.9)$$

Here, because the objective function $G_{buy-back}(Q)$ is a concave function, by $\frac{dG_{buy-back}(Q)}{dQ} = 0$, the optimal order quantity Q^* of the buy-back contract for the buyer can be obtained, as shown in equation (5.10).

$$Q^* = \frac{p_e(K - n) + 2p_w n - (K + n)(v_o + p_r)}{(p_e - v_o - p_r)} - \frac{m(p_e - v_s)}{(p_r + v_o - v_s)} \quad (5.10)$$

5.2.2 Call option contract

We design a call option contract model using the same demand function of a buy-back model for both a buyer and a supplier. We assume that all costs at the first stage are not considered for calculating expected value at second stage.

(1) Buyer's perspective

We examine various cases and formulate the expected profit function for a buyer by the cases, and assume that: $0 < p_w \le p_{ec}$, $0 \le v_s, p_o \le p_w, p_{ec}$, $0 \le v_o$ and $p_o + p_{ec} \le p_r + v_o$.

Case 1. A case where the possible minimum demand D exceeds the final order quantity $(Q + q_o)$ $(Q + q_o < l - m,)$: $q_e^* = q_o$.

Even if a buyer exercises all options q_o, the final order quantity$(Q + q_o)$ can not meet a demand D in this case. Consequently, the optimal exercise quantity is $q_e^* = q_o$ due to a shortage, and as the expected profit function, we have

$$\begin{aligned} E_1^* &= p_r(Q + q_o) - p_{ec}q_o - v_o \int_{l-m}^{l+m} (D - Q - q_o) f(D \mid l) dD \\ &= p_r(Q + q_o) - p_{ec}q_o - v_o \int_{l-m}^{l+m} (D - Q - q_o) \frac{1}{2m} dD \\ &= p_r(Q + q_o) - p_{ec}q_o - v_o(l - (Q + q_o)) \end{aligned} \tag{5.11}$$

where l can be decided by $Q + q_o + m < l \le K + n$ which comes from $Q + q_o + m < l$ and an interval $[K - n, K + n]$ for the l.

Case 2. A case where the possible demand D exceeds the final order quantity a little: $q_e^* = q_o$.

A difference with Case 1 is that a demand D can be met, if a buyer exercises all options q_o purchased. And either an overage inventory or shortage may occur depends on an option quantity for exercising in this case. As same with Case 2 of the previous buy-back contract, in this case, two optimal solutions can be considered: $0 < q_e^* < q_o$ or $q_e^* = q_o$. Since this case is related to Case 3 to 4, we formulate the expected profit function referring to from Case 2 to 4. First, we deal with the maximum expected profit when the q_e^* is given as q_o.

$$E_{2-4}^* = -p_{ec}q_e + \frac{1}{2m} \int_{l-m}^{Q+q_e} p_r D + v_s(Q + q_e - D) dD + \frac{1}{2m} \int_{Q+q_e}^{l+m} p_r(Q + q_e) - v_o\Big(D - (Q + q_e)\Big) dD$$

(5.12)

By $\frac{dE_2^*}{dq_e} = 0$, an optimal option quantity q_e^* for call option can be obtained as

$$q_e^* = l + m - \frac{2m(p_{ec} - v_s)}{(p_r + v_o - v_s)} - Q \tag{5.13}$$

On the other hand, if $q_e^* = l + m - \frac{2m(p_{ec}-v_s)}{p_r+v_o-v_s} - Q > q_o$, the $q_e^* = q_0$, while if the $q_e^* = l + m - \frac{2m(p_{ec}-v_s)}{p_r+v_o-v_s} - Q < 0$, the $q_e^* = 0$, due to $0 \le q_e \le q_0$. Therefore, an interval of the l to be the $q_e^* = q_0$ is given as $l > Q+q_o-m+\frac{2m(p_{ec}-v_s)}{(p_r+v_o-v_s)}$, and the l is decided by $Q+q_o-z < l \le Q+q_o+m$ where $z = m - \frac{2m(p_{ec}-v_s)}{(p_r+v_o-v_s)}$. We can obtain the expected profit function satisfying the l as

$$E_2^* = -p_{ec}q_o + \frac{1}{2m}\int_{l-m}^{Q+q_o} p_r D + v_s(Q+q_o-D)dD + \frac{1}{2m}\int_{Q+q_o}^{l+m} p_r(Q+q_o) - v_o(D-(Q+q_o))dD \tag{5.14}$$

Case 3. A case where the possible demand D contains $[Q, Q + q_e]$: $q_e^* = (l + z - Q)$.

In this case, an optimal exercise quantity is $q_e^* = l + z - Q$, because a demand D contains an initial order Q contrary to Case 2. We derive an interval of the l where a buyer's expected profit is maximized when $q_e^* = l + m - \frac{2m(p_{ec}-v_s)}{(p_r+v_o-vs)} - Q$. The buyer's expected profit function can be written by

$$\begin{aligned}
E_3^* &= -p_{ec}q_e + \frac{1}{2m}\int_{l-m}^{Q+q_e} p_r D + v_s(Q+q_e-D)dD + \frac{1}{2m}\int_{Q+q_e}^{l+m} p_r(Q+q_e) - v_o\Big(D-(Q+q_e)\Big)dD \\
&= -p_{ec}(l+z-Q) + \frac{1}{2m}\int_{l-m}^{Q+(l+z-Q)} p_r D + v_s\Big(Q + (l+z-Q) - D\Big)dD \\
&+ \frac{1}{2m}\int_{Q+(l+z-Q)}^{l+m} p_r\Big(Q + (l+z-Q)\Big) - v_o\Big(D - (Q + (l+z-Q))\Big)dD \\
&= -p_{ec}(l+z-Q) + \frac{1}{2m}\int_{l-m}^{l+z} p_r D + v_s(l+z-D)dD \\
&+ \frac{1}{2m}\int_{l+z}^{l+m} p_r(l+z) - v_o(D-l-z)dD
\end{aligned} \tag{5.15}$$

where l can be decided by $Q - z < l \le Q + q_0 - z$ when the z is given as $m - \frac{2m(p_{ec}-v_s)}{(p_r+v_o-v_s)}$, which comes from $q_e^* = l + m - \frac{2m(p_{ec}-v_s)}{(p_r+v_o-v_s)} - Q > 0$ and $q_e^* = l + m - \frac{2m(p_{ec}-v_s)}{(p_r+v_o-v_s)} - Q < q_o$.

Case 4. A case where the possible demand D is less than the final order quantity(Q) a little: $q_e^* = 0$.

In this case, a demand D can be met even though a buyer dose not exercise options q_o(i.e. $l - m \leq Q < l + m$). Therefore, an optimal exercise quantity is $q_e^* = 0$, and the buyer's maximum expected profit function is

$$E_4^* = \frac{1}{2m}\int_{l-m}^{Q} p_r D + v_s(Q-D)dD + \frac{1}{2m}\int_{Q}^{l+m} p_r Q - v_o(D-Q)dD \tag{5.16}$$

where l can be decided by $Q - m < l < Q - z$.

Case 5. A case where the possible maximum demand D is less than the final order (Q) ($l + m < Q$): $q_e^* = 0$.

In this case, it is clear that a maximum profit realized at $q_e^* = 0$. Because an overage inventory is certainly occurred in this case, the expected profit can be written as a summation of the expected salvage value and profit.

$$E_5^* = \frac{1}{2m}\int_{l-m}^{l+m} p_r D\, dD + \frac{1}{2m}\int_{l-m}^{l+m} v_s(Q-D)dD \tag{5.17}$$

where l can be decided by $K - n < l < Q - m$ which comes from $Q - m > l$ and an interval $[K - n, K + n]$ for the l.

As a result, an optimal solution for a call option contract is to exercise q_e^* options, which is given as

$$q_e^* = \begin{cases} q_o, & if \quad Q + q_o + m < l \leq K + n \\ q_o, & if \quad Q + q_o - z < l \leq Q + q_o + m \\ (l+z) - Q, & if \quad Q - z < l \leq Q + q_o - z \\ 0, & if \quad Q - m < l \leq Q - z \\ 0, & if \quad K - n < l \leq Q - m \end{cases} \tag{5.18}$$

On the other hand, we can derive a total expected profit for a call option contract as shown in equation (5.19), from Case 1-5.

$$G_{call}(Q, q_o) = -p_w Q - p_o q_o + \frac{1}{2n}\int_{K-n}^{Q-m}\Big(p_r l + v_s(Q - l)\Big)dl$$

$$
\begin{aligned}
&+\frac{1}{2n}\int_{Q-m}^{Q-z}\Big(\frac{1}{2m}\int_{l-m}^{Q} p_rD + v_s(Q-D)dD + \frac{1}{2m}\int_{Q}^{l+m}(p_r+v_o)Q - v_oD\,dD\Big)dl\\
&+\frac{1}{2n}\int_{Q-z}^{Q+q_o-z}\Big(-p_{ec}(l+z-Q) + \frac{1}{2m}\int_{l-m}^{l+z} p_rD + v_s(l+z-D)dD\\
&+\frac{1}{2m}\int_{l+z}^{l+m}(p_r+v_o)(l+z) - v_oD\,dD\Big)dl\\
&+\frac{1}{2n}\int_{Q+q_o-z}^{Q+q_o+m}\Big(-p_{ec}q_o + \frac{1}{2m}\int_{l-m}^{Q+q_o} p_rD + v_s(Q+q_o-D)dD\\
&+\frac{1}{2m}\int_{Q+q_o}^{l+m}(p_r+v_o)(Q+q_o) - v_oD\,dD\Big)dl\\
&+\frac{1}{2n}\int_{Q+q_o+m}^{K+n}\Big(p_r(Q+q_o) - p_{ec}q_o + v_o(Q+q_o-l)\Big)dl
\end{aligned}
\tag{5.19}
$$

And optimal solutions of Q and q_o from $\frac{dG_{call}(Q,q_o)}{dQ} = 0$ and $\frac{dG_{call}(Q,q_o)}{dq_o} = 0$ can be obtained as follows.

$$
Q^* = K + n + m - \frac{2n(p_w - p_o - v_s)}{(p_{ec} + v_s)} - \frac{m(p_{ec} - v_s)}{(p_r + v_o - v_s)} \tag{5.20}
$$

$$
q_o^* = \frac{2n(p_w - p_o - v_s)}{p_{ec} + v_s} - \frac{2np_o}{(p_r + v_o - p_{ec})} - m \tag{5.21}
$$

(2) Supplier's perspective

We now turn our attention to a supplier, and consider an option contract from the supplier's perspective. In details, we maximize the expected profit of the supplier $G_M(p_{ec}, p_o)$ through an optimization of p_{ec} and p_o. We introduce additional variables with some assumptions with respect to a relation between the variables.

1. Additional variables: v_j(unit salvage value for supplier), p_c(cost of production)
2. We assume that: $p_r > p_{ec} > p_w \geq v_j,\ p_c > v_s,\ p_o > 0$.

The expected profit function of supplier $G_M(p_{ec}, p_o)$ can be described as shown in equation (5.22).

$$
G_M(p_{ec}, p_o) = p_wQ + p_oq_o - p_c(Q + q_o) + \int_{K-n}^{Q-z} q_ov_jf(l)dl + \int_{Q-z}^{Q+q_o-z}\Big((l + z - Q_o)p_{ec}
$$

$$+\Big(q_o - (l+z-Q)\Big)v_j\Big)f(l)dl + \int_{Q+q_o-z}^{K+n} q_o p_{ec} f(l)dl \tag{5.22}$$

Here, if we substitute equation(5.20) and (5.21) for above equation (5.22), optimal solutions(p_o, p_{ec}) for the supplier can be obtained. For instance, by $\frac{dG_M(p_o,p_{ec})}{dp_o} = 0$, the optimal p_o^* is given by

$$p_0^* = -\frac{(p_{ce} - v_o - p_r)\Big(p_w p_{ec} + v_s(v_j - p_c) + p_{ec}(-v_j + v_s + p_c)\Big)}{-2(v_o + p_r)v_s + v_j(v_o + p_r + v_s) + p_{ec}(-2v_j + v_o + p_r + v_s)}$$
$$+\frac{(p_{ec} - v_o - p_r)\Big(p_{ec}^3 m - p_{ec}^2(2p_w n + m(v_o + p_r + 2v_s)) + p_{ec}(2p_w n(-v_j + 2v_o + 2p_r + v_s)\Big)}{2n(v_o + p_r - v_s)\Big(p_{ec}(2v_j - v_o - p_r - v_s) + 2(v_o + p_r)v_s - v_j(v_o + p_r + v_s)\Big)}$$
$$+\frac{(p_{ec} - v_o - p_r)\Big(v_s(2v_j n - 2n(v_o + p_r) + m(2v_o + 2p_r + v_s)\Big) + 2n(-p_{ec} + v_o + p_r)^2(p_{ec} - v_s)p_c}{2n(v_o + p_r - v_s)\Big(p_{ec}(2v_j - v_o - p_r - v_s) + 2(v_o + p_r)v_s - v_j(v_o + p_r + v_s)\Big)}$$
$$+\frac{(p_{ec} - v_o - p_r)\Big((v_o + p_r)(2p_w^n(v_j - 2v_s) + v_s(-2v_j n - m v_s + 2n v_s))\Big)}{2n(v_o + p_r - v_s)\Big(p_{ec}(2v_j - v_o - p_r - v_s) + 2(v_o + p_r)v_s - v_j(v_o + p_r + v_s)\Big)} \tag{5.23}$$

5.2.3 Put option contract

In this section, when a demand is uniformly distributed, we design a put option contract model, in which a buyer can return purchased goods at the first stage to a supplier at the second stage as much as contracted quantities by options. A difference with a buy-back contract is that the buyer has a duty to pay an option price, in addition a purchase price of the supplier from the buyer is nearly equivalent to a wholesale price.

(1) Buyer's perspective

We assume that: $0 < p_{ep} \leq p_w$, $0 \leq v_s, p_o \leq p_{ep}, p_w$, $0 \leq v_o, v_s \leq p_{ep} - p_o$.

Case 1. A case where the possible minimum demand D exceeds the final order quantity $(Q < l - m)$: $q_e^* = 0$.

In this case, it is obviously that an optimal solution is $q_e^* = 0$, and the maximum expected profit considering an opportunity loss in an interval of demand $D \in [l - m\, l + m]$ can be described as shown in equation (5.24).

$$E_1^* = p_r Q - v_o \int_{l-m}^{l+m} (D-Q) f(D \mid l) dD = p_r Q - v_o \int_{l-m}^{l+m} (D-Q)\frac{1}{2m} dD = p_r Q - v_o(l-Q) \quad (5.24)$$

where l can be decided by $Q + m < l \leq K + n$ which comes from $Q < l - m$ and an interval $[k - n, k + n]$ for the l.

Case 2. A case where the final order exceeds the possible minimum demand D a little: $q_e^* = 0$.

In this case, because either an overage inventory or shortage may occur depends on an option quantity for exercising, three optimal solutions can be considered: $q_e^* = 0$, $0 < q_e^* < q_o$ and $q_e^* = q_o$. First, we here deal with a maximum profit when the $q_e^* = 0$. An equation 5.25. shows the expected profit function referring to from Case 2 to 4.

$$E_{2-4}^* = p_{ep} q_e + \frac{1}{2m} \int_{l-m}^{Q-q_e} p_r D + v_s\Big((Q-q_e) - D\Big) dD + \frac{1}{2m} \int_{Q-q_e}^{l+m} p_r(Q-q_e) - v_o\Big(D - (Q-q_e)\Big) dD \quad (5.25)$$

If we derive as the same way with Case 2 of a call option, the optimal option quantity q_e^* can be obtained as

$$q_e^* = Q - \Big(l + m - \frac{2m(p_{ep} - v_s)}{(p_r + v_o - v_s)}\Big) \quad (5.26)$$

Here, since if the $q_e^* = Q - \Big(l + m - \frac{2m(p_{ep}-v_s)}{(p_r+v_o-v_s)}\Big) < 0$, $q_e^* = 0$ from $0 \leq q_e \leq q_o$, we can get $l > Q - z$ where $z = m - \frac{2m(p_{ep}-v_s)}{(p_r+v_o-v_s)}$. And based on a summation of the expected salvage value and profit, as well as a difference between the profit and opportunity loss, we can formulate the expected profit function, as shown in equation (5.27).

$$E_2^* = \frac{1}{2m} \int_{l-m}^{Q} p_r D + v_s(Q - D) dD + \frac{1}{2m} \int_{Q}^{l+m} p_r Q - v_o(D - Q) dD \quad (5.27)$$

where l can be decided by $Q - z < l \leq Q + m$.

Case 3. A case where the possible demand D contains $[Q - q_e, Q]$: $q_e^* = Q - (l + z)$.

In this case, an optimal exercise quantity is $q_e^* = Q - \left(l + m - \frac{2m(p_{ep} - v_s)}{(p_r + v_o - v_s)}\right)$ as same with Case 2. If we formulate the expected profit function in consideration of an opportunity loss and overage inventory, it can be described as

$$
\begin{aligned}
E_3^* &= p_{ep}q_e + \frac{1}{2m}\int_{l-m}^{Q-q_e} p_r D + v_s(Q - q_e - D)dD + \frac{1}{2m}\int_{Q-q_e}^{l+m} p_r(Q - q_e) - v_o\Big(D - (Q - q_e)\Big)dD \\
&= p_{ep}\Big(Q - (l+z)\Big) + \frac{1}{2m}\int_{l-m}^{Q-(Q-(l+z))} p_r D + v_s\Big(Q - \Big(Q - (l+z)\Big) - D\Big)dD \\
&+ \frac{1}{2m}\int_{Q+(Q-(l+z))}^{l+m} p_r\Big(Q - \Big(Q - (l+z)\Big)\Big) - v_o\Big(D - \Big(Q - (Q - (l+z))\Big)\Big)dD \\
&= p_{ep}\Big(Q - (l+z)\Big) + \frac{1}{2m}\int_{l-m}^{l+z} p_r D + v_s(l + z - D)dD \\
&+ \frac{1}{2m}\int_{l+z}^{l+m} p_r(l+z) - v_o(D - l - z)dD
\end{aligned}
\tag{5.28}
$$

Here l can be satisfied by $q_e^* = Q - \left(l + m - \frac{2m(p_{ep} - v_s)}{(p_r + v_o - v_s)}\right) > 0$ and $q_e^* = Q - \left(l + m - \frac{2m(p_{ep} - v_s)}{(p_r + v_o - v_s)}\right) < q_o$. Therefore, we have $Q - q_o - z < l \leq Q - z$.

Case 4. A case where the possible demand D is less than the final option quantity a little: $q_e^* = q_o$.

This is corresponding to a case where an optimal exercise quantity $q_e^* = q_o$; although a buyer return purchased goods to a supplier as much as contracted quantities, the final order quantity is equal to or exceeds the possible demand D. The expected profit function is given by

$$
E_4^* = p_{ep}q_o + \frac{1}{2m}\int_{l-m}^{Q-q_o} p_r D + v_s(Q - q_o - D)dD + \frac{1}{2m}\int_{Q-q_o}^{l+m} p_r(Q - q_o) - v_o\Big(D - (Q - q_o)\Big)dD
\tag{5.29}
$$

where l can be decided by $Q - q_o - m < l \leq Q - q_o - z$.

Case 5. A case where the possible demand D is less than the final order quantity ($Q - q_o > l + m$): $q_e^* = q_o$.

In this case, it is clear that an optimal exercise quantity $q_e^* = q_o$, and the expected profit function can be written as

$$E_5^* = p_{ep}q_o + \frac{1}{2m}\int_{l-m}^{l+m} p_r D\,dD + \frac{1}{2m}\int_{l-m}^{l+m} v_s\Big((Q-q_o)-D\Big)dD \tag{5.30}$$

where l can be decided by $K-n < l \leq Q-q_o-m$ which comes from $Q-q_o-m > l$ and an interval $[k-n, k+n]$.

As a result, an optimal solution for a put option contract is to exercise q_e^* options, which is given by

$$q_e^* = \begin{cases} 0, & if \quad Q+m < l \leq K+n \\ 0, & if \quad Q-z < l \leq Q+m \\ Q-(l+z), & if \quad Q-q_o-z < l \leq Q-z \\ q_o, & if \quad Q-q_o-m < l \leq Q-q_o-z \\ q_o, & if \quad K-n < l \leq Q-q_o-m \end{cases} \tag{5.31}$$

And from Case 1-5, we can derive a total expected profit for the put option contract as shown in equation (5.32).

$$\begin{aligned} G_{put}(Q,q_o) &= -p_wQ - p_oq_o + \frac{1}{2n}\int_{K-n}^{Q-q_o-m}\Big(p_{ep}q_o + (p_r-v_s)l + v_s(Q-q_o)\Big)dl \\ &+\frac{1}{2n}\int_{Q-q_o-m}^{Q-q_o-z}\Big(p_{ep}q_o + \frac{1}{2m}\int_{l-m}^{Q-q_o}(p_r-v_s)D + v_s(Q-q_o)dD \\ &+\frac{1}{2m}\int_{Q-q_o}^{l+m} p_r(Q-q_o) - v_o\Big(D-(Q+q_o)\Big)dD\Big)dl + \frac{1}{2n}\int_{Q-q_o-z}^{Q-z}\Big(p_{ep}\Big(Q-(l+z)\Big) \\ &+\frac{1}{2m}\int_{l-m}^{l+z}(p_r-v_s)D + v_s(l+z-D)dD + \frac{1}{2m}\int_{l+z}^{l+m}(p_r+v_o)(l+z) - v_oD\,dD\Big)dl \\ &+\frac{1}{2n}\int_{Q-z}^{Q+m}\Big(\frac{1}{2m}\int_{l-m}^{Q} p_rD + v_s(Q-D)dD + \frac{1}{2m}\int_{Q}^{l+m}(p_r+v_o)Q - v_oD\,dD\Big)dl \\ &+\frac{1}{2n}\int_{Q+m}^{K+n}\Big(p_rQ - v_o(l-Q)\Big)dl \end{aligned} \tag{5.32}$$

Here, we can obtain the optimal solutions of Q and q_o from $\frac{maxG_{put}(Q,q_o)}{dQ} = 0$ and $\frac{maxG_{put}(Q,q_o)}{dq_o}$ as shown in equation (5.33) and (5.34).

$$Q^* = K + n - \frac{2n(p_w + p_o - p_{ep})}{v_o + p_r - p_{ep}} + \frac{m(p_{ep} - v_s)}{p_r + v_o - v_s} \tag{5.33}$$

$$q_o^* = \frac{2n(p_r + v_o - p_w - p_o)}{v_o + p_r - p_{ep}} + \frac{2p_o n}{p_{ep} - v_s} - m \tag{5.34}$$

(2) Supplier's perspective

In the same way with a buyer's perspective, we use the following additional variables and some assumptions:

1. Additional variables: v_j(unit salvage value for supplier), p_c(cost of production)
2. We set $0 < p_{ep} \leq p_w$, $0 \leq v_s < v_j$, $p_o \leq p_c, p_{ep}, p_w < p_r$ and $0 \leq v_o$.

The expected profit function of a supplier $G_M(p_{ep}, p_o)$ can be written as

$$G_M(p_{ep,p_o}) = p_w Q + p_o q_o - p_c Q + \int_{K-n}^{Q-q_o-z} q_o(v_j - p_{ep}) f(l)dl + \int_{Q-q_o-z}^{Q-z} \Big(q_o - \big(Q-(l+z)\big)\Big) v_j$$

$$-\big(Q-(l+z)\big) p_{ep} f(l)dl + \int_{Q-q_o-z}^{K+n} p_{ep} \times 0 f(l)dl \tag{5.35}$$

5.2.4 Hybrid option contract

We formulate in this section a hybrid option contract which is a combination of a call and put option contract. By using the hybrid option, a buyer can return purchased goods or order additionally according to a demand change. We derive seven cases depending on a value of l.

(1) Buyer's perspective

We assume that: $0 < p_{ep} \leq p_w \leq p_{ec}$, $0 \leq v_s, p_o \leq p_{ep}, p_w, p_{ec} < p_r$, $0 \leq v_o$, $v_s \leq p_{ep} - p_o$, and $p_o + p_{ec} \leq p_r + v_o$.

Case 1. A case where the possible minimum demand D exceeds the final order quantity ($Q + q_o < l - m$): $q_e^* = q_o$.

In this case, since an order quantity is always less than the possible demand, an optimal exercise quantity is $q_e^* = q_o$. An opportunity loss may occur in this case, consequently, we can formulate the expected maximum profit by a difference between the expected profit and loss in an interval $[l-m, l+m]$. The expected profit function can be written as

$$E_1^* = -p_{ec}q_o + p_r(Q+q_o) - v_o\int_{l-m}^{l+m}\Big(D-(Q+q_o)\Big)f(D\mid l)dD = -p_{ec}q_o + p_r(Q+q_o) - v_o\Big(l-(Q+q_o)\Big) \tag{5.36}$$

where l can be decided by $Q+q_o+m < l \leq K+n$ which comes from $Q+q_o < l-m$ and an interval $[k-n, k+n]$ for the l.

Case 2. A case where the possible demand d exceeds the final order quantity a little: $q_e^* = q_o$.

In this case, since two optimal solutions can be considered: $0 < q_e^* < q_o$ and $q_e^* = q_o$, we first deal with $q_e^* = q_o$. And this case is related to Case 3 and 4, we formulate the expected profit function considering Case 2, 3 and 4, as shown in below.

$$E_{2-4}^* = -p_{ec}q_e + \frac{1}{2m}\int_{l-m}^{Q+q_e} p_rD + v_s(Q+q_e-D)dD + \frac{1}{2m}\int_{Q+q_e}^{l+m} p_r(Q+q_e) - v_o\Big(D-(Q+q_e)\Big)dD \tag{5.37}$$

At this time, the optimal exercise quantity is given by $q_e^* = l+m-\frac{2m(p_{ec}-v_s)}{(p_r+v_o-v_s)}-Q$. Because if the $q_e^* = l+m-\frac{2m(p_{ec}-v_s)}{(p_r+v_o-v_s)}-Q > q_o$, the q_e^* is equal to q_o, while if the $q_e^* = l+m-\frac{2m(p_{ec}-v_s)}{(p_r+v_o-v_s)}-Q < 0$, the q_e^* is equal to 0. Therefore, we can obtain $l > Q+q_o-m+\frac{2m(p_{ec}-v_s)}{(p_r+v_o-v_s)}$. Here, if let $z(c)$ be $m-\frac{2m(p_{ec}-v_s)}{p_r+v_o-v_s}$, we can simplify the l as $l > Q+q_o-z(c)$.

On the other hand, when $q_e^* = q_o$, the expected profit function considering both the expected loss and overage inventory can be described as shown in equation (5.38).

$$E_2^* = -p_{ec}q_0 + \frac{1}{2m}\int_{l-m}^{Q+q_o}(p_r-v_s)D + v_s(Q+q_o)dD + \frac{1}{2m}\int_{Q+q_o}^{l+m} p_r(Q+q_o) - v_o\Big(D-(Q+q_o)\Big)dD \tag{5.38}$$

where l can be decided by $Q+q_o-z(c) < l \leq Q+q_o+m$.

Case 3. A case where the possible demand D contains $[Q, Q+q_e]$: $q_e^* = Q-\Big(l+z(c)\Big)$.

In this case, there is no big difference between the final order and possible demand, and an optimal exercise quantity q_e^* is given as $Q - \big(l + z(c)\big)$ from Case 2. Because both an opportunity loss and overage inventory may occur in this case, we can formulate based on those, as shown in equation (5.39).

$$E_3^* = -p_{ec}\Big((l + z(c) - Q)\Big) + \frac{1}{2m}\int_{l-m}^{l+z(c)} (p_r - v_s)D + v_s\big(l + z(c)\big)dD$$
$$+\frac{1}{2m}\int_{l+z(c)}^{l+m} p_r\big(l + z(c)\big) - v_o\Big(D - \big(l + z(c)\big)\Big)dD \tag{5.39}$$

where l can be decided by $Q - z(c) < l \leq Q + q_o - z(c)$ of which the demand l satisfies $q_e^* = l + m - \frac{2m(p_{ec}-v_s)}{(p_r+v_o-v_s)} - Q > 0$ and $q_e^* = l + m - \frac{2m(p_{ec}-v_s)}{(p_r+v_o-v_s)} - Q < q_o$.

Case 4. A case where there is no necessary for exercising option because the possible demand D is nearly equivalent to the final order quantity: $q_e^* = 0$.

In this case, contrary to Case 3, even if a buyer does not exercise options q_o, a demand is met. Therefore, an optimal exercise quantity is $q_e^* = 0$, and when $q_e^* = 0$ the expected profit function can be described as

$$E_4^* = \frac{1}{2m}\int_{l-m}^{Q} (p_r - v_s)D + v_s Q\, dD + \frac{1}{2m}\int_{Q}^{l+m} p_r Q - v_o(D - Q)dD \tag{5.40}$$

Here, demand l can be decided by $Q - z(p) \leq l \leq Q - z(c)$ where $z(p) = m - \frac{2m(p_{ep}-v_s)}{(p_r+v_o-vs)}$ that will be discussed in Case 5.

Case 5. A case where the possible demand D contains $[Q - q_e, Q]$: $q_e^* = Q - \big(l + z(p)\big)$.

In this case, there is no big difference between the final order and demand, but a buyer exercise put options contrary to Case 4. An optimal exercise quantity can be derived by $q_e^* = Q - \big(l + z(p)\big)$ as same way from Case 2 to 4. Here, if let $z(p)$ be $m - \frac{2m(p_{ep}-v_s)}{(p_r+v_o-v_s)}$, we can simplify the optimal exercise quantity as $q_e^* = Q - \big(l + z(p)\big)$. The expected profit function can be described by

$$E_5^* = p_{ep}\Big(Q - \big(l + z(p)\big)\Big) + \frac{1}{2m}\int_{l-m}^{l+z(p)} (p_r - v_s)D + v_s\big(l + z(p)\big)dD$$
$$+\frac{1}{2m}\int_{l+z(p)}^{l+m} p_r\big(l + z(p)\big) - v_o\Big(D - (l + z(p))\Big)dD \tag{5.41}$$

where l can be decided by $Q - q_o - z(p) < l \leq Q - z(p)$ of which the demand l satisfies $q_e^* = Q - \left(l + m - \frac{2m(p_{ep}-v_s)}{(p_r+v_o-v_s)}\right) > 0$ and $q_e^* = Q - \left(l + m - \frac{2m(p_{ep}-v_s)}{(p_r+v_o-v_s)}\right) < q_o$.

Case 6. A case where the possible demand D is less than the final order quantity a little: $q_e^* = -q_o$.

In this case, a different point with Case 5 is that a buyer can avoid risks against an overage by exercising all options q_o For this case, an optimal exercise quantity can be given as $q_e^* = -q_o$. When $q_e^* = -q_o$, the expected maximum profit and demand l can be written as

$$E_6^* = p_{ep}q_o + \frac{1}{2m}\int_{l-m}^{Q-q_o}(p_r - v_s)D + v_s(Q-q_o)dD + \frac{1}{2m}\int_{Q-q_o}^{l+m} p_r(Q-q_o) - v_o\Big(D-(Q-q_o)\Big)dD \tag{5.42}$$

where l can be decided by $Q - q_o - m < l \leq Q - q_o - z(p)$, since the optimal exercise quantity is $q_e^* = -q_o$ when $q_e^* = Q - \left(l + m - \frac{2m(p_{ep}-v_s)}{(p_r+v_o-v_s)}\right) > q_o$.

Case 7. A case where the possible demand D is less than the final order quantity ($Q - q_o > l + m$): $q_e^* = -q_o$.

In this case, even if a buyer exercise put options q_o, a demand is met. Therefore, an optimal exercise quantity is $q_e^* = -q_o$, and at that time, the expected profit can be written as

$$E_7^* = p_{ep}q_o + \frac{1}{2m}\int_{l-m}^{l+m} p_r D\, dD + \frac{1}{2m}\int_{l-m}^{l+m} v_s\Big((Q-q_o) - D\Big)dD \tag{5.43}$$

where l can be decided by $K - n < l \leq Q - q_o - m$ which comes from $Q - q_o > l + m$ and an interval $[K - n, K + n]$ for the l.

As a result, an optimal solution for a hybrid option contract is to exercise q_e^* options, which is given as

$$q_e^* = \begin{cases} q_o, & if \quad Q + q_o + m < l \leq K + n \\ q_o, & if \quad Q + q_o - z(c) < l \leq Q + q_o + m \\ l + z(c) - Q, & if \quad Q - z(c) < l \leq Q + q_o - z(c) \\ 0, & if \quad Q - z(p) \leq l \leq Q - z(c) \\ l + z(p) - Q, & if \quad Q - q_o - z(p) < l \leq Q - z(p) \\ -q_o, & if \quad Q - q_o - m < l \leq Q - q_o - z(p) \\ -q_o, & if \quad K - n < l \leq Q - q_o - m \end{cases} \tag{5.44}$$

From Case 1-7, we can derive a total expected profit for the hybrid option contract as shown in equation (5.45).

$$
\begin{aligned}
&G_{hybrid}(Q,q_o) = -p_wQ-p_oq_o+\frac{1}{2n}\int_{K-n}^{Q-q_o-m} p_{ep}q_o+(p_r-v_s)l-v_s(Q-q_o)dl\\
&+\frac{1}{2n}\int_{Q-q_o-m}^{Q-q_o-z(p)}\Big(p_{ep}q_o+\frac{1}{2m}\int_{l-m}^{Q-q_o}(p_r-v_s)D+v_s(Q-q_o)dD\\
&+\frac{1}{2m}\int_{Q-q_o}^{l+m}p_r(Q-q_o)-v_o\big(D-(Q-q_o)\big)dD\Big)dl+\frac{1}{2n}\int_{Q-q_o-z(p)} Q-z(p)\Big(p_{ep}\big(Q-(l+z(p))\big)\\
&+\frac{1}{2m}\int_{l-m}^{l+z(p)}(p_r-v_s)D+v_s(l+z(p))dD+\frac{1}{2m}\int_{l+z(p)}^{l+m}p_r(l+z(p))-v_o\big(D-(l+z(p))\big)dD\Big)dl\\
&+\frac{1}{2n}\int_{Q-z(p)}^{Q-z(c)}\Big(\frac{1}{2m}\int_{l-m}^{Q}(p_r-v_s)D+v_sQ\,dD+\frac{1}{2m}\int_{Q}^{l+m}p_rQ-v_o(D-Q)dD\Big)dl\\
&+\frac{1}{2n}\int_{Q-z(c)}^{Q+q_o-z(c)}\Big(-p_{ec}\big((l+z(c)-Q)\big)+\frac{1}{2m}\int_{l-m}^{l+z(c)}(p_r-v_s)D+v_s(l+z(c))dD\\
&+\frac{1}{2m}\int_{l+z(c)}^{l+m}p_r(l+z(c))-v_o\big(D-(l+z(c))\big)dD\Big)dl+\frac{1}{2n}\int_{Q+q_o-z(c)}^{Q+q_o+m}\Big(-p_{ec}q_o\\
&+\frac{1}{2m}\int_{l-m}^{Q+q_o}(p_r-v_s)D+v_s(Q+q_o)dD+\frac{1}{2m}\int_{Q+qo}^{l+m}p_r(Q+q_o)-v_o\big(D-(Q+q_o)\big)dD\Big)dl\\
&+\frac{1}{2n}\int_{Q+q_o+m}^{K+n}-p_{ec}q_o+p_r(Q+q_o)-v_o\big(l-(Q+q_o)\big)dl
\end{aligned}
\tag{5.45}
$$

Therefore, we can obtain the optimal solutions of Q and q_o from $\frac{dG_{hybrid}(Q,q_o)}{dQ}=0$ and $\frac{dG_{hybrid}(Q,q_o)}{dq_o}=0$ as shown in equation (5.46) and (5.47).

$$
\begin{aligned}
&Q^* = K+\frac{n(v_o+p_r+v_s-2p_w)}{p_r+v_o-v_s}\\
&+\frac{(p_r+v_o+v_s-p_{ec}-p_{ep})\Big(m(p_{ec}^2+p_{ep}^2)+2n\big(p_{ep}(v_o+p_r-p_w)+p_{ec}(v_s-p_w)\big)}{(p_r+v_o-v_s)\big((p_{ec}+p_{ep})^2+4(v_o+p_r)v_s-p_{ep}(3v_o+3p_r+v_s)-p_{ec}(v_o+p_r+3v_s)\big)}\\
&+\frac{(p_r+v_o+v_s-p_{ec}-p_{ep})\Big(\big(2p_wn-m(p_{ep}+p_{ec})\big)(v_o+p_r+v_s)-(4n-2m)(v_o+p_r)v_s}{(p_r+v_o-v_s)\big((p_{ec}+p_{ep})^2+4(v_o+p_r)v_s-p_{ep}(3v_o+3p_r+v_s)}
\end{aligned}
$$

$$\frac{-2np_o(v_o + p_r - v_s)\Big)}{-p_{ec}(v_o + p_r + 3v_s)\Big)} \tag{5.46}$$

$$q_o^* = \frac{2n\Big(p_{ep}(p_w - v_o - p_r) + p_{ec}(p_w - v_s) + p_o(v_o + p_r - v_s) + 2v_s(v_o + p_r)\Big)}{\Big(p_{ec} + p_{ep} - 2(v_o + p_r)\Big)(p_{ec} + p_{ep} - 2v_s) + (p_{ec} - p_{ep})(v_o + p_r - v_s)}$$
$$-\frac{m\Big(p_{ec}^2 + p_{ep}^2 + 2(v_o + p_r)v_s\Big)+\Big(2np_w - (p_{ec} + p_{ep})m\Big)(v_o + p_r + v_s)}{\Big(p_{ec} + p_{ep} - 2(v_o + p_r)\Big)(p_{ec} + p_{ep} - 2v_s) + (p_{ec} - p_{ep})(v_o + p_r - v_s)} \tag{5.47}$$

(2) Supplier's perspective

We use the following additional variables and some assumptions.

1. Additional variables: v_j(unit salvage value for the supplier), p_c(cost of production)
2. We set $0 < p_{ep} \le p_{ec},\ v_s < v_j,\ p_w > p_c \ge v_s, 0 \le v_s, p_o \le p_c, p_{ep}, p_w, p_{ec} < p_r, 0 \le v_o, v_s \le p_{ep} - p_o, p_o + p_{ec} \le p_r + v_o$

The expected profit function of a supplier $G_M(p_{ec}, p_{ep}, p_o)$ can be written as

$$G_M(p_{ec}, p_{ep}, p_o) = p_wQ+p_oq_o-p_c(Q+q_o)-q_op_{ep}\int_{K-n}^{Q-q_o-m} f(l)dl+2q_ov_j\int_{K-n}^{Q-q_o-m} f(l)dl$$
$$-q_op_{ep}\int_{Q-q_o-m}^{Q-q_o-z(p)} f(l)dl+\int_{Q-q_o-m}^{Q-q_o-z(p)} f(l)dl2q_ov_j-\frac{q_op_{ep}}{2}\int_{Q-q_o-z(p)}^{Q-z(p)} f(l)dl$$
$$+\frac{3q_ov_j}{2}\int_{Q-q_o-z(p)}^{Q-z(p)} f(l)dl+q_ov_j\int_{Q-z(p)}^{Q-z(c)} f(l)dl+\frac{q_op_{ec}}{2}\int_{Q-z(c)}^{Q+q_o-z(c)} f(l)dl$$
$$+\frac{q_ov_j}{2}\int_{Q-z(c)}^{Q+q_o-z(c)} f(l)dl+q_op_{ec}\int_{Q+q_o-z(c)}^{Q+q_o+m} f(l)dl+q_op_{ec}\int_{Q+q_o+m}^{K+n} f(l)dl$$
$$= p_wQ+p_oq_o-p_c(Q+q_o)-q_o(p_{ep}-2v_j)\frac{\Big((Q-q_o-m)-(K-n)\Big)}{2n}$$
$$-q_o(p_{ep}-2v_j)\frac{\Big((Q-q_o-z(p))-(Q-q_o-m)\Big)}{2n}-\frac{q_o(p_{ep}-3v_j)}{2}\frac{\Big((Q-z(p))-(Q-q_o-z(p))\Big)}{2n}$$
$$+q_ov_j\frac{\Big((Q-z(c))-(Q-z(p))\Big)}{2n}+\frac{q_o(p_{ec}+v_j)}{2}\frac{\Big((Q+q_o-z(c))-(Q-z(c))\Big)}{2n}$$

$$+q_o p_{ec}\frac{\Big((Q+q_o+m)-(Q+q_o-z(c))\Big)}{2n}+q_o p_{ec}\frac{\Big((K+n)-(Q+q_o+m)\Big)}{2n} \tag{5.48}$$

5.3 Numerical example: comparison of contracts

We examine, in this section, the proposed models' availability and risks presenting a lower expected profit than other comparable contracts, from predictable demand changes, by means of comparative studies. First, from a buyer's perspective, we compare a call option contract with a put option contract, and then show a contract with higher expected profit by demand sections. In addition, we also compare the presented four contract models (buy-back contract, call option contract, put option contract, and hybrid option contract) in section 5.2 with a non-flexible news-vendor model. From a supplier's perspective, similarly, we compare the call option contract with the put option contract, as well as a comparison of call-put-hybrid contracts.

5.3.1 Buyer's perspective

(1) A comparison between a call and a put option contract

In given demand sections, we examine which option's availability is better by a comparison of a call option contract and put option contract. For the logical comparison, we carry out an experiment with some conditions; we first set that both the call and put option have the same expected profits, and then analyze a comparative advantage of each option model when an average demand l is distributed between $l = 800$ and $l = 1200$. In details, we set an unit option price $p_o(put) = 18.96$ in order for the expected profits of both the option models to be the same, and then calculate the comparative advantage using $(\frac{E_{max}}{E_{min}} - 1) \times 100(\%)$ where $E_{max(min)}$ presents the maximum(minimum) expected profit. A summarized parameter set for this experiment is presented in Table 5.2.

Figure 5.2 shows that a put option is better over the interval $1025 \leq l \leq 1200$ while a call option is better over the interval $800 \leq l < 1025$. A point($l = 975$) presents a starting point which the put option quantity will be decreased, and is also a switching point where both the call and put option's comparative advantage are changed. In addition, because $l(= 1075)$ is a finishing point where all call options are exercised, a difference of the expected profits begins to reduce. Ultimately, in case where the possible demand is less than the final order quantity based on a demand forecasting at the first stage, the expected profit of call option is higher, while the expected profit of put option is higher in case where the possible demand exceeds the final order quantity.

Table 5.2: A comparison between a call option and a put option

	Q	q_o	Purchase interval	p_o	p_{ec}/p_{ep}	Expected profit
Call option	1019	83	[1019, 1102]	10	120	89144
Put option	1096	87	[1009, 1096]	18.96	100	89144

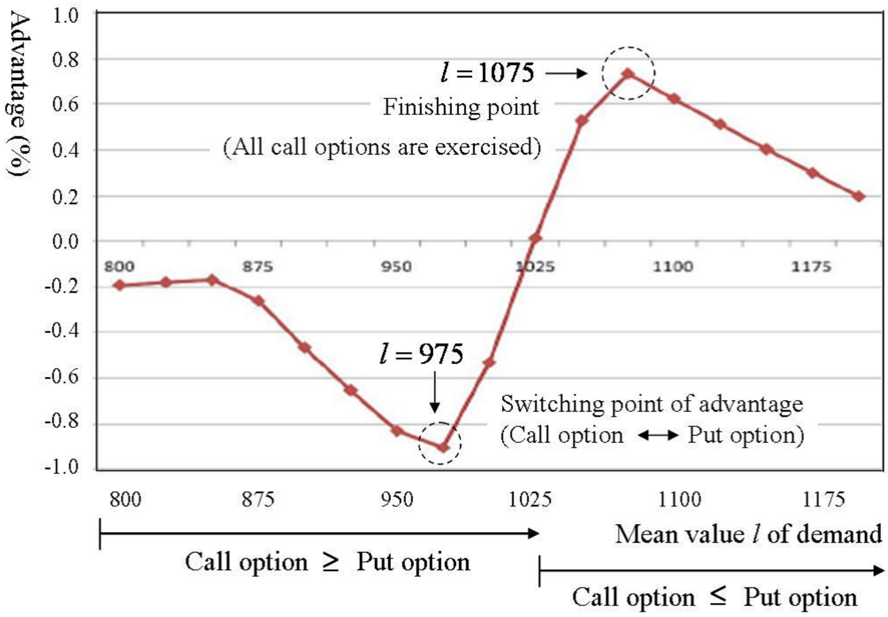


Figure 5.2: Call-put comparison: comparative advantages

(2) A comparison presented models and newsvendor model

A newsvendor model is known as a typical non-flexible contract model, in which a buyer can order at the beginning of selling season only once, in addition, a market price for all products is an unit wholesale price p_w. In this model, the buyer decides Q to maximize the expected profit for a cost function defined as

$$Max_Q G_B^{NV} = p_r E[D \wedge Q] + v_B E[Q - D]^+ - v_o E[D - Q]^+ - p_w Q \tag{5.49}$$

where an optimal solution for Q can be obtained by $Q = F^{-1}(\frac{p_r + v_o - p_w}{p_r + v_o - v_B})$.

In this section, we compare the presented four option models with a newsvendor model.

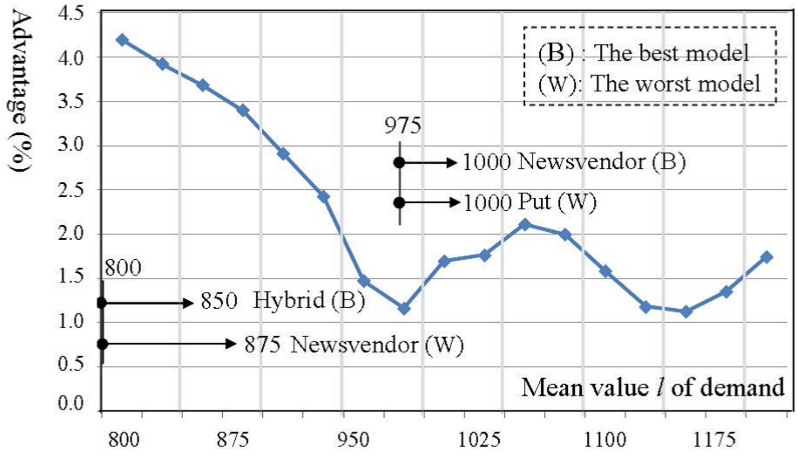
In the same way as the previous section, we analyze models' availability under the same expected profits. An average demand l is distributed between $l = 800$ and $l = 1200$. For comparative studies, we use parameters as follows: $p_r = 200$, $p_w = 100$, $p_o = 10$, $p_e = 80$, $p_{ec} = 120$, $p_{ep} = 100$, $v_o = 40$, $v_s = 30$, $m = 150$, $n = 200$ and $K = 1000$. We also set option prices in order for the expected profit of all option models to be the same, as follows: $p_e = 49.06$, $p_o(call) = 10$, $p_o(put) = 18.96$ and $p_o(hybrid) = 29.95$. In addition, we consider that an initial order Q is given as $1067(= 800 + \frac{2}{3} \times 400)$ when l follows an uniform distribution($2n = 400$). At this time, the expected profit of newsvendor model can be obtained by equation (5.50).

$$
\begin{aligned}
G_{NV}(Q) = -p_w Q + \frac{1}{2n}\int_{K-n}^{Q-m}\Big(\frac{1}{2m}\int_{l-m}^{l+m} p_r D + v_s(Q-D)dD\Big)dl \\
+\frac{1}{2n}\int_{Q-m}^{K+n}\Big(\frac{1}{2m}\int_{l-m}^{Q} p_r D + v_s(Q-D)dD + \frac{1}{2m}\int_{Q}^{l+m}(p_r+v_o)Q - v_o D\, dD\Big)dl \quad (5.50)
\end{aligned}
$$

Table 5.3: A comparison between presented models and a newsvendor model

	Q	q_o	Purchase interval	p_o	$p_e/p_{ec}/p_{ep}$	Expected profit
Buy-back	1080	-	-	-	49.06	89144
Call option	1019	83	$[1019, 1102]$	10	120	89144
Put option	1096	87	$[1009, 1096]$	18.96	100	89144
Hybrid option	1056	45	$[1011, 1101]$	29.95	put=100 call=120	89144

Figure 5.3 presents sections of the maximum(or minimum) expected profit by option models, when an average demand l is distributed uniformly. In case of $l = [800, 850]$ at $t = 2$, the expected profit of hybrid option is the highest while the expected profit of newsvendor model is the lowest in case of $l = [800, 875]$. And in case of $l = [875, 950]$, the expected profit of call option is the highest while the expected profit of buy-back model is the lowest in case of $l = [900, 950]$. In the same way, the newsvendor model, the buy-back model, the put option model has the highest expected profit in case of $l = [975, 1000]$, $l = [1025, 1175]$ and $l = 1200$, respectively, while the put option model, the call option model, the newsvendor model has the lowest expected profit in case of $l = [975, 1000]$, $l = [1025, 1125]$ and $l = [1150, 1200]$ in sequence. In this point, the most significant point to remember related to a selection of optimal option models is that the expected profit of hybrid model is not the lowest in any cases as shown in Figure 5.3, in addition all models using the options show basically a better performance than the traditional newsvendor model.



Max. of Ex. Profit	Hybrid	Call	Newsvendor	Buy-back	Put
Min. of Ex. Profit	Newsvendor	Buy-back	Put	Call	Newsvendor

Figure 5.3: A comparison between all option models: comparative advantages

5.3.2 Supplier's perspective

(1) A comparison between a call and a put option contract

In this section, several comparative studies focusing on call-put option contracts are carried out for a supplier. We adopt parameters as follows: $p_r = 200$, $p_w = 100$, $p_c = 40$, $v_j = 60$, $v_s = 30$, $v_o = 40$, $m = 150$, $n = 200$, and $K = 1000$. And we also set $p_{ec} = 129.5$, $p_{ep} = 75.0$ according to price constraints($p_{ec} \geq p_w$, $p_{ep} \leq p_w$). In Table 5.4, a put option-1 presents a option with price constraints while a put option-2 stands for a option without the price constraints. And T.P is total production volume, REP is the expected profit of a buyer, MEP is the expected profit of the supplier, respectively.

Table 5.4: A comparison between option models: REP/MEP

	Q	q_o	TP	p_o	$p_{ec/ep}$	REP	MEP
Call option	981	134	1115	9.97	106.5	89788.3	65899.2
Put option-1	1115	134	1115	16.47	106.5	89788.3	65899.2
Put option-2	1113	138	1113	13.13	100	89800.6	65890.6
Hybrid option	1042	78	1120	7.62	put=75 call=129.5	89723.7	66063.9
Newsvendor	1067	-	1067	-	-	88699	64020

While Table 5.4 shows the expected profit of each model, Table 5.5 shows a total expected profit(REP+MEP) and its growth in contradistinction to a traditional newsvendor model. Therefore, it is clear that a hybrid option model should be selected for a whole supply chain if a supplier is in strong partnership with a buyer.

Table 5.5: A comparison between option models: Total profit/Growth

	Total expected profit	Growth(%)
Call option	155687.5	+1.94%
Put option-1	155687.5	+1.94%
Put option-2	155691.2	+1.95%
Hybrid option	155787.6	+2.01%
Newsvendor	152719	-

(2) A comparison of call-put-hybrid and newsvendor model

For a comparison of the presented models(call option, put option, and hybrid option) and a traditional newsvendor model, based on modified parameters, we carry out new experiments focusing on a demand uncertainty. In details, we consider two cases focusing on the demand uncertainty: (1) rise the demand uncertainty($m = 200, n = 300$), (2) reduce the demand uncertainty($m = 60, n = 180$). Parameter settings are as follows: $p_r = 200$, $p_w = 100$, $p_c = 40$, $v_j = 60$, $v_s = 30$, $v_o = 40$, $K = 1000$. The results are summarized in Table 5.6 and Table 5.7.

Table 5.6: A comparison between option models: high demand uncertainty

	Q	q_o	TP	p_o	$p_{ec/ep}$	REP	MEP
Call option	972	208	1180	9.16	111.02	85459.8	69164.6
Put option	1180	208	1180	20.18	111.02	85459.8	69164.6
Hybrid option	1062	127	1188	6.27	put=69 call=137.5	85302.1	69486.4
Newsvendor	1100	-	1100	-	-	83666.7	66000

Table 5.7: A comparison between option models: low demand uncertainty

	Q	q_o	TP	p_o	$p_{ec/ep}$	REP	MEP
Call option	1007	133	1140	0.78	156.99	92480.4	66557.1
Put option	1140	133	1140	57.77	156.99	92480.4	66557.1
Hybrid option	1052	107	1159	0.39	put=45 call=210	91942.8	67280.4
Newsvendor	1060	-	1060	-	-	91075	63600

5.4 Supply chain optimization by hybrid option contract

From a viewpoint of maximization of total expected profits of a supply chain, we design in this section a hybrid option contract of which the expected profit is formulated by a summation of the expected profits from both a buyer(retailer) and a supplier(manufacturer). After formulation, we examine an availability of the model through a simple example.

5.4.1 Hybrid option contract for a supply chain optimization

Our model (G_{jp}) has an integrated profit function of which the optimal solutions(Q^*, q_o^*), which can be described as

$$
\begin{aligned}
G_{JP} &= G_R + G_M \\
&= -p_w Q - p_o q_o + \frac{1}{2n}\int_{K-n}^{Q-q_o-m} p_{ep}q_o + (p_r - v_s)l - v_s(Q-q_o)\ dl \\
&+ \frac{1}{2n}\int_{Q-q_o-m}^{Q-q_o-z(p)} \{p_{ep}q_o + \frac{1}{2m}\int_{l-m}^{Q-q_o}(p_r - v_s)D + v_s(Q-q_o)\ dD + \frac{1}{2m}\int_{Q-q_o}^{l+m} p_r(Q-q_o) - v_o(D-(Q-q_o))\ dD\}dl \\
&+ \frac{1}{2n}\int_{Q-q_o-z(p)}^{Q-z(p)} \{p_{ep}(Q-(l+z(p))) + \frac{1}{2m}\int_{l-m}^{l+z(p)}(p_r - v_s)D + v_s(l+z(p))\ dD + \frac{1}{2m}\int_{l+z(p)}^{l+m} p_r(l+z(p)) - v_o(D-(l+z(p)))\ dD\}dl \\
&+ \frac{1}{2n}\int_{Q-z(p)}^{Q-z(c)} \{\frac{1}{2m}\int_{l-m}^{Q}(p_r - v_s)D + v_s Q\ dD + \frac{1}{2m}\int_{Q}^{l+m} p_r Q - v_o(D-Q)\ dD\}dl \\
&+ \frac{1}{2n}\int_{Q-z(c)}^{Q+q_o-z(c)} \{p_{ec}((l+z(c)-Q)) + \frac{1}{2m}\int_{l-m}^{l+z(c)}(p_r - v_s)D + v_s(l+z(c))\ dD + \frac{1}{2m}\int_{l+z(c)}^{l+m} p_r(l+z(c)) - v_o(D-(l+z(c)))\ dD\}dl \\
&+ \frac{1}{2n}\int_{Q+q_o-z(c)}^{Q+q_o+m} \{-p_{ec}q_o + \frac{1}{2m}\int_{l-m}^{Q+q_o}(p_r - v_s)D + v_s(Q+q_o)\ dD + \frac{1}{2m}\int_{Q+q_o}^{l+m} p_r(Q+q_o) - v_o(D-(Q+q_o))\ dD\}dl \\
&+ \frac{1}{2n}\int_{Q+q_o+m}^{K+n} -p_{ec}q_o + p_r(Q+q_o) - v_o(l-(Q+q_o))\ dl \\
&+ p_w Q + p_o q_o - p_c(Q+q_o) + (-q_o)(p_{ep} - 2v_j)\tfrac{\{(Q-q_o-m)-(K-n)\}}{2n} \\
&+ (-q_o)(p_{ep} - 2v_j)\tfrac{\{(Q-q_o-z(p))-(Q-q_o-m)\}}{2n} + (-\tfrac{q_o}{2})(p_{ep} - 3v_j)\tfrac{\{(Q-z(p))-(Q-q_o-z(p))\}}{2n} \\
&+ (q_o)(v_j)\tfrac{\{(Q-z(c))-(Q-z(p))\}}{2n} + (\tfrac{q_o}{2})(p_{ec} + v_j)\tfrac{\{(Q+q_o-z(c))-(Q-z(c))\}}{2n} \\
&+ (q_o)(p_{ec})\tfrac{\{(Q+q_o+m)-(Q+q_o-z(c))\}}{2n} + (q_o)(p_{ec})\tfrac{\{(K+n)-(Q+q_o+m))\}}{2n}
\end{aligned}
\tag{5.51}
$$

where $G_R(Q, q_o)$ is the expected profit of a buyer, $G_M(p_{ec}, p_{ep}, p_o)$ presents the expected profit of a supplier, respectively.

Therefore, using equation (5.51), optimal solutions(Q^*, q_o^*) from $\frac{dG_{JP}(Q,q_o)}{dQ} = 0$ and $\frac{dG_{JP}(Q,q_o)}{dq_o} = 0$ can be obtained, as shown in equation (5.52).

$$
\begin{aligned}
Q^* &= K + \frac{n(v_o+p_r+v_s-2p_c)}{(p_r+v_o-v_s)} \\
&+ \frac{(-2v_j+v_o+p_r+v_s)\Big(-m(p_{ec}^2+p_{ep}^2-2v_j((p_{ec}+p_{ep})-(v_o+p_r+v_s))-2v_s(v_o+p_r))+4n(v_j-v_s)(v_o+p_r-p_c)\Big)}{4(v_j-v_o-p_r)(v_j-v_s)(v_o+p_r-v_s)} \\
q_o^* &= \frac{\Big(4n(v_j-v_s)(v_o+p_r-p_c)-m(p_{ec}^2+p_{ep}^2-2(v_o+p_r)v_s+2v_j(v_o+p_r+v_s-p_{ec}-p_{ep}))\Big)}{4(p_r+v_o-v_j)(v_j-v_s)}
\end{aligned}
\tag{5.52}
$$

5.4.2 Numerical example

We examine the presented hybrid model in section 5.4.1 by a simple example. We adopt parameters as follows: $p_r = 200$, $p_w = 100$, $p_o = 10$, $p_{ec} = 120$, $p_{ep} = 100$, $v_o = 40$, $v_s = 30$, $p_c = 40$, $v_j = 60$, $m = 150$, $n = 200$ and $K = 1000$. We compare the expected profit of the hybrid model(whole-sc) designed from a viewpoint of supply chain optimization in section 5.4.1 with a hybrid model(buyer) formulated from a viewpoint of a buyer in section 5.2.4. Table 5.8 shows comparative advantages and their growths in contradistinction to a traditional newsvendor model for each case. We can see here that the designed hybrid model(whole-sc) can expect more profits compared to the hybrid model(buyer). The below IEP presents an integrated expected profit.

Table 5.8: Comparative advantages between a hybrid(whole-sc) and a hybrid(buyer) model

	$p_{ec/ep}$	REP	MEP	IEP
Hybrid (whole-sc)	put=100 call=120	90091.3 (+1.57 %)	68321.9 (+6.72 %)	158413.2 (+3.73 %)
Hybrid (buyer)	put=100 call=120	90484 (+2.01 %)	65818.5 (+2.80 %)	156302 (+2.34 %)
Newsvendor	-	88699	64020	152719

5.5 Brief summary and discussion

The unpredictable demand change is not only the biggest threat to keep a stable operating for firms, but also an uncontrollable factor. This leads to a generalized fact thing that most of management technologies focus on the change, as the first priority in the business management. For this reason, a flexibility to response efficiently the change is strongly required. In this chapter, we have been discussed ways to design flexible supply contracts using financial options, considering the demand change. It has also been examined the expected profit function and its optimal solution, not only for both a supplier and a buyer, but also a whole supply chain. From this, the supplier and buyer have an order flexibility, as a right to avoid the expected loss and to obtain additional opportunities in a supply chain. Furthermore, in contrast to the previous studies focused on only a maximization of the expected profits, we have been proposed a risk analysis, too. Through comparative studies, in the given demand sections, the best and the worst contract types were proposed, in details.

For the future researches, the followings can be discussed. First, an evidence to improve advantages of a hybrid option contract model is insufficient in case of using a numerical example only. In case of a supplier-led option contract, in contrast to our results, the hybrid option contract cannot always be good compared to other contract types. Second, we assumed that an apparel product allows an uniform distribution, but it is needed to consider other distributions fitting for characteristics of the product. Third, only variables about profits and risks were considered in this study. However, such as a transportation cost, a human resource, and so forth, various restrictions related to available resources are needed to consider, as possible. Finally, we need to consider what game conditions can make a maximization of the expected profit between a supplier and a buyer. Obviously, an order quantity of the buyer can greatly be depended by a price of the supplier. Contrary to the buyer's perspective, the price can also be decided by a total order quantity, for instance, through a price discount policy for a large transaction. It ultimately leads to a discussion about a kind of interaction game in which a decion-making for both the buyer and supplier depends on the policies of business partner. Although, in this study, we presented the optimal solutions under given the price conditions related to an option and its exercising, the discussion may lead to more interesting analysises and results.

Chapter 6

Collective intelligence technology

We examine, in this chapter, a prediction risk. It mainly includes a knowledge-based prediction and its availability with respect to a price convergence in a prediction market [1].

6.1 Knowledge-based prediction and a prediction market

A forecast often is incorrect. Nobody can perfectly guarantee the forecast of which possibility is realized, since too many factors related to the forecast make it difficult. We had no alternatives but to raise a probability, based on reliable data and available experiences. We believe it and behave according to the probability game with a high or low level of accuracy. For the game, there are many approaches, which are mainly focused on the objective data: (1) patterns of time series, (2) case and effect for the prediction, also known as a scenario design based on numerical results, and (3) a combination of the (1) and (2). However, there is an advanced prediction tool, a prediction market, which can support the objective data through the subjective data of forecasters.

Information is often widely dispersed, it is highly desirable to find a mechanism to collect and combine that information. To predict a future event, a prediction market(PM) is known as an extremely effective tool to aggregate widely dispersed information and knowledge among economic actors. In practice, many cases and studies related to an usefulness of the market have been reported; a common conclusion is that it is sufficiently reliable. IEM(Iowa Electronic Market), the oldest prediction market, experimented with various participants in order to predict a result of US presidential election from 1988 to 2000; it was a zero-sum game in which successful forecasters received payment from people who didn't predict exactly. The result was quite amazing. According to an actual result of the IEM, an error between the actual result of the presidential election and the last price of the IEM was less than 1.5%, exactly 1.37% [43]. This suggests that it was calculated by the error 1.37% if you betted by 48.63% at the day before the actual election day for the win of Al Gore who obtained an approval rating of 50%. Such results were more accurate and reliable than other surveys of public opinions. This can fully explain that a lot of firms including famous

[1]This chapter has been published in INFORMATION-An International Journal, Volume 14, Issue 1, 2011

companies such as GE, Microsoft, HP, have been adopted the PM or preparing it, not only to predict some future events but also to ask new ideas. The prediction market is actually a non-statistical prediction model which has an unique incentive system to aggregate information and knowledge. It is considerably interesting because it is exactly based on a kind of brain betting system.

A prediction market usually manages a process for aggregating information effectively, because almost anyone can participate, and the potential for profit(and loss) creates strong incentives to search for better information [44]. The prediction market, as an artificial market, is a real-time prediction with a high accuracy and unique market mechanism. In the market, a price of virtual product(called prediction security in this study) which can be considered as a market probability for some events is occurred, by agents who trade virtual currency or real money for their profits based on individual knowledge and information. And the converged trading price by an iterative knowledge trading process becomes a target prediction value, which is fundamentally obtained from an equilibrium of supply and demand in the market mechanism. Specifically, the price convergence as a market probability is certainly required in the iterative knowledge trading among the agents with a micro-macro loop, which is the most important concept to interpret the market mechanism, to obtain a reliable prediction value. In this chapter, after designing the market for an agent simulation, we hence examine the price convergence considering categorized various types of the agents, to get a better understanding of the convergence possibility by studying the prediction market mechanism, heterogeneous agents and interactions of the agents in the micro-macro loop. The interactions of the agents and market are related to what conditions should be satisfied for the convergence of market price. We believe that this convergence is a minimum requirement of real world application of the methodology, the prediction market.

6.2 Literature review

A multi-agent approach is known as another feasible way to interpret a supply-demand relation, a prediction mechanism and social phenomena. Even if studies using the multi-agent are executed in a virtual space, quite valuable and interesting results that help us understand a fluctuating equilibrium price in a real market can be obtained. Practically, various studies with respect to a prediction market, an artificial society, and an economic and social complex, as well as a forecasting using the agents have been conducted in various fields, and an availability of the multi-agent approach has also been shown by many previous studies. First, from a viewpoint of interpretation of the prediction market and agent behavior, Vernon L. Smith(1962) examines a market behavior and its mechanism by experiments. According to the experiments discussed in the paper that have followed some patterns consisting of different types of the agents(buyer and seller), he investigates a supply and demand competitive equilibrium based on bids, offers and transactions of the agents [45][46]. Charles F. Manski(2006) presents a formal analysis of price determination from a relation of individual beliefs of agents and equilibrium price in the prediction market where agents have heterogeneous beliefs that are about an occurrence of some events [47]. And William et al.(2005)

present an evolutionary system describing a dynamical behavior of heterogeneous markets with various types of the agents, and observe the evolutionary phenomena in an asset pricing model [48]. Second, in the field of market system and policy using agents, Yuhsuke Koyama et al.(2007) present an U-Mart system and experiments for a market price from 150 students. They first deliver a minimum knowledge and skill to play the U-Mart and identify an educational activities to understand complex economic phenomena and to teach their mechanisms using the U-Mart [49]. Neil F. Jhonson et al.(2001) report a technique quantifying predictive capability based on multi-agent games over different time scales and markets with an identification of profit opportunities through a prediction of fluctuating financial time series [50]. Sílvio M. Duarte Queirós et al.(2007) develop a model with many interacting agents to measure a volatility of financial markets in consideration of random interactions among the agents [51]. Bong-sung chu et al.(2011) analyze a price convergence in a prediction market by multiagent simulation with a micro-macro loop [52].

For an effective collection and practical use of dispersed information, a prediction market (PM) adopts an interactive market and price mechanism. This approach is very useful for substituting traditional prediction methodologies with a system of knowledge transfer and use, such as statistical extractions of data, surveys and expert interviews which can be quite limiting. As unique characteristics of the PM, in 2002, Nicholas Chan(2002) proposed [53]:

- Accuracy: a mechanism aims at making profits can give participants an incentive to provide their newest and high-class information for the prediction market, so that information are updated rapidly and continuously.
- Interactive learning: participants evaluate a market value based on not only their information and beliefs, but also information and actions of other participants.
- Salability: in contrast to a survey, it can inherently be extended because of low restrictions for trading goods or participants. The amount of information available on the formation of price increases in proportion to the number of participants.
- Unarticulated needs: it is pretty useful for evaluating of unarticulated needs which cannot be decided by a consumer preference or a buying behavior.

A prediction market using an interactive price system has a theoretical basis on an efficient market hypothesis and Hayek hypothesis. At first, in the Hayek hypothesis, the price system in a comparative market is an effective tool to collect dispersed information among participants. A function of the price system is to control economic activities by collecting information and transfer, according to his hypothesis. Through the price, individual decides how to produce and how to use limited sources at the lowest cost. This suggests that the price is an implied signal presenting a lot of information and knowledge in our society, so that economic actors control their activities by changing the price, hourly. That is, his hypothesis says that the price is a kind of tool for information transfer, and this logic can be applied to the prediction market with the price system. On the other hand, a market price of an efficient market hypothesis by Fama in 1970 is a theory in which the price reflects immediately almost accessible information by participants, which has been one of the most important research fields in finance. He categorized the efficient markets into three types depending on which types and scopes of information reflect a stock price. By his hypothesis, since available all information have already been reflected in the stock price, only new information can cause the future's price fluctuation. As the rest to support the theoretical basis, there is a rational expectation equilibrium, an extended model of general equilibrium theory, in which an equilibrium market price reflects all information of participants in the rational expectation equilibrium considering a feedback of potential information from the market price. In addition, Charles F. Manski proposed an analytical logic about a prediction of the prediction market [54]. He derived an equilibrium price defined as a particular quantile of distributions of traders' beliefs when traders are risk-neutral price takers with heterogeneous beliefs. And he demonstrated market probabilities by a relationship between the price and distribution.

6.3 Design of a prediction market using multi-agent

In a prediction market with many heterogeneous agents, all the agents(traders) revise their beliefs to determine private prediction values(micro index) considering a fluctuation of price of prediction security(macro index). An integrated price of the prediction securities is continuously revised by an iterative knowledge trading of each agent, and it is utilized for a revision of the prediction value, as a micro-macro loop. When the price as a market probability is converged by the micro-macro loop, a final prediction value can be obtained. To use the prediction market for a demand forecasting, above all, a design of reasonable trade mechanism to control the price of prediction security and trading volume is required. In particular, the detailed design of trade process for the agents and a market maker that plays a role as a mediator is exceedingly important because it is quit difficult to describe the practical micro-macro loop with the heterogeneous agents and their interactions. For this reason, requirements for the reasonable prediction market design with the heterogeneous agents in the micro-macro loop are increasing annually.

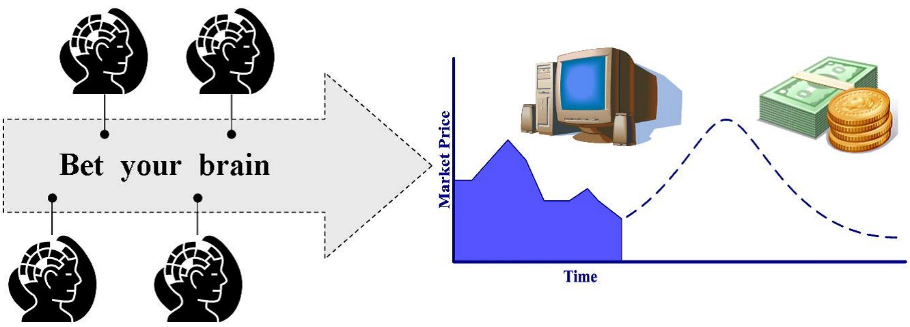


Figure 6.1: Prediction market

Figure 6.1 shows an overview of a prediction market consisting of agents and a virtual trading system. In this section, to realize the Figure 6.1, we design the prediction market which consists of traders, a market maker and prediction security. The traders are artificial agents in our study, and the security is a target of forecasting with two attributes: (1) quantity and (2) price. And the market maker is considered as an invisible hand of the market which forms a market price of the security through a trading among the agents. Our approach for analyzing forecasting processes and detailed market mechanism is principally based on interactions between heterogeneous agents and a market maker in a micro-macro loop. In this section, we describe the agents' behaviors, the market maker and those interactions through a mathematical model with a probability distribution. We use a demand density distribution of the agent and the market maker, a prediction probability of the agent and market maker, price sections. The following notations will here be used for the design of prediction market.

Table 6.1: A summary of notation for a design of a prediction market

Variable	Definition
$f(x)$	Demand density distribution of agent for a demand quantity x
$\psi(a,b)$	Prediction probability of agent who predicts the demand quantity x falls in the corresponding interval [a, b]
$g(x)$	Demand density distribution of a market maker for the demand quantity x
$q(a,b)$	Prediction probability of market maker who predicts the demand quantity x falls in the corresponding interval [a, b]
$p(a,b)$	Unit price of prediction security in an interval [a, b]
v	Purchasing quantity of prediction security
u	The amount of money of agent

6.3.1 Agent design

We fully focus on a tacit knowledge aggregation process by a prediction market and study on a price convergence by various agents' characteristics. The tacit knowledge defined as a cognitive process or subjective knowledge that is difficult to describe and transfer to other people objectively, as opposed to explicit knowledge, is changed to the explicit knowledge in the prediction market. The agents' different tacit knowledge are described in our market by means of various behavioral characteristics and individual probability distributions. In details, each agent $i(i = 1, 2, ..., n)$ who has a perceived demand probability density function(p.d.f) $f_i(x)$ and trades prediction securities which can be thought of as virtual products in the prediction market, based on a $f_i(x)$ and given price information, a demand probability density function $g(x)$ of a market maker. Here, the $f_i(x)$ is given as the subjective probability of each agent in which a prediction of each agent falls to an interval [a, b] with a probability $\psi(a,b)$, as shown in equation (6.1).

$$\psi(a,b) = \int_a^b f_i(x)dx. \tag{6.1}$$

where $0 \le \psi(a,b) \le 1$.

For this study, we use a normal distribution for a prediction distribution, which can be described in Figure 6.2. The subjective opinions of agents on a demand forecasting can diversely be described by means of a change of an average μf and a standard deviation σf. For example, if the standard deviation is large, an agent forecasts by a wide range, and vice versa.

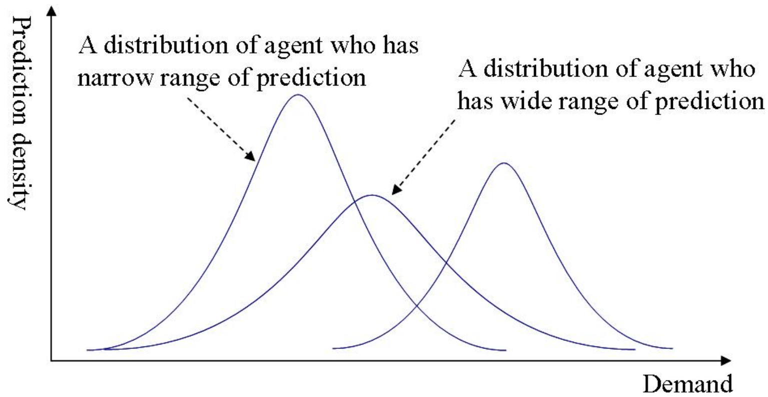


Figure 6.2: Prediction distribution $f_i(x)$

The traders (agents) have been learning a capability to revise their private p.d.f $f_i(x)$, and buying or selling some of their own securities are allowed with given trading periods. And they determine an interval [a, b] and purchasing quantity v revising iteratively the $f_i(x)$, and be awarded only if a market demand falls into the predicted interval [a, b]. When the interval [a, b] and purchasing quantity v are determined, a total purchase price (TP) and the expected gain or utility (E) of each agent are assumed to be calculated upon below functions,

$$TP = p(a,b)v \tag{6.2}$$

and

$$\begin{aligned} &Maximize\ \ E = \psi(a,b)\cdot log\big(u - p(a,b)v + \eta v\big) + \big(1 - \psi(a,b)\big)\cdot log\big(u - p(a,b)v\big) \\ &Sub.\ \ a \ge 0, \quad b,\, v > 0 \end{aligned} \tag{6.3}$$

where η represents a rewarding rate and its initial value. If $\eta < 1$, a market maker is profitable, while if $\eta > 1$, an agent is profitable in the prediction market.

6.3.2 Design of a market maker and a micro-macro loop

The variable interval prediction security (VIPS) is a security that enables agents who decide v and an interval $[a, b]$ to earn a dividend when an actual demand is generated in their prediction intervals. Whereas this plays a major role in reflecting tacit knowledge of agents in a prediction market, the prediction intervals of the agents are difficult to be accorded because of a flexibility of the VIPS. This, in conclusion, forces trades of the agents to be hard. Therefore, we design here a market maker in order for the trades to be smooth. The agents trade with the market maker.

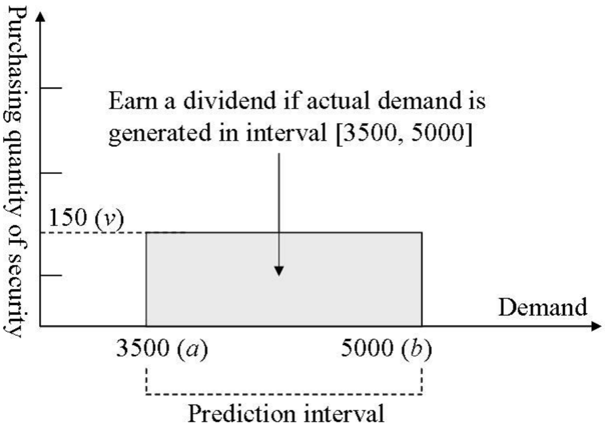


Figure 6.3: Variable interval prediction security (VIPS)

A market maker is a mediator to provide a market price (UP) of each prediction security with an interval [a, b] and to aggregate knowledge from individuals. A total purchasing cost is simply calculated through a multiplying total purchasing quantities v by an unit price of the prediction security $p(a, b)$. The main attribute of the market maker is probability density function of a market price $g(x)$. The market maker aggregates traders' order information to create a market price, and a market demand can be obtained by a demand-supply function, which is linear to simplify the consideration.

$$UP = p(a, b) = \int_a^b g(x)dx, \quad p(a, b) = \lambda q(a, b) + \theta, \tag{6.4}$$

where $0 \leq p(a, b) \leq 1$.

On the other hand, the most important principle is a micro-macro loop to understand a prediction market mechanism with a market maker, which gives a feedback link between a micro structure and macro structure. In this study, a simulation is carried out based on the micro-macro loop in which $g(x)$ of a market maker is updated by individual $f_i(x)$ of agents, at the same time, the $f_i(x)$ gets a feedback from the integrated $g(x)$. That is, the micro-macro loop is basically described as iterative interactions between the g(x) of market maker and f(x) of agents, as shown in Figure 6.4. An integrated prediction value is derived by giving a fundamental principle and background to the market maker who control a whole market.

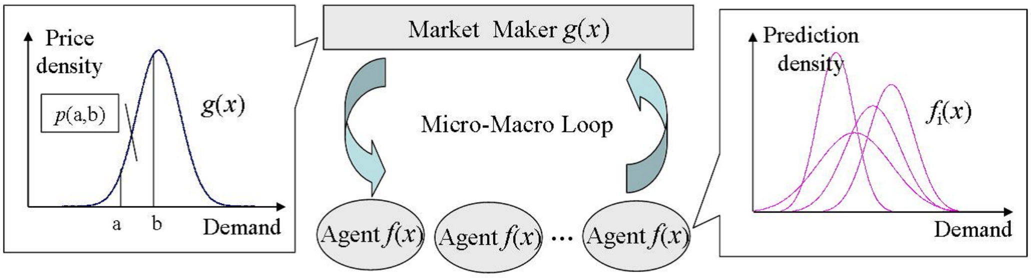


Figure 6.4: Micro-macro loop: $g(x)$ and $f(x)$

A multi-agent simulation with a market maker algorithm based on a micro-macro loop is carried out by the following steps.

Step 1. Create trader agents who have unique parameters of $f(x)$.
Step 2. Initialize (μ, σ^2) of $g(x)$: we use a normal distribution for simplicity.
Step 3. The agents revise their $f(x)$ considering a previous deal and current $g(x)$ and then decide whether to buy or to sell some of prediction securities $[a, b, v]$.
Step 4. After all traders put orders, update the parameters of (μ, σ^2) of the $g(x)$, and allocate new orders to each agent.

To control a prediction market smoothly, we design four trading rules, as followings.

- Loan prohibition: we strictly prohibit a loan of agent for a prediction accuracy. If the loan is allowed, a market price might be dominated by an agent who get an initiative position.
- Permission for negative money stock: to raise a flexibility of security trading, we assume that a short selling is allowed for all trader agents so that we guarantee continuous trading. In other words, an agent can stay in the market trading without money stock.
- Trade restriction: to aggregate balanced knowledge from agents who participate in the prediction market, we restrict transaction numbers or times of each agent. That is, additional trades of the agent within a given period are not permitted, unless all transactions of other agents are completed.
- Forced savings: in case where the amount of money of an agent exceeds twice value of an initial money, we force the agent to save that excess money. This rule is also to prevent the market dominated by some rich agents hence to create a reasonable market.

6.4 Multi-agent simulation

In this section, we will discuss a multi-agent simulation process. It involves a revision of prediction distribution of each agent, a purchase of prediction security, and a revision of price distribution of a market maker. For the simulation, several assumptions are primarily made on the agents and market maker as an initialization before examining the processes.

- We assume that $f(x)$ of trader agents and $g(x)$ of a market maker follow normal distributions.
- We create N trader agents participating in a prediction market. Each agent($i \in N$) has p.d.f $f_i(x)$ with mean μf_{i0} and variance σf_{i0}^2, and be allotted with an initial money on hand u_{i0}.
- We define four types of parameters describing characteristics of the agent i: e_i, h_i, m_i, n_i, where e_i and h_i mean receptive capacities of macro results in a micro-macro loop, m_i means an information acceptance level, n_i means an information reliance level.
- We create a market maker whose $g(x)$ has mean μg_0 and variance σg_0^2, initially.

6.4.1 Simulation process

We explain a detailed simulation process in a micro-macro loop, based on an initialized market environment mentioned above. An iterative process of the simulation is carried out according to the below steps.

Step 1. First, a trader agent i is selected, randomly.

Step 2. The agent i revises his/her mean μf_{i0} and variance σf_{i0}^2 of $f_i(x)$ observing a $g(x)$ and other external information.

Step 3. The agent i predicts a demand for next period and purchase securities, i.e., determine a lower limit a_i, upper limit b_i, and purchasing quantity v_i.

Step 4. The market maker revises the $g(x)$ from the a_i,b_i,v_i of the agent i.

Step 5. Iterate Step 1-4, until a given transaction number is completed, or parameters of the $g(x)$ are converged.

From section 6.4.2, above **Step 2, 3 and 4** will be discussed in details; how to revise a $f_i(x)$ and $g(x)$ and how to purchase a prediction security, respectively.

6.4.2 Revision of $f_i(x)$: Step 2

We discuss Step 2 mentioned above in detail in this section. Practically, an agent i can revise his/her p.d.f $f_i(x)$ in consideration of both a $g(x)$ of market maker and various types of external information in our prediction market. For this reason, we consider the below two approaches for a revision of the p.d.f $f_i(x)$.

(1) Revision observing parameters of the $g(x)$
(2) Revision observing the external information other than the $g(x)$

The mean μf_{ij} and variance σf_{ij}^2 of the $f_i(x)$ are revised according to the below equation (6.5) and (6.6).

$$\mu f_{ij} = ((1-\alpha_{ij})\mu f_{ij-1} + \alpha_{ij}\mu g_k) \cdot (1-EI) + EI \cdot U_{\mu i} \tag{6.5}$$

$$\sigma f_{ij}^2 = ((1-\beta_{ij})\sigma f_{ij-1}^2 + \beta_{ij}\sigma g_k^2) \cdot (1-EI) + EI \cdot U_{\sigma i} \tag{6.6}$$

where j is a revision index of agent i, k is a revision index of market maker, EI is a switching parameter, $U_{\mu i}$, $U_{\sigma i}$ are parameters for reasonable level of acceptance of external information which are set to be initial values of simulation, and α, β are weighting coefficients($0 \leq \alpha_{ij}$, $\beta_{ij} < 1$), respectively.

The weighting coefficients are subjected to an influence of unique characteristics of each agent, and are calculated in each period, using $\alpha_{ij} = e_i \times Rnd_{0-1}$ and $\beta_{ij} = h_i \times Rnd_{0-2}$ where $0 \leq e_i, h_i < 1$, Rnd_{0-1} and Rnd_{0-2} are random number taking a value in an interval [0, 1). The reason why we multiply the Rnd_{0-1} and Rnd_{0-2} are to reflect a general human character in a real world. That is, unlike a programmed robot, people do not always behave based on only their characteristics. In most cases, their decision-making processes include many random factors reflecting various influences coming from surrounding environments.

Because agents can revise their $f_i(x)$ not only observing a $g(x)$ but also observing external information, a selection of reasonable revision approach is important. In this study, a revision approach is selected according to a switching parameter EI appeared in equation (6.5) and (6.6), which is described as

$$EI = \begin{cases} 1 & Rnd_{0-1} \geq m_i \; and \; Rnd_{0-2} \geq n_i \\ 0 & other \end{cases} \tag{6.7}$$

where m_i represents an opportunity of external information for agent i, and n_i is a threshold to believe or accept the external information, which initially be assigned to all agents. That is, agents can get the external information if only random number Rnd_{0-1} is higher than the threshold m_i. In addition, the external information can also be reliable if only random number Rnd_{0-2} is higher than the threshold n_i.

6.4.3 Purchase of a prediction security: Step 3

An agent i who aims to maximize his/her expected gain(E_i) purchases v_i quantities of securities determining a prediction interval $[a_i, b_i]$. Since equation (6.3) is a concave function and differentiable, to maximize the expected gain(E_i), the optimal purchase quantities v_i of agent i can be derived as

$$v_i = \frac{\psi_i - p}{p(1-p)} \cdot u \tag{6.8}$$

Substituting equation (6.8) into equation (6.3), we can obtain below equation (6.9).

$$E_i = \psi_i log\frac{\psi_i}{p} + (1-\psi_i)log\left(\frac{1-\psi_i}{1-p}\right) + log\,u \tag{6.9}$$

where $p = p(a,b)$ and $\psi_i = \psi_i(a,b)$.

Above equation (6.8) and (6.9) can be obtained according to the following process. In equation (6.3), because u doesn't depend on (a,b,v), and $p(a,b)$ and $\psi(a,b)$ also don't depend on the v, we can obtain the v_i to maximize the equation (6.3), from equation (6.10) to equation (6.12). Here, let's consider the $p(a,b)$ as a p, and also the ψ_i as a q for the sake of convenience.

$$\frac{\partial E}{\partial v_i} = q \cdot \frac{1-p}{u+(1-p)\cdot v_i} - (1-q)\cdot\frac{p}{u-pv_i} = 0. \tag{6.10}$$

Through a multiplying both sides by $(u+(1-p))v)(u-pv)$, $(q(1-p)-(1-q)p)u-(q(1-p)p)+(1-q)p(1-p))v_i = 0$.

We obtain

$$v_i = \frac{q(1-p)-(1-q)p}{q(1-p)p+(1-q)p(1-p)} \cdot u = \frac{q-p}{p(1-p)} \cdot u = \frac{\psi_i - p}{p(1-p)} \cdot u \tag{6.11}$$

And substituting equation (6.11) into equation (6.3), we have

$$\begin{aligned}
E &= q \cdot log\Big(u - p \cdot \frac{q-p}{p(1-p)} \cdot u + \frac{q-p}{p(1-p)} \cdot u\Big) + (1-q)\,log\,\Big(u - p \cdot \frac{q-p}{p(1-p)} \cdot u\Big) \\
&= q \cdot log\Big(u + \frac{q-p}{p} \cdot u\Big) + (1-q)\,log\,\Big(u - \frac{q-p}{1-p} \cdot u\Big) \\
&= q \cdot log\frac{q}{p} \cdot u + (1-q)\,log\,\Big(\frac{1-q}{1-p} \cdot u\Big) \\
&= q \cdot log\frac{q}{p} + q \cdot\ log\,u + (1-q)\,log\,\Big(\frac{1-q}{1-p}\Big) + (1-q)\,log\,u \\
&= q \cdot log\frac{q}{p} + (1-q)\,log\,\Big(\frac{1-q}{1-p}\Big) + log\,u
\end{aligned}$$

If we substitute ψ_i into above equation, finally we can derive the following equation (6.12) as same with equation (6.9).

$$E_i = \psi_i log\frac{\psi_i}{p} + (1-\psi_i)log\left(\frac{1-\psi_i}{1-p}\right) + log\,u \tag{6.12}$$

6.4.4 Revision of $g(x)$: Step 4

We can consider two cases for a revision of $g(x)$: (1) long position ($v_i > 0$) and (2) short position ($v_i < 0$).

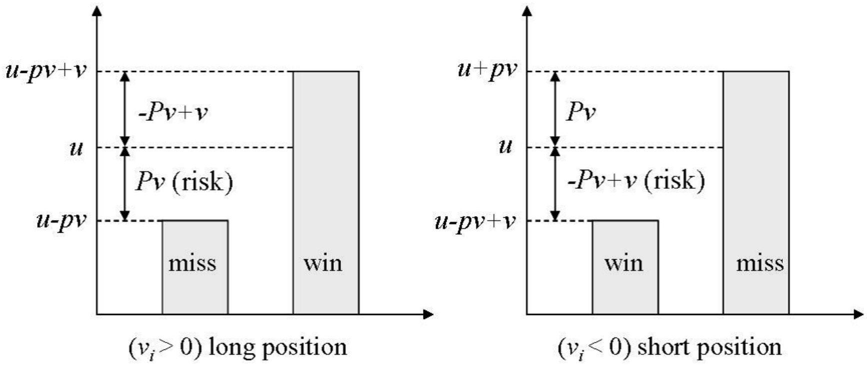


Figure 6.5: Risk of a long position and short position

(1) Case 1: long position ($v_i > 0$)

In this case, the mean and variance of a $g(x)$ will be revised by the weighted mean, as shown in equation (6.13) and (6.14).

$$\mu g_{k+1} = (1-\gamma)\mu g_k + \gamma\frac{a+b}{2} \tag{6.13}$$

$$\sigma g_{k+1}^2 = (1-\gamma)\sigma g_k^2 + \gamma\left(\frac{b-a}{3}\right)^2 \tag{6.14}$$

$$\gamma = \frac{pv_i}{w} \tag{6.15}$$

where γ is a weighting parameter, and w is an adjustment coefficient.

The reason why we use $(b-a)/3$ in equation (6.14) is that we assume most agents putting their prediction intervals reasonably close to a variance of market maker's price distribution.

(2) Case 2: short position ($v_i < 0$)

In this case, the mean and variance of a $g(x)$ will be revised as shown in equation (6.16) and (6.17).

$$\mu g_{k+1} = (1-\gamma)\mu g_k + \gamma \frac{a+b}{2} \tag{6.16}$$

$$\sigma g_{k+1}^2 = (1+\gamma)\sigma g_k^2 - \gamma \left(\frac{b-a}{3}\right)^2 \tag{6.17}$$

$$\gamma = \frac{(1-p)v_i}{w} \tag{6.18}$$

We can see that equation (6.16) has the same formulation with Case 1. However, because γ has a negative value($p \leq 1, v_i < 0$) in this case, μg_{k+1} is revised toward a negative direction, although an agent makes a correct prediction. To prevent this kind of contradiction, caused by the negative value of v_i(sell), we inverse a sign of a weighting parameter as shown in equation (6.17).

6.5 Analysis on price convergence by numerical experiments

In this section, we observe, by a simulation, a transition of price distribution $g(x)$ of a market maker in a market mechanism. Furthermore, to identify a convergence of the price distribution, we also observe experiment conditions: behaviors of heterogeneous agents based on their original characteristics, a receiving level of information, and a reliability of information. To obtain reliable results, we carry out the simulation under various conditions, repeatedly, and then discuss the results focusing on the convergence possibility of price. For this simulation, detailed experimental designs are as follows.

- There are 10 agents($i = 1, 2, ..., 10$) who aim to get better gain with the subjective p.d.f $f_i(x)$ in a prediction market. Each of the agents has 5 units of initial money on hand.
- The p.d.f. $f_i(x)$ is modeled to reflect their own knowledge and beliefs about a market demand, and is given by a normal distribution (μ_i, σ_i^2) as mentioned in Section 3.
- The p.d.f $f_i(x)$ of agent i is initialized: μf_{i0} is given by uniform random numbers of an U[0, 1), and σf_{i0}^2 is given by uniform random numbers of an U[1/3, 1/2).
- In cases where p.d.f. $f_i(x)$ is revised by observed external information, the μf_{ij} and σf_{ij}^2 are given by uniform random numbers of an $U_{\mu i}$=[0, 1] and $U_{\sigma i}$=[0.25, 0.75), respectively.
- The $g(x)$ is given by a normal distribution $N(0, 1)$.

- The transaction number between the market maker's $g(x)$ and agent's $f(x)$ is set to be 500. An adjustment coefficient w=100.

From section 6.5.1 to 6.5.3, we analyze a price convergence through the mean value and variance of $g(x)$, in the designed prediction market with different types of agents: (1) standard agents, (2) honest agents and obdurate agents, and (3) agents with external information reception. And in section 6.5.4, we finally evaluate a summarized result of numerical experiments.

6.5.1 Standard agent

At first, we simulate a prediction market with standard agents who behave based on initial experimental settings, without any changes of parameters. The below Figure 6.6 presents a convergence process of $g(x)$ of a market maker in case of the standard agent.

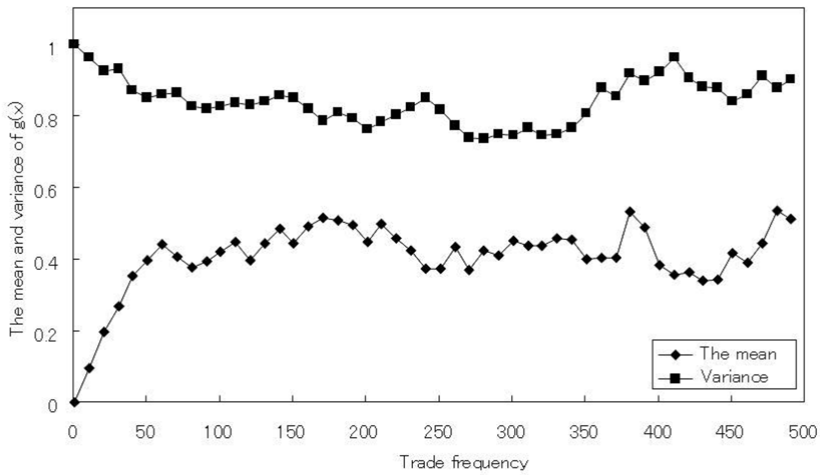


Figure 6.6: Price convergence in case of standard agents

In the Figure 6.6, we can observe a tendency to converge in variance, while the mean value still fluctuates after 400 times simulation run.

6.5.2 Honest agent and obdurate agent

For this case, we adjust initial parameters with respect to characteristics of agents, and classify two types of agents: honest agent and obdurate agent. We define the two agent groups as follows. First, the honest agents are easy to be affected by macro results such as a

$g(x)$ and external information, which can be modeled by setting high uniform numbers of $0.75 \leq e_i, h_i < 1.0$. On the contrary, obdurate agents are difficult to be affected by external situations and macro results of a micro-macro loop. That is, because the agents have an unique and obdurate opinion on a demand forecasting, we can model it by setting low uniform numbers to e_i and h_i, for example, $0 \leq e_i, h_i < 0.25$.

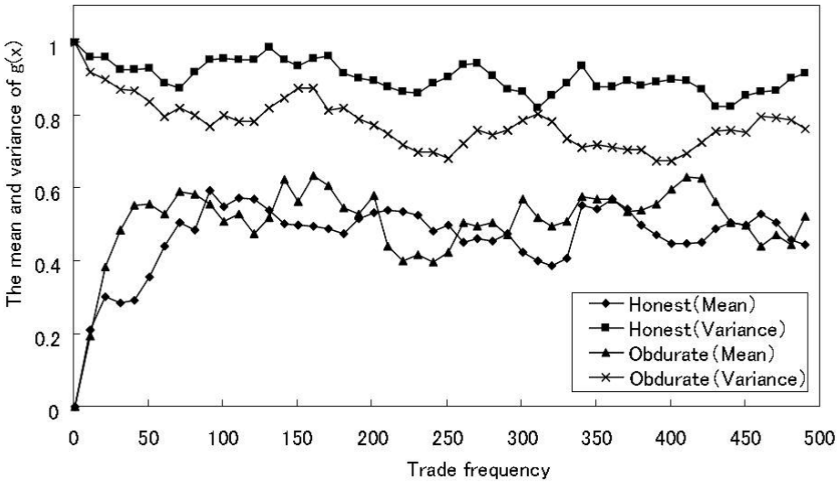


Figure 6.7: Price convergence in case of honest agents and obdurate agents

Figure 6.7 presents a result of two simulations. First simulation contains 100% honest agents, and second simulation has 100% obdurate agents. The first simulation with the honest agent groups has a clear tendency to converge, while the second simulation with the obdurate agents does not show a clear convergence in the mean and variance of a $g(x)$.

6.5.3 Agent with an external information reception

We classify two agent groups in this section. We first define agents who decide mainly their behaviors based on external information and call external information-based agents, which can be modeled by setting parameters: $0 \leq m_i, n_i < 0.25$. Second, we define agents who value their own knowledge and beliefs, ignore external information, and call original knowledge-based agents. This type of agents can be modeled by setting parameters: $0.75 \leq m_i, n_i < 1.0$.

Figure 6.8 presents a result of two simulations. The inside of the figure shows a simulation result with 100% external information-based agents. And the outside shows a result with 100% original knowledge-based agents. In the simulation with 100% external information-based agents, we can identify that the mean value of a $g(x)$ is not converged, while the mean value of the $g(x)$ in the simulation with original knowledge-based agents shows a tendency to converge.

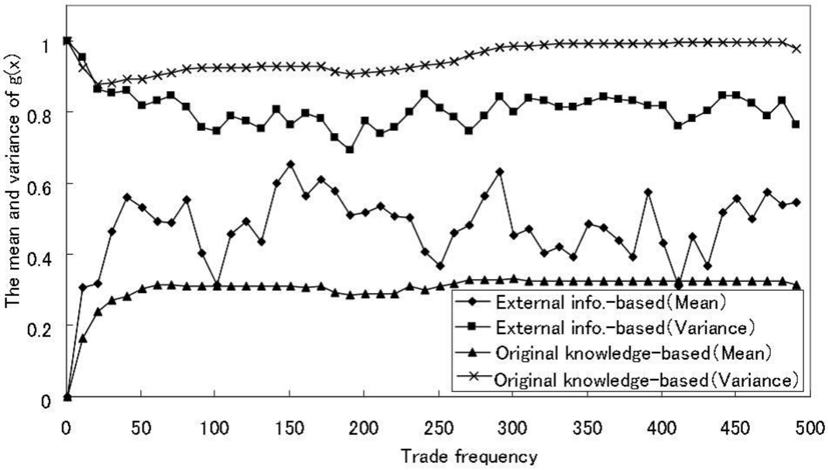


Figure 6.8: Price convergence in case of agents with an external information reception

6.5.4 Evaluation of a convergence

As we can see in the previous simulation, a convergence could not definitely be determined by an observation of the simulation process or fluctuating mean value or variance. The convergence should be evaluated using a suitable criterion measuring level of fluctuation. Therefore, we introduce a convergence coefficient proposed by Smith[45], as shown in equation (6.19).

$$C = \frac{\sigma}{Z} \cdot 100 \tag{6.19}$$

where σ presents a standard deviation, and Z is the mean of time series data.

We consider that a reasonable level of convergence evaluation is to set $C \leq 10$. Because our purpose is to examine a validity of convergence logic and to observe a convergence tendency and possibility within limits of parameter dependency of agents. We do not argue that this is a level of which can be evaluated perfectly a degree of the convergence. Without a loss of generalarity, we investigate in this study the last 100 simulation runs (401-500) to evaluate the convergence using a convergence coefficient.

The combined results of analysis for a convergence possibility appeared in Table 6.2. While convergence coefficients of both honest and original knowledge-based agents have not exceeded, the rest cases have exceeded. Therefore, we can identify that the two agent groups(honest agents, original knowledge-based agents) have clear convergence tendencies in this simulation, compared with other agent groups.

Table 6.2: The convergence coefficient C of agent groups

Agent type	Mean	Variance
Standard agent	17.2	7.4
Honest agent	7.1	4.7
Obdurate agent	14.8	5.4
External information-based agent	17.3	4.9
Original knowledge-based agent	5.7	4.3

6.6 Brief summary and discussion

As a qualitative and empirical approach, a prediction market is an objective prediction system referring subjective knowledge, which can certainly be an useful tool for a knowledge-based prediction through aggregating dispersed information and knowledge. In a virtual market, individual information or knowledge is described as an integrated market price by an interactive micro-macro loop. In other words, the market can be a knowledge trading system that enables the market price to express a stochastic index to predict the future events. For the rest, it has so many interesting characteristics. Specifically, an unique incentive system plays a key role in a collection of high-class information and knowledge, so that it involves a possibility to maintain continuous updating of the information and knowledge. The availability and excellence of such market have been verified by numerous studies, since making an appearance of IEM, the first prediction market in 1988. In practice, many firms have extensively been using the market for decision problems not only a demand forecasting but also a derivation of key factors related to a business.

This study provides a convergence possibility for several cases of agent types and combinations. Exactly, a prediction accuracy can be validated if only aggregated knowledge from all participators in a market is converged as a meaningful result. However, although the proposed prediction market using VIPS can give us a lot of prediction flexibilities. It is necessary to be investigated the convergence possibility in various circumstances, because a perfect convergence cann't be guaranteed in the prediction market using the variable interval prediction method and multi-agent in a micro-macro loop. Therefore, our discussion about the price convergence by types of agents in this study is pretty valuable to interpret an essential character of the prediction market. However, we have more many things to discuss for a successful forecasting in the prediction market: the ways to induce high-class information into the market or to make a low ratio of low-class information, an efficient market design and management, trading rules and mechanism design.

Chapter 7

Dynamic cubic neural network

In a supply chain, ineffectiveness mostly comes from an inaccuracy in demand forecasting at operational level. If a constructed long-term strategy based on the expected performance in predicting uncertainties causes a mistake an error, it may not be able to avoid huge losses from a prediction risk. However, it is not easy to consider all factors leading to the risk because a demand with nonlinearity is simply not depended on several specified factors. Furthermore, the demand forecasting can be based on a combination of micro-macro information related to human judgments for the future events and information of what have been observed the past [55]. As micro factors, a price of product, a market situation whether competitive products exist or not, a design, and original functions can be considered, while a market mechanism, a supply-demand equilibrium, and a consumer behavior can be considered from a broad view. This chapter concerns a dynamic prediction method, dynamic cubic neural network(DCNN), which is able to reflect the consumer behavior and human judgment related to the price and functions of product, of course the historical data observed, for the nonlinear model [1].

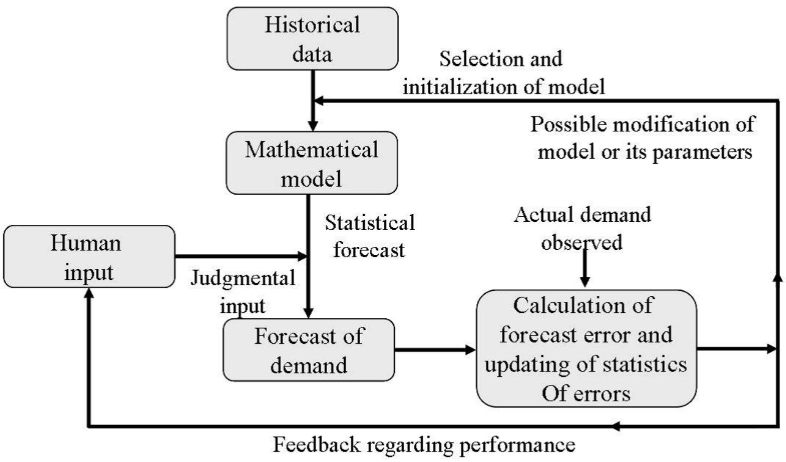


Figure 7.1: Forecasting framework with human inputs and the past data (by Edward S. et al.)

[1]This chapter has been published in INFORMATION-An International Journal, Volume 14, Issue 4, 2011

7.1 Nonlinear models for prediction

The various statistical models were developed for successful forecasts using historical demand data. However, not many forecasting methods are available, if there are no sufficient or available historical demand data, for example, a new product. Especially, even though sufficient historical data are prepared, it is not easy to predict a demand with strong nonlinearity. A chaos time-series, Delphi method, fuzzy and artificial neural netwrok(ANN) are the typical nonlinear models.

(1) Chaos time-series

The prediction of chaos time-series is a problem to estimate a submerged dynamic system $z_{t+1} = F(z_t, z_{t-1}, z_{t-2}, ..., z_{t-d+1})$ in time-series data $z_t : t = 0, 1, ..., T$. Generally, since the dynamic system $F : R^D \mapsto R^1$ can be considered as a nonlinear function, a functional space $C(R^d, R^1)$, $\tilde{F}$ can be used for F [56]. The nonlinear dynamics F in vary small local space has been known that it can be approximated, linearly. The local linear prediction method is a methodology using such characteristics. In addition, as a local linear prediction, DVS(deterministic versus stochastic) is to evaluate chaos characteristics, qualitatively. It enables a deterministic nonlinear prediction model to transform a character into a stochastic linear prediction model. On the other hand, there is a nonlinear prediction method for the entire space. That is known as a multilayer perceptron(MLP) which is often used for an artificial neural network(ANN). The efficiency of the MLP consisting of a linkage of sigmoid functions which has attracted much attention as a linear function by an introduction of back-propagation(BP) algorithm and sigmoid function. Using the MLP with 3 layer $\tilde{F} : R^d \mapsto R^1$, the nonlinear prediction model of chaos time-series data z_{t+1} can be written as

$$\tilde{F}(\Omega z_t, ..., z_{t-d+1}) = \sum_{j=1}^{h} \omega_j \sigma\Big(\sum_{i=1}^{d} \omega_{h+(j-1)d+i}\, z_{t+1-i} + \omega_{h+hd+j}\Big) \tag{7.1}$$

where $\Omega = (\omega_1, \omega_2, ..., \omega_{h(d+2)})$ is a coefficient presenting strength of connection between neurons, d is an input, h is the number of layer, respectively.

(2) Delphi method

As an interactive forecasting process for a consensus of opinion among a group of experts, a Delphi method is a kind of communication techniques which relies on an intuitive opinion or an empirical judgment of the experts. It is chiefly used when middle or long-term issues have to be discussed as a typical methodology for a forecasting. By Eto et al.(2003), it reduces a tacit and complex knowledge to a single statement and makes it possible to judge upon [57]. Questionnaires are distributed to the group of experts by Dalkey, N. C. and Helmer, O.(1963) [58]. Responses are synthesized and used as a feedback to the experts in the next round, for a series of rounds. In details, it refers to the following steps: (1) Define a problem to be discuss, (2) Give the group of experts the problem, (3) Collate the responses that the experts send back to, (4) Give the group of experts the collation with the request to score each item, and (5) Repeat the process as necessary. By a repetitive feedback process, it is able to obtain desire results.

(3) Fuzzy method

A fuzzy theory provides a theoretical basis to deal with fuzziness, which is pretty useful in processing natural language of human on the computer [59]. It includes a fuzzy set defined as set membership with n some number of possibilities $f : [0,1]^n \rightarrow [0,1]$, fuzzy logic focusing on an ambiguity in describing events rather some uncertainties cause the event as an extension of a Boolean logic, and fuzzy number consisting of a connected set of possible values with the membership function between 0 and 1. The fuzzy theory is being applied in various fields: linguistics, control, neural network, pattern recognition, as well as operations research. Especially, to predict nonlinear time-series data, the fuzzy logic and fuzzy reasoning(known as approximate reasoning or generalized modus ponens, 'IF x_1 is A_1 and, ..., x_n is A_n, Then y is B') are widely being used for a fuzzy prediction system.

(4) Artificial neural network(ANN)

An artificial neural network(ANN) consisting of simple neurons and a learning mechanism aims at achieving human intelligence through a modeling of human brain with a highly complex nonlinear information process. The most common ANN model is a multilayer perceptron(MLP) which is known as a supervised network. A back-propagation(BP) algorithm called generalized delta rule, is widely used as the learning algorithm in which an error between input and desired output is fed back and then used to adjust the connected weights between nodes. For both linear and nonlinear relationships, the ANN has being successfully applied to many fields, especially, a recognition and forecasting, because it has an unique and useful characteristics as followings.

(a) Learning function : ANN creates an internal structure by changing its own internal state under a given input pattern and desired output, which is the biggest different point from other structures.
(b) Abstraction function : ANN can abstract a desired type from its own experiences learned which leading to reliable results of pattern recognition.
(c) Generalization function : ANN can appropriately response to new types of input which have never been experienced after learning. This suggests that it can be applied for the inputs as a generalized type through accumulated internal knowledge.
(d) Association and classification functions : ANN has an ability to connect input information with output information. That is, when some input patterns are given, a desired out connecting the input is obtained. In addition, it can classify numerous data based on discovered characteristics.

7.2 Consumer behavior and a dynamic prediction

The deep understanding of a consumer behavior and market mechanism is the core for a successful demand forecasting, and also greatly helps in analyzing overall tendencies of demand change. The occurrence of demand can be based on an interaction of the consumer behavior and market mechanism. Obviously, a consumer creates demand in consideration of a demand function of the market, and the market mechanism is also modified by a feedback from the consumer behavior. In this section, we will discuss about Bass model and consumer behavior, as well as the market mechanism.

7.2.1 Bass model and a consumer behavior

Bass model(Bass, Frank M., 1969) representing a diffusion process of a new product is well known and widely applied in both a forecasting and developing product life cycle plans [60]. The model provides a conceptual structure to explain how the new product diffuses through an interaction between two types of consumers who defined as innovators and imitators, in which the timing of a consumer's initial purchase is related to the number of previous buyers [61]. The model logically describes that the consumer generally expresses a sensitive response to how market information are dispersed within a market mechanism over time and produces an adoption curve as a diffusion process of the product based on the market information and relative adoption time. For this reason, the Bass model is often used for a predictiion of the first time purchase with a number of assumptions which include an initial purchase rate, a coefficients of innovation and imitation, a potential market size, the nature of the competition between the innovators(users) and the imitators(potential users) [62]. A description of the innovator and imitator to explain the new product diffusion process can be considered as the biggest point in the Bass model. In this context, Rogers(1983) proposed four main elements related to the diffusion of new product: innovation, communication channels, time and social system, and classified the innovator and imitator into five groups [63].

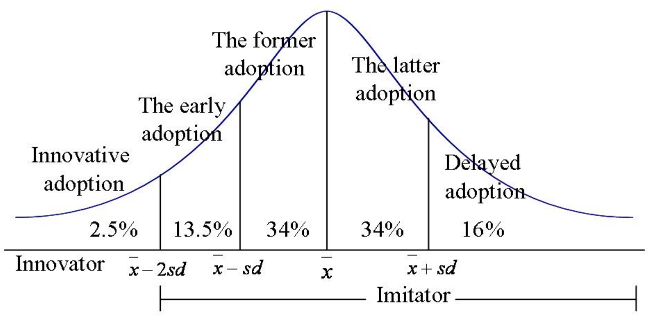


Figure 7.2: Classification of an innovator and an imitator (by Rogers)

According to the theory, only the first 2.5% is an innovator, the rest four groups are all imitators who have a percentage of 97.5%. The imitator groups are divided again by the time to imitate the innovator group: 13.5%, 34%, 34%, and 16%, in sequence.

Since a publication of the Bass model in 1969 by Frank M. Bass, many related researches about a basic model and methodologies of parameter estimation, have been published: flexible diffusion models and diffusion models based on individual adoption decisions, applied researches in the field of a business and marketing have been published. The related literatures are summarized in Table 7.1, by Vijay Mahajan et al.(1990) [64].

Table 7.1: Emergence of a diffusion modeling literature in marketing (By Vijay M.)

Time period	Research areas
1960s	Formulation of relationship between imitators and innovators Estimation when data are available: ordinary least squares estimation procedure
1970s	Dynamic diffusion models: market saturation changes over time Multi-innovation diffusion models: other innovations influence diffusion of an innovation Space/time diffusion models: diffusion of an innovation occurs simultaneously in space and time Multistage diffusion models: adopters pass through a series of stages in the innovation-decision process Forecasting: problems in use of diffusion models for forecasting
1980s	Unbundling of adopters Definition of innovators and imitators Development of diffusion models from individual-level adoption decisions Estimation when no prior data are available: Algebraic estimation procedures Estimation when data are available: Time-invariant parameter estimation procedures Systematic(or random) variation in diffusion model parameters over time Flexible diffusion patterns in terms of timing and magnitude of peak of adoption curve Multi-generation models: timing and adoption of different generations of an innovation Multistage diffusion models: effect of negative word of mouth in the innovation decision process Diffusion models with marketing mix variables: effect of price, advertising, personal selling, distribution, and timing of new product introduction on diffusion patterns Product/market attribute-based diffusion models: effect of social system characteristics and perceived product attributes on diffusion patterns Controlled diffusion models: effect of supply restrictions on diffusion patterns Multi-adoption diffusion models: incorporation of repeat sales and replacement sales in diffusion patterns Competitive diffusion models: effect of competitive actions in terms of pricing, advertising, and number of brands on diffusion patterns Forecasting problems in the use of diffusion models Testing of hypotheses related to diffusion of innovations across countries Derivation of optimal pricing, advertising, and timing strategies

7.2.2 Market dynamics and a neural network

A market economy is dynamically formed by an interaction between a consumer behavior and a market mechanism. The dynamic market place has a strong nonlinearity affected by various micro-macro factors, which makes it harder to predict a demand. Under the circumstance, a limitation of general statistical models using the past data is cleared. Statistical models using historical data of what have been observed in the past has always been one of the most popular approaches for the demand forecasting. However, this suggests that not many forecasting methods are available if there are no available historical demand data: for instance, new products. This problem leads to an argument that in case of the new products without the historical demand data, it can be considered both the consumer behavior-based diffusion process of the products and a nonlinear prediction system to reflect a dynamic nature for the successful demand forecasting. The dynamics of market place requires more reliable and strong prediction models reflecting the consumer behavior and nonlinearity. For this reason, a combination of the Bass model and nonlinear prediction system such as a neural network can be a practical alternative.

On the other hand, artificial neural network models have been shown to be an effective approach for a linear or nonlinear forecasting, as well as pattern recognitions which are the most commonly used methods to deal with dynamic nature if they have a recurrent structure with feedback. The neural network models, contrary to statistical models, provide more effective and dynamic approaches for analyzing nonlinear processes of fluctuating demand through the feedback and iterative learning which is designed to determine as an appropriate set of connection strengths between nodes on the network, because the neural network with multi-layers and one or more hidden layers can be described as a dynamic system defined from a nonlinear state equation [65], [66].

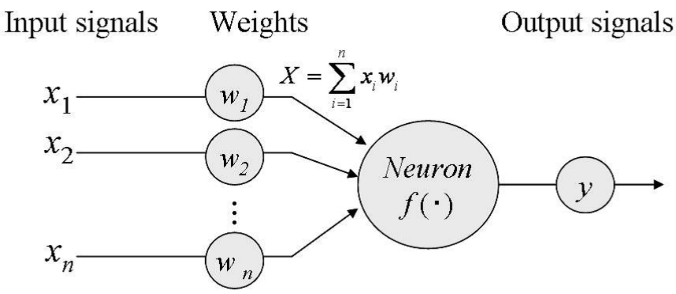


Figure 7.3: Simple artificial neural network

For a dynamic forecasting, we propose in this chapter a dynamic cubic neural network that consists of an iterative modification mechanism for an activation function and cubic architecture based on a concept of Bass model with interactive consumer behaviors. In our model, an output scope of the activation function of hidden layer is appropriately modified for every period, according to a demand momentum which is defined by a demand inertia and price acceleration plays a key role in adjustment of output in iterative learning processes.

7.3 Architecture of a DCNN(dynamic cubic neural network)

To predict a new product sales considering a diffusion process and original features, we adopt a network with a dynamic and cubic architecture whose flexibility is modified by a demand momentum [67]. We begin with a representation of the DCNN(dynamic cubic neural network), and then discuss essential elements and functions of the network in details. Figure 7.4 shows the architecture of DNNN with interaction layers(innovation layer, imitation layer), and an integration layer.

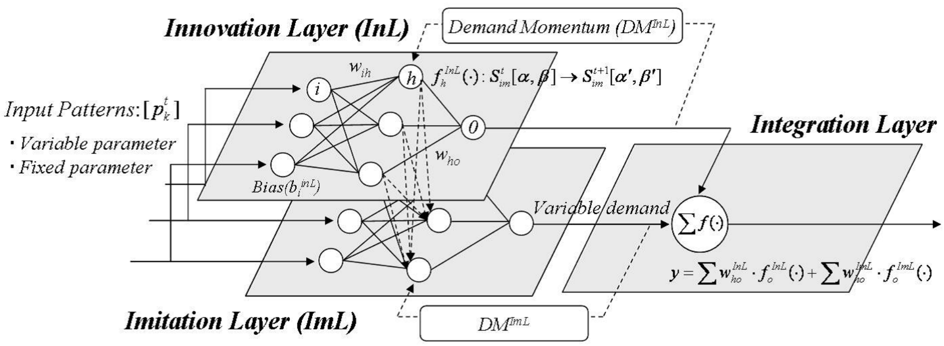


Figure 7.4: Architecture of a dynamic cubic neural network(DCNN)

Our model is a feed-forward system, as presented in Figure 7.4, consists of two interaction layers describing an innovative and imitative behavior, and one integration layer. Each layer consists of input nodes, hidden nodes and an output node, and designed to minimize the Root Mean Square(RMS) error $\sqrt{\sum_{p=1}^{td}\sum_{o}(t_p - o_{op})^2}$ between the desired value t_p and predicted output o_{op} in iterative learning processes with an error back-propagation algorithm. The input nodes accept a number of data sets which are given as fixed and variable parameters of a product. And the variable parameters and predicted output create a demand momentum $DM^{InL,ImL}$ for the interaction layers.

As the main concept of the proposed model is based on two consumer groups' buying behavior of a Bass model in which a potential user's purchase is related to the number of previous buyers while innovators are independent for a buying behavior, we consider that an output of hidden node of the imitation layer $f_h^{ImL}(\cdot)$ is affected by outputs of the innovation layer $f_h^{InL}(\cdot)$. At time t, the predicted output of the imitation layer is defined as

$$f_o^{ImL}(\cdot)^t = \left[\sum_{h=1}^{n}\Big\{\Big(\sum_{i=1}^{m} p_i \cdot w_{ih}^{ImL}\Big) + \xi \cdot \Big(\sum_{i=1}^{m} p_i \cdot w_{ih}^{InL}\Big)\Big\} \cdot w_{ho}^{ImL} + b_h^{ImL}\right]^t \tag{7.2}$$

where p_i is the number of input patterns with variable and fixed parameters of a product in the data set, $w_{ih}^{ImL}(w_{ih}^{InL}, w_{ho}^{ImL})$ represents connection strengths between i and h node of imitation layer(connection strengths between i and h node of the innovation layer, connection strengths between h and o node of imitation layer), ξ represents an imitation coefficient($0 \leq \xi \leq 1$) for an imitation ratio adjustment, b_h^{ImL} represents a bias of hidden node h for the imitation layer, and index $i(=1,2,..,m)$ numbering input nodes, index $h(=1,2,...n)$ numbering hidden nodes, respectively.

On the other hand, an integration layer simply combines an innovation layer and imitation layer. An output of the integration layer $f_o^{IntL}(\cdot)^t$ is given as shown in equation (7.3).

$$
\begin{aligned}
f_o^{IntL}(\cdot)^t &= f_o^{ImL}(\cdot)^t + f_o^{InL}(\cdot)^t \\
&= \left[\sum_{h=1}^{n} \left\{ f_h^{ImL}(\cdot) + \xi \cdot f_h^{InL}(\cdot) \right\} \cdot w_{ho}^{ImL} + b_h^{ImL} \right]^t + \left[\sum_{h=1}^{n} f_h^{InL}(\cdot) \cdot w_{ho}^{InL} + b_h^{InL} \right]^t
\end{aligned} \tag{7.3}
$$

where

$$
f_h^{ImL}(\cdot)^t = \sum_{i=1}^{m} p_i \cdot w_{ih}^{ImL}, \quad f_h^{InL}(\cdot)^t = \sum_{i=1}^{m} p_i \cdot w_{ih}^{InL} \tag{7.4}
$$

7.4 Dynamic learning with a demand momentum

To cope with limitations of statistical data and to reflect a dynamic nonlinearity, we propose a dynamic learning process in this section. A change of product parameters by time period and its demand change are reflected into the process as a demand momentum. For this, we will discuss the parameters affecting a generation of demand, in addition to a definition of the demand momentum.

7.4.1 Demand momentum(DM)

A consumer behavior refers to how a consumer makes a purchase decision under given market environments, a product price and specification. Consumers consider various factors, when they make the purchasing decision [68]. The factors with respect to the decision can be classified into two categories: (1) quantitative factors such as a price and product specification, and (2) qualitative factors such as personal views toward brand or design preference and the instinct of imitation that is affected by previous buyers. For these reasons, we design a DCNN model using a product specification and price as input data, and introducing a concept of innovators and imitators from the Bass model. We preponderantly discuss about the product specification data as quantitative factors and a demand momentum. The product specification data are used as input data, while they also used to generate the demand momentum with associated a feedback from outputs. What is shown in Figure 7.5 is the concept of 'Demand Momentum(DM)' which is generated by input parameters and a fluctuating demand with time in a network.

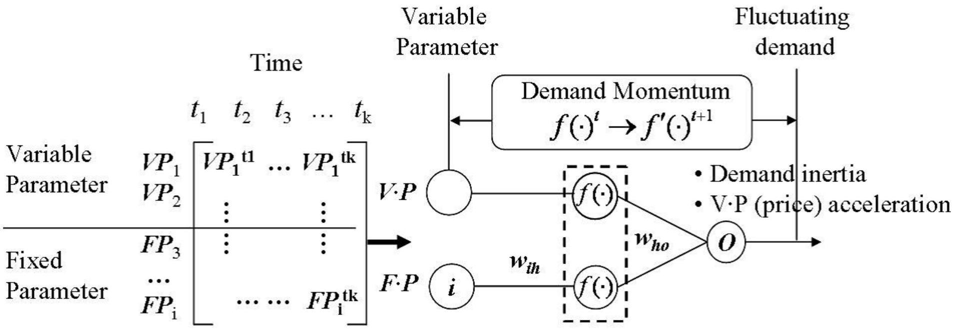


Figure 7.5: Concept of a demand momentum(DM)

The proposed DCNN model is a neural network with a demand momentum in three-dimensional architecture to predict a new product sales forecasting in which the demand momentum is defined in order to measure a strength of power which gives rise to a demand fluctuation.

Definition. The demand momentum DM_s^t of product $s(= 1, 2, ...l)$ in DCNN model is a strength of accelerative power which gives rise to a dynamic demand fluctuation for the product s from time $t-1$ to t, which can be defined from a demand inertia DI_s^t and acceleration of variable parameters AP_s^t.

$$DM_s^t = DI_s^t \cdot AP_s^t = -\left[\frac{1}{Demand\ volatility_s} \times \frac{\triangle Variable\ parameter_s}{\triangle Time}\right]_{t-1}^{t} \tag{7.5}$$

If a demand function $f(t)$ of product s is changed at time interval $[t, t + \triangle t]$, we have

$$Demand\ volatility_s = \frac{f_s(t + \triangle Time) - f_s(t)}{\triangle Time} \tag{7.6}$$

In this point, to consider a learning effect, we introduce an average momentum TDM for every period($t-1 \to t$), which has range, $0.5 \leq TDM^t \leq 1.5$.

$$\begin{aligned} &TDM^t[min : 0.5 \sim max : 1.5] \\ &where\ \ TDM^t = \sum_{s=1}^{l} DM_s/l\ (s = 1, 2, ..., l) \end{aligned} \tag{7.7}$$

7.4.2 Update of an activation function

Based on the defined demand momentum, we discuss a dynamic modification of activation functions of hidden nodes. Our model adopts an architecture that can meet requirements for a dynamic learning through a continuous modification of the activation function. This suggests that we ultimately have different activation functions for every period to support faster and precise adjustment of the proposed DCNN model. The activation function of a hidden node mainly plays a role in information processing as a neuron, and provides trained output. The most frequently used activation function is a sigmoid function out of logistic functions which can be written as

$$o_h = f(input) = \frac{1}{1 + e^{-input}} \tag{7.8}$$

The momentum has not only a direction but also a strength toward the direction, contrary to a tendency that only has a direction such as a scalar value. This is a greatly important concept in our model which will be designed for a dynamic learning with various input data. For instance, the next period's output scope and strength of activation function can be decided according to whether the previous period's demand momentum was increased or decreased, using the momentum with both the direction and its strength. Parameters of hidden nodes are updated by a function associated with the demand momentum. We have multiple numbers of hidden nodes representing consumer groups with a preference on product specifications and prices. For example, some consumers put more weight on their decisions to design, while others put more weight on easy use. And those groups have two kinds of behaviors along with time. For such dynamic learning with a recurrent architecture, we propose an adaptable activation function of a hidden node of which output is affected by the proposed demand momentum in each learning. We first define an adjustment coefficient α and β to control the maximum scope of output and slope of activation function, and then set those coefficients as the generalized average demand momentum TDM, as shown in equation (7.9).

$$o_h^t = f^t(input) = \left[\frac{\alpha}{1 + e^{-(input_h \cdot \beta)}}\right]^t, \ \ where\ \alpha, \beta = TDM$$

and

$$input = \begin{cases} if \ \ \text{Innovation layer,} \ \left[\sum_{i=1}^{m} p_i \cdot w_{ih}^{InL}\right]^t \\ if \ \ \text{Imitation layer,} \ \left[\sum_{i=1}^{m} p_i \cdot w_{ih}^{ImL} + \xi \cdot \left(\sum_{i=1}^{m} p_i \cdot w_{ih}^{InL}\right)\right]^t, \end{cases}$$

$$where\ \ 0 \leq \xi \leq 1, \ \ t = 1, 2, ..., \infty \tag{7.9}$$

The most commonly used learning algorithm for a feed-forward neural network is an error back-propagation(BP) algorithm, called generalized Delta rule, using supervised learning. To obtain a desired level of error, connecting weights between nodes are updated according to a certain rule searching the error surface using a gradient descent method [69]. Using the BP algorithm, we simply address a dynamic learning algorithm with a demand momentum and adaptable activation function. The algorithm is carried out according to the below steps.

Step 1. Initialize all weights w^{ImL}, w^{inL} of innovation and imitation layer as small random numbers and training pattern pairs with variable and fixed parameters, and set a learning rate η, an imitation coefficient $\xi(0 \sim 1)$, a learning number and desired error t_p.

Step 2. For each training pattern pairs, calculate a generalized average demand momentum DM^{+}(Increased demand momentum), DM^{-}(Decreased demand momentum) $\rightarrow TDM^t$ ($t = 1, 2, ...$) for every period, and then modify an output scope and slope of activation function $f^t(input)$ based on the obtained TDM^t to compute a suitable predicted output o_h^t for an individual period(t).

Step 3. Minimize an error between the predicted output o_h^t and desired output t_p.

$$\begin{aligned} &Minimize\ \ e = t_p - \left[\frac{\alpha}{1 + e^{-(input_h \cdot \beta)}}\right]^t \\ &Sub.\ \ t_p > 0 \\ &\qquad \alpha, \beta = TDM \end{aligned} \tag{7.10}$$

And update weights w^{ImL}, w^{inL}, for example, a case of weights w_{ho} between hidden and output nodes:

$$w_{ho}^t = w_{ho}^{t-1} + [\Delta w_{ho}]_{t-1}^t,\ \ where\ [\Delta w_{ho}] = \eta \cdot \delta_o^{t-1} \cdot o_h^{t-1} \tag{7.11}$$

where

$$\delta_o^{t-1} = -\frac{\partial \sqrt{\sum_{p=1}^{td}(t_p - o_o^t)^2}}{\partial\, input_o} \tag{7.12}$$

$$o_h^{t-1} = \left[\frac{\alpha}{1 + e^{-(input_h \cdot \beta)}}\right]^{t-1} \alpha, \beta = TDM \tag{7.13}$$

where o_h is an output of a hidden node, δ_o is a delta value(error) of an output node, $input_o(input_h)$ input value into the output node(hidden node), respectively.

Step 4. Iterate above **Step.1-3**, until a designated learning number is completed, or desired error t_p is satisfied.

7.5 Computational experiment

Up to this point, we have presented a theoretical overview of DCNN model. In this section, we show a simple forecasting example using the proposed DCNN model.

7.5.1 Initial settings

We use an adaptive logistic function with a generalized demand momentum TDM, an imitation coefficient ξ which is set to be 0.25~1.0, an initial learning rate $\eta = 0.12$ and BP algorithm for the proposed DCNN which has 4-12-1 architecture of each interaction layer. In the model, for an adaptability of the learning rate, we also adopt an elastic learning rate η obtained from a sliding mode surface so that the learning efficiency and stability are guaranteed in iterative learning processes. And we set that the learning process is terminated if the number of iterations reach 100,000(maximum), or RMS(Root Mean Square) error drops to 0.085.

As data sets, sales volume of a new digital camera is generated prior to the experiments, which fit to a Bass model. The main reasons we choose the camera as a forecast target is that the proposed DCNN model in this study are the features of sales data, a short life-cycle, a high demand uncertainty, etc., in a real business. The data fits an innovative and imitative buying behavior of the Bass model dealing with a product in which a repurchase doesn't take into consideration. As the input data, we use four quantitative parameters, which are summarized in below Table 7.2.

Table 7.2: Input parameters for learning: a camera

Parameter type	Specification	Remark
Variable	Price	Reflect the range of fluctuating on the weekly basis
Fixed	LCD size / Pixel / Weight	

In our experiment, total 480 pairwise input data from 10 digital cameras(A~ J Camera) are generated, and are used to learning for 12 periods. We use various types of demand functions which are randomly generated, due to a difficulty in obtaining actual demand data. In the demand functions for input data, a range of price fluctuating is observed on the weekly basis so that it periodically leads to a dynamic changing of demand momentum with a desired output for every period.

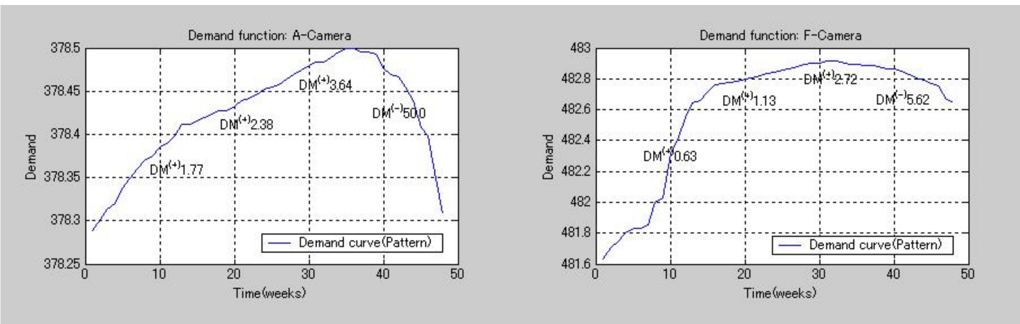


Figure 7.6: Generated demand curves for A and F camera

Figure 7.6 presents the generated demand curves with demand momentums $DM^{(+)/(-)}$ for camera A($365, 1.3-megapixel, 2.5-inch LCD display, 160g) and camera F($420, 3.0-megapixel, 3.5-inch LCD display, 400g).

7.5.2 Computational results

The proposed DCNN model set by initial data has been implemented with MATLAB 6.5. We set input patterns and all experiment parameters, such as an initial learning rate η, a desired error(RMS) and learning number, to be the same for a network of innovation layer and imitation layer, because influences on the experiment from all these settings should be eliminated in learning processes. In addition, in order for the learning processes to be efficient and stable, we set the elastic learning rate η; if $RMS^t < RMS^{t-1}$, the elastic learning rate $\eta = \eta \times 1.15$ or else the rate $\eta = \eta \times 0.65$. We converted the data into decimal numbers 0 to 1 before the learning process, because all data type for the learning were continuous real numbers. Figure 7.7 shows learning rates and RMS errors of two interaction layers; the top shows RMS and learning rate of innovation layer while the bottom shows RMS and learning rate of imitation layer, respectively. The innovation layer was trained in 50,127 learning numbers and 0.019417 learning rate while the imitation layer was trained in 42,631 learning numbers and 0.013312 learning rate.

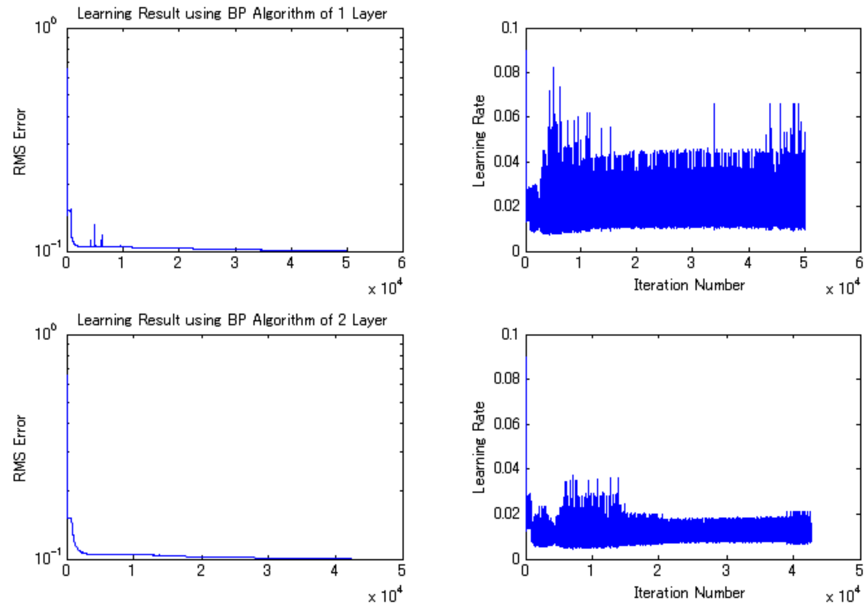


Figure 7.7: Learning results: RMS errors and learning rates for both layers

Based on the trained networks, we predicted a sales of a new camera($325, 2.7-megapixel, 3.0-inch LCD display, 190g) of which price is set to be weekly decreased at the rate of 1.5%.

Figure 7.8 presents the forecasting results for every period, where the top graph shows a demand for innovation layer, the middle graph shows a demand for imitation layer, and the bottom graph shows an integrated demand, respectively.

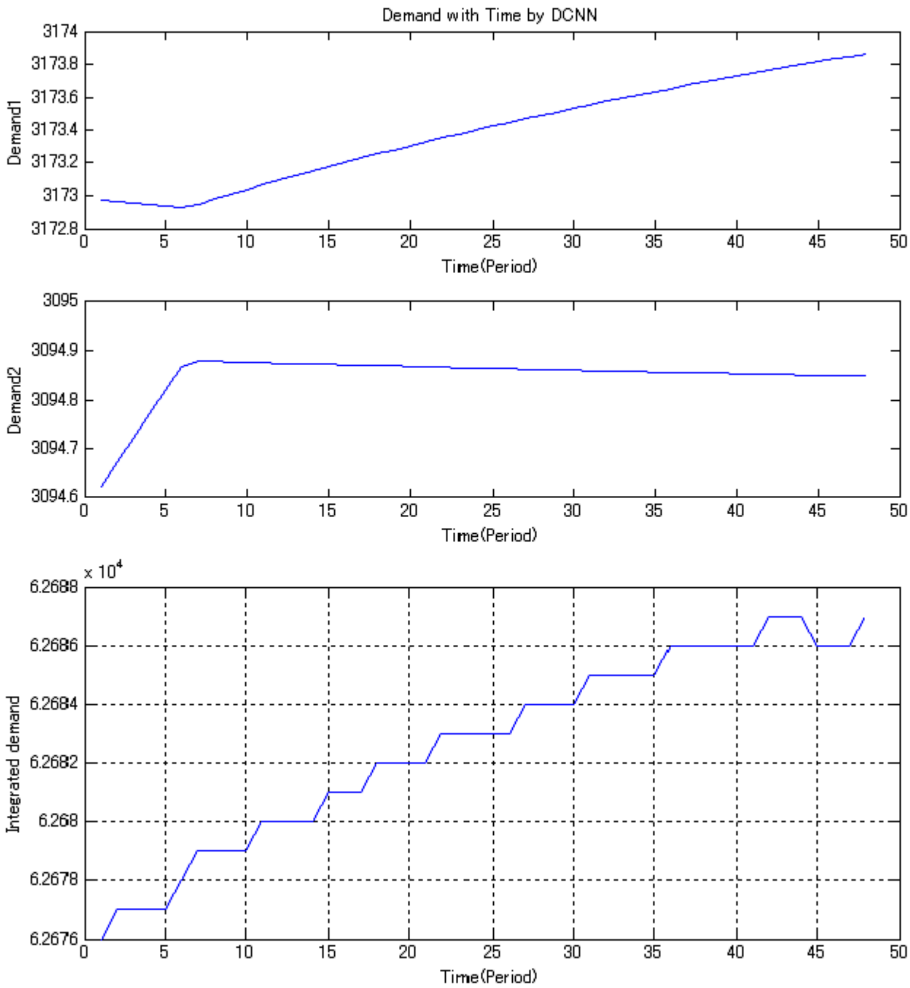


Figure 7.8: Forecasting results

7.5.3 Comparison with an ANN

We compare a DCNN with ANN(Artificial Neural Network) in this section to investigate what conditions are more suitable for the proposed DCNN model. We assume that:

(1) Demand of a new camera is generated according to a logistics growth curve representing a diffusion process of a new camera.
(2) Customer type(innovator and imitator) can clearly be divided in the market.

(3) The consumer behavior of imitators is affected by innovators who purchase a new product without any affections by other customers. This kind of relationship is described by an imitation coefficients (ξ).

We evaluate forecast errors using MAD(Mean Absolute Deviation: $= \frac{1}{n}\sum_{i=1}^{n} \mid AD_i - FD_i \mid$ where AD and FD are an actual and forecasted demand respectively), and track those by periods. Even though an ANN shows a better forecasting accuracy in some periods, we can identify that a DCNN model can generally be more valid in a market. Specifically, the forecasting accuracy of the DCNN is the highest when an imitation coefficient is given as 1. In section from ξ =0.5 to ξ =1.0, the higher the imitation coefficient, the lower forecasting error compared to the ANN. In addition, in case of $\xi = 0.75$ and $\xi = 1.0$, it has shown higher forecasting accuracies, as time(period) goes by. Table 7-3 presents the results summarized.

Table 7.3: Comparison results (MAD)

		0p ~ 16p	17p ~ 32p	33p ~ 48p	Whole period
DCNN	(ξ = 1.00)	1,424.39	753.33	177.96	785.23
	(ξ = 0.75)	1,762.42	1,089.98	417.30	1,089.90
	(ξ = 0.50)	993.91	1,673.46	2,352.68	1,673.35
	(ξ = 0.25)	757.39	1,434.78	2,111.97	1,434.71
ANN		1,039.50	1,719.03	2,398.13	1,718.89

However, we do not have any direct evidences that the proposed DCNN model is always better than an ANN. As the main reasons, followings can be discussed. The first is a learning process with too many parameters with respect to the number of observations, in which an overfitting may occur between a desired pattern and predicted output in some cases. The second is an importance of selecting data for learning; for instance, data noise can be learned. Finally, we need to address a structure of neural network and parameters for learning. Generally, forecasting results can greatly be changed according to the number of hidden units, a learning rate and how to set the desired pattern. This is a fundamental limit of the ANN which depends on parameter sets greatly.

7.6 Brief summary and discussion

In order to predict the future demand for a new product which is not taken into consideration of a repurchase, we have conducted a new DCNN model of which architecture is designed based on an innovative and imitative behavior of a Bass model. Our approaches to design the model are mainly characterized as an adaptive network configuration with a dynamic learning process, in which variable parameters and fluctuating demand of learning patterns create a demand momentum to control outputs of activation functions, in addition to a structural interaction described by the innovative and imitative consumer behavior. These characteristics can be usefully utilized not only to predict the new product considering a diffusion process but also to adjust a suitable network for a dynamic forecasting. Especially, one of the major advantages of our approach is that no stochastic estimations for forecasting parameters and coefficients are required. Instead, we assume that a product specification and dynamically changing price will have an essential influence to the demand, and the proposed DCNN model will provide step by step the best estimation to the demand, adjusting parameters of hidden layer (demand momentum) and connection strength (weights between input nodes and hidden nodes, weights between hidden nodes and output nodes); an input pattern-based dynamic demand process is structurally conducted by the cubic architecture and the demand momentum we defined.

Our experimental results showed that the future demand of a new camera using the proposed DCNN model had higher accuracy compare with a traditional ANN. Although a price of the new camera was set to be decreased, an imitation layer was not much effected by the price down compared to an innovation layer. Furthermore, an integrated demand had a tendency to increase when the price gone down.

Although we successfully constructed the first DCNN model for a demand forecasting, it still under investigation at the stage 'IDEA generation', remains with many problems for robustness, and should be validated from the various viewpoints. This study can be extended into several directions. We have only considered quantitative parameters to predict a sales of a new product, whereas in practice, most consumers comprehensively consider not only the quantitative parameters, but also qualitative parameters such as a design or brand preference, color and competitive products, etc.. In addition, our model has assumed that a price as a main parameter has a great influence on a demand momentum, and demand fluctuation as well. However, because a demand curve moves by a complex set of factors, a market condition and supply-demand relation should also be considered to define the demand momentum of which accelerative power leads to the demand fluctuation. And a large scale agent simulation is also one direction toward the future research.

Chapter 8

Conclusions

8.1 Summary and an outlook

In this thesis, from the viewpoint of a supply chain risk, we have been widely and intensely dealt with various approaches for functional business processes of a supply chain.

Chapter 2: We extracted and analyzed supply chain risk drivers(SCRDs) leading to a direct or indirect risks. For the work, a framework consisting of (1) supply chain processes and (2) general business attributes was proposed, and total 10,181 articles from 68 journals published during the past four decades were used for a text mining and multivariate statistics. Total 133 SCRDs were extracted and analyzed by a clustering technique and GRI, as well as time-series analysis. This work is pretty useful, since most of controllable risks can be removed or mitigated if the causes are cleared.

Chapter 3: An outsourcing risk was discussed in this chapter. We proposed an economic make-or-buy decision model in multi-stage production processes. Fixed costs and variable costs were used for a break-even analysis, and an effective and unique solution procedure also was proposed. This work is useful; although there are many reasons for outsourcing at operational and strategic level such as a technical problem, a flexible capacity, a cost cutting, and core competence, a real business heavily depends on the cost which is a top priority.

Chapter 4: A manufacturing risk related to an economical use of a production equipment was discussed in this chapter. We formulated a production equipment replacement problem under a failure uncertainty was given. This work focused on a maintenance opportunity and risks in operation of the production equipment. EOS(End of Service) related to maintenance contract and VaR(Value at Risk) for the failure uncertainty were considered as major concepts to describe this problem. We showed economical replacement times in two cases: (1)accepting failure risk, and (2)renewal of maintenance contract to avoid the risk.

Chapter 5: In this chapter, a supply and purchase risk was discussed. This work focused on a flexibility of adjusting order quantity as a right to avoid the expected loss and to obtain additional opportunities, when a demand was distributed uniformly. We designed four types of supply contracts (buy-back, call, put and hybrid option), and proposed optimal solutions (initial order quantity and option quantity for buyers, an option price for suppliers). We also showed the best and worst contracts by demand sections, in contrast to the previous studies focused only on a maximization of the expected profits.

Chapter 6: A prediction risk was discussed in this chapter. Using a multi-agent system, we designed a prediction market with a mechanism to collect and combine widely dispersed information and knowledge. As a major concept for the market design, a micro-macro loop with interactive relationships among agents was used, where heterogeneous agents(traders) revise their beliefs to determine private prediction values (micro) in consideration of a price of prediction security (macro). And we also examined a possibility of price convergence in the market by agent types and market environments.

Chapter 7: Like the preceding chapter, a major approach in this chapter was also a prediction risk. We proposed a new DCNN model based on consumer behaviors (innovator and imitator) of Bass model representing a diffusion process of a new product. The model has an iterative modification mechanism for updating activation function, and an output scope of the function of hidden nodes is appropriately modified for every learning period, according to a demand momentum which is defined by a demand inertia and acceleration of variable input parameters. Our approach is quite useful because ineffectiveness mostly comes from an inaccuracy in demand forecasting.

8.2 Discussion for the future of a supply chain

At the conclusion, we discuss briefly about the future of a supply chain. To handle risks, spending much time for this issue is a pretty meaningful work, because new risks may appear if the supply chain is changed in the future. As one of the leading works for this area, there is a supply chain 2020 project by the MIT center for transportation & logistics(CTL). This research is quite broad and far-researching, and aims to develop scenarios of the future that will help a supply chain community to explore different strategies and operating models to support the overall business strategy. By understanding what might happen and how various developments will influence the future supply chain, they have been being tried to predict the supply chain of the future [70]. In this multiyear research, a comprehensive list of the key drivers that can potentially transform supply chains in the future with vision has been presented from surveys and various publications. As a tool to predict the future supply chain, they have used (1) scenario planning and (2) excellent supply chain research framework. They have developed three baseline scenarios which provide a rich background information to motivate supply chain strategy discussions.

Figure 8.1: Three baseline scenarios (by MIT SCM2020)

The research framework from summarizing prediction on the future supply chains using the conceptual supply chain model contains external factors and supply capabilities. They focused not only macro factors' trends, but also supply chain strategies, practices that influence the macro factors.

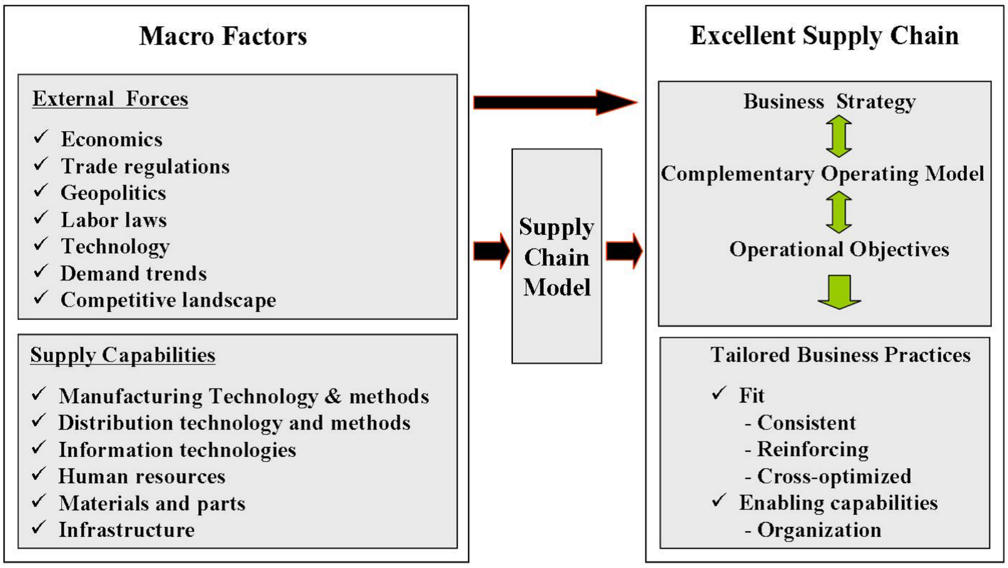


Figure 8.2: Research framework for future supply chain (by MIT SCM2020)

They categorized the predictions into two groups: (A) macro factors, and (B) supply chain visions. In addition, they described detailed impacts on a supply chain by types(structured study or unstructured study), likelihood of prediction coming to fruition by the year 2020, occurrence of the topic in various publications, and relevance of prediction to the future of supply chains. Those can be explained as a cause and effect relation; various factors and visions impact on the supply chain, which cause finally a change of the supply chain. For example, for the A group, macro factors such as sophisticated customers and customized new needs influence on the supply chain in which a higher customization and an agile demand forecasting are required, which finally lead to a change of the supply chain. That is, in the future, the supply chain should become agile to be very effective to support a diverse product, customer in an efficient manner. It is clear that the supply chain has changed by environmental factors so far, and keep changing by many related factors. By their results, a global supply chain, a dynamic supply chain, a green (or reverse) supply chain, a knowledge (or information) supply chain, a virtual supply chain, and an intelligent supply chain will be actively issued in the future.

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Appendix A

Journal List

Table A.1: Journal list: (DB) SSCI-Business

No.	Name of Journal	Number of Articles
1	INTERNATIONAL BUSINESS REVIEW	103
2	THE JOURNAL OF BUSINESS	247
3	JOURNAL OF BUSINESS AND PSYCHOLOGY	150
4	JOURNAL OF BUSINESS RESEARCH	145
5	JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT	452
6	JOURNAL OF MARKETING RESEARCH	84
7	JOURNAL OF RETAILING	176
8	JOURNAL OF WORLD BUSINESS	292
9	MARKETING SCIENCE	190
10	LONG RANGE PLANNING	271

Table A.2: Journal list: (DB) SSCI-Business Finance

No.	Name of Journal	Number of Articles
11	GENEVA PAPERS ON RISK AND INSURANCE-ISSUE AND PRACTICE	116
12	GENEVA RISK AND INSURANCE REVIEW	29
13	JOURNAL OF INDUSTRIAL ECONOMICS	182
14	JOURNAL OF RISK AND INSURANCE	140
15	JOURNAL OF RISK AND UNCERTAINTY	68

Table A.3: Journal list: (DB) SSCI-Management

No.	Name of Journal	Number of Articles
16	ACAMEMY OF MANAGEMENT JOURNAL	44
17	ACADEMY OF MANAGEMENT PERSPECTIVES	255
18	ACAMEMY OF MANAGEMENT REVIEW	26
19	ADMINISTRATIVE SCIENCE QUARTERLY	22
20	AFRICAN JOURNAL OF BUSINESS MANAGEMENT	1
21	BRITISH JOURNAL OF MANAGEMENT	143
22	CALIFORNIA MANAGEMENT REVIEW	215
23	DECISION SCIENCE	40
24	EMJ-ENGINEERING MANAGEMENT JOURNAL	45
25	EUROPEAN MANAGEMENT JOURNAL	233
26	HARVARD BUSINESS REVIEW	132
27	IMA JOURNAL OF MANAGEMENT MATHEMATICS	22
28	INDUSTRIAL AND CORPORATE CHAGE	16
29	INDUSTRIAL AND INNOVATION	181
30	INFORMATION AND MANAGEMENT	119
31	INTERFACES	66
32	INT'L JOURNAL OF LOGISTICS-RESEARCH AND APPLICATION	178
33	INT'L JOURNAL OF MANAGEMENT REVIEWS	42
34	INT'L JOURNAL OF OPERATIONS AND PRODUCTION MANAGEMENT	275
35	INT'L JOURNAL OF TECHNOLOGY MANAGEMENT	233
36	JOURNAL OF BUSINESS LOGISTICS	95
37	JOURNAL OF ECONOMICS AND MANAGEMENT STRATEGY	22
38	JOURNAL OF ENGINEERING AND TECHNOLOGY MANAGEMENT	238
39	JOURNAL OF INTERNATIONAL BUSINESS STUDIES	54
40	JOURNAL OF MANAGEMENT	297
41	JOURNAL OF OPERATIONS MANAGEMENT	401
42	JOURNAL OF ORGANIZATIONAL CHANGE MANAGEMENT	151
42	JOURNAL OF PRODUCT INNOVATION MANAGEMENT	257
44	JOURNAL OF SMALL BUSINESS MANAGEMENT	60
45	M&SOM-MANUFACTURING & SERVICE OPERATIONS MANAGEMENT	120
46	MANAGEMENT DECISION	90
47	MANAGEMENT INTERNATIONAL REVIEW	83
48	MANAGEMENT SCIENCE	159
49	MIT SLOAN MANAGEMENT REVIEW	85
50	OMEGA-INT'L JOURNAL OF MANAGEMENT SCIENCE	173
51	OPERATIONS RESEARCH	164
52	R&D MANAGEMENT	161
53	SMALL BUSINESS ECONIMICS	62
54	STRATEGIC MANAGEMENT JOURNAL	33
55	TOTAL QUALITY MANAGEMENT & BUSINESS EXCELLENCE	179

Table A.4: Journal list: (DB) SCI-Manufacturing engineering

No.	Name of Journal	Number of Articles
56	INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH	184

Table A.5: Journal list: (DB) SCIE-Industrial engineering

No.	Name of Journal	Number of Articles
57	COMPUTER & INDUSTRIAL ENGINEERING	103
58	COMPUTER & OPERATIONS RESEARCH	84
59	IIE TRANSACTIONS	13
60	INTERNATIONAL JOURNAL OF PRODUCTION ECONOMICS	701
61	JOURNAL OF MANAGEMENT IN ENGINEERING	72
62	JOURNAL OF MANUFACTURING SYSTEMS	108
63	PROBABILITY IN THE ENGINEERING AND INFORMATIONAL SCIENCE	9
64	PRODUCTION PLANNING & CONTROL	221
65	QUALITY AND RELIABILITY ENGINEERING INTERNATIONAL	77
66	RELIABILITY ENGINEERING & SYSTEM SAFETY	83
67	SAFETY SCIENCE	68
68	SYSTEM ENGINEERING	86

Appendix B

SCRD (Supply Chain Risk Driver)

Table B.1: Extracted SCRDs focusing on business attributes

Business attribute	Supply chain risk drivers
Quality	Reliability and validity of the quality management Level of quality improvement of tools and techniques Underlying organizational culture for the quality Level of autonomy to take risk on new product novelty keeping the quality Level of organizational performance Way to use the former experiences Way of waste management control Parallels between the development of quality management and environmental management systems Existence of international environmental management standard ISO 14001 Level of lean production Needs and wishes of the present society Level of parts and material recovery
Cost	Mass producing of customized products (contradiction) Traditional monetary measure based on present worth Outsourcing in an uncertain context Choice of foreign investors between full ownership and sharing ownership with a local firm Pressure from customers to improve products' environmental performance Effectiveness of a mandate Maintaining flexibility Waste of time Material waste Labor costs Cost of disassembly, component inspection and repair, remanufacturing and recycling

Table B.2: (continued) Extracted SCRDs focusing on business attributes

Business attribute	Supply chain risk drivers
Delivery	Level of coordination of the whole channel
	Product line design for a distribution channel
	Variances of demand and lead-time
	Environmental impact
	Accuracy of stock information
	Immediate order
	Delayed order
	Level of access to accurate and timely information on the status, location, and condition of products moving in the supply chain
	Design of logistics distribution systems
Environment	Sustainable product life-cycle
	Recognition of new opportunities
	Changes (in supplier and customer bases, distribution networks, corporate re-engineering, business climate, government legislation, ...)
	Sectoral transformations
	Globalization of business
	Policy makers and corporate decision makers
	Terrorism and corruption while trade negotiations have declined
	Regular solicitation of stakeholder perspectives
	Revolt, Strike
	Leadership styles
	Close supplier relationships in uncertain environments
	Socio-cultural context
	Continuous development of technology
	Gap between theory and management theory
Flexibility	Various product-mix
	Volatility of product demand
	Flexibility in manufacturing operations
	Market demand volatility
	Multi-functionality of resources
	SC agility
	Internal integration, External integration (learning orientation)
	Managerial flexibility
	Levels of diversification
	Resource commonality and substitutionality
	Worker deployment flexibility
	Level of network solution
	Flexibility for the time to market
	Internationalization of markets and competition
	Capacity constraints

Table B.3: (continued) Extracted SCRDs focusing on business attributes

Business attribute	Supply chain risk drivers
Assessment	Coordinating product design, production design, and supply chain design decisions Identifying future research opportunities Product innovativeness Development time Level of supplier involvement in new product development Product portfolio Reliability and validity of the data Managers who are simply not familiar with risk-assessment models People who believe their experiences and intuition to be more reliable than models based on forecasts
Strategy	Choice between recycled and virgin materials Integration (vertical, horizontal) Manufacturing virtuality Level of contribution of knowledge Level of education of teaching risk management Competence of risk manager Integration of different strategic management perspectives (ex. resource-based view, evolutional perspectives, ...) Corporate culture (ex. that rewards only on-time, on-budget) Negotiation with suppliers or with buyers Strategic flexibility Pace of change National competitiveness Speedy and accurate analytical capabilities

Table B.4: Extracted SCRDs focusing on supply chain processes

SC process	Supply chain risk drivers
R&D	Conflicts between discretion (e.g. spontaneity, desire for change and breaking of rules) and formality (e.g. structure, stability, and following the rules) Project budgets (investments) Level of expected results

Table B.5: (continued) Extracted SCRDs focusing on supply chain processes

SC process	Supply chain risk drivers
R&D (continued)	Project specific, private uncertainties (e.g. uncertainty of research results) Level of training of R&D manpower Level of development of conducive innovation environments Product performance Project schedules (stability etc.) Level of communication interactivity Cultural and geographical distance (difference) Project governance structure (e.g. internal development, co-operation or contracting) Diversity of knowledge Level of autonomy of researcher
Procurement	Allocation of scarce resource Schedule stability Existence of natural resource Tax rates Change of ownership structure or organization design Level of financial resource Frequency of partner selection Resource commonality and substitutionality
Production	Regardless of time Regardless of location Value(accuracy) of forecasts Production flexibility Worker isolation and harassment Dangerous conditions on the production line Level of accident cover-ups Poor quality of life for workers Society requires increasing information on products (data on the origin of products including details of production conditions, etc.) Worker satisfaction Quality of the software Process of testing Quantity of products to have in the line
Distribution	Inventory costing focus exclusively on the rate of return Decision between centralize stock and dual distribution systems Design of production-distribution networks Compromise between cost and customer service level

Table B.6: (continued) Extracted SCRDs focusing on supply chain processes

SC process	Supply chain risk drivers
Distribution (continued)	Stochastic demand by retailer and by period
	Order lead-time
	Allocation lead-time
	Operating costs
	Buffer stock holding costs
	Backorder costs
	Purchasing costs
	Product modularity
Retail	Choosing optimal retail assortments
	Existence of infrequently purchased or low cost performance products
	Assessing the robustness of assortments with regard to shifts in customer preferences
	Price setting
	Choosing between a direct channel, a manufacturer-owned retail channel, and an independent retail channel
	Market unmeasurely uncertain (requirements etc.)
	Responsiveness to changing market/customer requirements
	BTO style
Customer	Customers' expect for services
	Customer's subjective expected value of the relationship
	Level of provided service (e.g. utilities, financial services, and telecommunications)
	Length of customers' prior experience with the organization
	Relationship between service quality and profitability
	Existence of customer bonds
	Creating engagement without clear benefit
	Spending too much time and money to engage low involvement customers
	Failing to anticipate how customers can exploit the conversation in unexpected ways
	Failing to realize that competitors may he listening
	Customer lifetime value(CLV)
	Accuracy of customer database
	Uninterrupted service
	Market requirements
	Level of customer's sympathy for green products
Whole SC	Level of human resource management
	Level of production management

Table B.7: (continued) Extracted SCRDs focusing on supply chain processes

SC process	Supply chain risk drivers
Whole SC (continued)	Information and technology transfer Firm's structure and control method Firm's strategy Business-government relations Integration level of production and administration Level of communication(integration) of shared rules and values (e.g. openness, politeness) Information flows in operations Vertical, horizontal and external information flows Wireless ICT applications like cellular networks (e.g. Wi-Fi, UMTS, 4G and WiMax) with reliability and connectivity problems (e.g. limited range, scalability and security) E-organizations (transformation for one-organization from the traditional organizations)

Appendix C

Classified SCRD

Table C.1: Classified final risk drivers

Cluster	No.	Risk driver
	1	Conflicts between discretion and formality
	2	Project budgets (finance)
	3	Level of expected results
	4	Level of development of conducive innovation environment
	5	Project partner selection
	6	Project resource allocations and support
	7	Level of autonomy of researcher
	8	Existence of natural resource
	9	Tax rates
	10	Frequency of supply partner selection
Cluster 1	11	Resource commonality and substitutionality and multi-functionality
	12	Regardless of time
	13	Regardless of location
	14	Value(accuracy) of forecasts
	15	Worker isolation and harassment
	16	Poor quality of life for workers
	17	Society requires increasing information on products
	18	Quality of the software
	19	Quantity of products to have in the line
	20	Inventory costing focus exclusively on the rate of return
	21	Decision between centralize stock and distribution systems
	22	Compromise between cost and customer service level
	23	Stochastic demand by retailer and by period

Table C.2: (continued) Classified final risk drivers

Cluster	No.	Risk driver
Cluster 1 (continued)	24	Order lead-time
	25	Buffer stock holding costs
	26	Purchasing costs
	27	Product modularity
	28	Existence of infrequently purchased or low cost performance products
	29	Assessment adequacy of the robustness of assortments with regard to shifts in customer preferences
	30	Price setting
	31	Market unmeasurely uncertain (requirements etc.)
	32	BTO style
	33	Customers expect for services
	34	Customers subjective expected value of the relationship
	35	Creating engagement without clear benefit
	36	Spending too much time and money to engage low involvement customers
	37	Failing to anticipate how customers can exploit the conversation in unexpected ways
	38	Failing to realize that competitors may he listening
	39	Reliability and validity of the quality management
	40	Level of quality improvement of tools and techniques
	41	Level of autonomy to take risk on new product novelty keeping the quality
	42	Way to use the former experiences
	43	Way of waste management control
	44	Parallels between the development of quality management and environmental management systems
	45	Level of parts and material recovery
	46	Mass producing of customized products (contradiction)
	47	Traditional monetary measure based on present worth
	48	Outsourcing in an uncertain context
	49	Choice of foreign investors between full ownership and sharing ownership with a local firm
	50	Effectiveness of a mandate
	51	Cash flows resulting from managerial actions
	52	Material waste
	53	Level of coordination of the whole channel
	54	Accuracy of stock information
	55	Immediate order
	56	Level of access to accurate and timely information on the status location and condition of products moving in the supply chain
	57	Design of logistic distribution systems
	58	Sustainable product life-cycle
	59	Recognition of new opportunities
	60	Terrorism and corruption while trade negotiations have declined
	61	Revolt strike

Table C.3: (continued) Classified final risk drivers

Cluster	No.	Risk driver
Cluster 1 (continued)	62	Continuous development of technology
	63	Gap between theory and management practice
	64	Various product-mix
	65	Volatility of product demand
	66	Level of internal integration
	67	Level of external integration (learning orientation)
	68	Managerial flexibility
	69	Worker deployment flexibility
	70	Level of network solution
	71	Flexibility for the time to market
	72	Product innovativeness
	73	Development time
	74	Level of supplier involvement in new product development
	75	Product portfolios
	76	Reliability and validity of the data
	77	Choice between recycled and virgin materials
	78	Integration (vertical, horizontal)
	79	Manufacturing virtuality
	80	Level of contribution of knowledge
	81	Negotiation with supplier or with buyers
Cluster 2	82	Cultural and geographical distance (difference)
	83	Globalization of business
	84	Internationalization of markets and competition
Cluster 3	85	Environmental impact
Cluster 4	86	Capacity constraints
Cluster 5	87	Product line design for a distribution channel
	88	Coordinating product design production design and supply chain design decisions
Cluster 6	89	Project governance structure
	90	Diversity of knowledge
	91	Change of ownership structure or organization design
	92	Choosing between a direct channel a manufacturer-owned retail channel and an independent retail channel
	93	Length of customers prior experience with the organization
	94	Existence of customer bonds
	95	Customer lifetime value(CLV)
	96	Accuracy of customer database
	97	Level of customers sympathy for green products

Table C.4: (continued) Classified final risk drivers

Cluster	No.	Risk driver
Cluster 6 (continued)	98	Underlying organizational culture for the quality
	99	Existence of international environmental management standard ISO 14001
	100	Needs and wishes of the present society
	101	Firms strategic orientations at the business level
	102	Pressure from customers to improve products environmental performance
	103	Policy makers and corporate decision makers
	104	Regular solicitation of stakeholder perspectives
	105	Leadership style
	106	Closed supplier relationships in uncertain environments
	107	Socio-cultural context
	108	Managers who are simply not familiar with risk-assessment models
	109	People who believe their experiences and intuition to be more reliable than models based on forecasts
	110	Competence of risk manager
	111	Integration of different strategic management perspectives
	112	A corporate culture
	113	Speedy and accurate analytical capabilities
Cluster 7	114	Product performance
	115	Project schedules (stability etc.)
	116	Dangerous conditions on the production line
	117	Worker satisfaction
	118	Allocation lead-time
	119	Operating costs
	120	Backorder costs
	121	Responsiveness to changing market / customer requirements
	122	Level of provided service
	123	Relationship between service quality and profitability
	124	Uninterrupted service
	125	Level of organizational performance
	126	Level of lean production
	127	Waste of time
	128	Labor costs
	129	Cost of disassembly component inspection and repair remanufacturing and recycling
	130	SC agility
	131	National competitiveness
Cluster 8	132	Production flexibility
	133	Level of accident cover-ups

Appendix D

Optimal Replacement Time

D-1. Let X and Y be

$$X = C + \sum_{t=1}^{T} \frac{E_t}{(1+i)^t} + \sum_{t=1}^{T} \frac{R_t}{(1+i)^t},\ \ Y = C + \sum_{t=1}^{T-1} \frac{E_t}{(1+i)^t} + \sum_{t=1}^{T-1} \frac{R_t}{(1+i)^t} \tag{D.1}$$

then $X - Y$ can be written as

$$X - Y = \frac{E_T}{(1+i)^T} + \frac{R_T}{(1+i)^T} \tag{D.2}$$

Using the equation (4.5), equation (D.1) and equation (D.2), we obtain

$$M(T) - M(T-1) = X \times \frac{i(1+i)^{T-1}}{(1+i)^{T-1}-1} \times \left(1 - \frac{i}{(1+i)^T - 1}\right) - Y \times \frac{1(1+i)^{T-1}}{(1+i)^{T-1}-1}$$

$$= \frac{i(1+i)^{T-1}}{(1+i)^{T-1}-1} \times \frac{i}{(1+i)^T-1} \times \left((X-Y) \times \frac{(1+i)^T-1}{i} - X\right)$$

$$= \frac{i(1+i)^{T-1}}{(1+i)^{T-1}-1} \times \frac{i}{(1+i)^T-1} \times \left(\left(\frac{E_T}{(1+i)^T} + \frac{R_T}{(1+i)^T}\right) \times \frac{(1+i)^T-1}{i} - X\right)$$

$$= \frac{i(1+i)^{T-1}}{(1+i)^{T-1}-1} \times \frac{i}{(1+i)^T-1} \times \left((E_T + R_T) \times \frac{(1+i)^T-1}{i(1+i)^T} - X\right)$$

$$= \left(-C + \sum_{t=1}^{T} \frac{E_T - E_t}{(1+i)^t} + \sum_{t=1}^{T} \frac{R_T - R_t}{(1+i)^t}\right) \times \frac{i(1+i)^{T-1}}{(1+i)^{T-1}-1} \times \frac{i}{(1+i)^T-1} \tag{D.3}$$

D-2. If $i > 0$, it is obvious that the capital recovery factor can be written as

$$\frac{i(1+i)^{T-1}}{(1+i)^{T-1}-1} \times \left(1 - \frac{i}{(1+i)^T - 1}\right) = \frac{\left(i(1+i)^{T-1}\right) \times \left((1+i)^T - (1+i)\right)}{((1+i)^{T-1}-1) \times ((1+i)^T - 1)}$$

$$= \frac{i(1+i)^T \times \left((1+i)^{T-1} - 1\right)}{((1+i)^{T-1}-1) \times ((1+i)^T - 1)} = \frac{i(1+i)^T}{(1+i)^T - 1} \tag{D.4}$$

D-3. Let X and Y be

$$X = C + \sum_{t=1}^{T} \frac{E_t}{(1+i)^t} + \frac{S_l}{(1+i)^{EOS}}, \ Y = C + \sum_{t=1}^{T-1} \frac{E_t}{(1+i)^t} + \frac{S_{l-1}}{(1+i)^{EOS}} \tag{D.5}$$

then $X - Y$ can be written as

$$X - Y = \frac{E_T}{(1+i)^T} + \frac{S_l}{(1+i)^{EOS}} - \frac{S_{l-1}}{(1+i)^{EOS}} \tag{D.6}$$

$M(T) - M(T-1)$ is therefore equal to

$$= \frac{i(1+i)^{T-1}}{(1+i)^T - 1} \times \frac{i}{(1+i)^T - 1} \times \left(\left(\frac{E_T}{(1+i)^T} + \frac{S_l - S_{l-1}}{(1+i)^{EOS}}\right) \times \frac{(1+i)^T - 1}{i} - X\right)$$

$$= \left(-C + \sum_{t=1}^{T} \frac{E_T - E_t}{(1+i)^t} - \frac{S_l}{(1+i)^{EOS}} + \frac{S_l - S_{l-1}}{(1+i)^{EOS}} \times \frac{(1+i)^T - 1}{i}\right)$$

$$\times \frac{i(1+i)^{T-1}}{(1+i)^{T-1} - 1} \times \frac{i}{(1+i)^T - 1} \tag{D.7}$$

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