Study on Multi-objective Optimization Model of Inventory Control and Supplier Selection Problem Under Uncertainty

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Study on Multi-objective Optimization Model of Inventory Control and Supplier Selection Problem Under Uncertainty

Doctoral Thesis

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(800 words)

Most companies are now facing dynamic challenges that require not only well-planning capacity, but also robust supply chain networks (SCN) that allow the members involved to address and respond any changes in a short notice. In particular, when inventory is stuck in the various stages of the supply chain, the company may be forced to operate at critical cash flow levels. On the other hand, among the various activities involved in SCN, purchasing is one of the most strategic functions because it provides opportunities to reduce costs across the entire supply chain. An essential task within the purchasing function is supplier selection. This comes from the fact that the cost of raw materials and component parts represents the largest percentage of the total product cost in most industries. From this point of view, this thesis addresses issues associated with inventory and supplier selection problem. We study both issues under uncertain environment and consider such problem using either stochastic approach or fuzzy approach.

At the first part, we studies multi-objective problem of periodic review inventory in two-echelon supply chain system under uncertainty in demand and lead time. We propose different strategies to solve the stock-out problem in serial replenishment system which requires a higher level of coordination. While stochastic approach is utilized to tackle the uncertainty, the multi-objective Differential Evolution (DE) is applied after giving its new algorithm to work with the problem. We reveal that the coordination strategy becomes more effective as the uncertainty increases in the system. Though retailers are required to keep a bit high inventory level to maintain a high responsiveness, this stock level is more effective to reduce the loss rate of supply chain.

At the second part, we studied multi-objective supplier selection by considering both qualitative and quantitative criteria. The fuzzy approach is applied due to the fact that most information required to assess supplier is not always available and/or usually not known precisely over the planning horizon. Concerning such characteristics, this research develops an integrated methodology of fuzzy multi-objective linear programming model for supplier selection. To improve the methodological process of deriving optimal solution, the enhanced two-phase fuzzy programming model has been proposed in this study. Through numerical experiment, we show some advantages of our proposed approach over the existing methods in providing a set of potential feasible solutions which guide DMs to select the best solution according to their preference.

At last part, we present multi-objective possiblistic mixed integer programming (MOPMIP) model of periodic review inventory problem in multi-manufacturer multi-retailer SCN. We attempt to develop a multi-objective model in a mixed imprecise and/or uncertain environment by incorporating the fuzziness of demand, lead time and cost parameters. A solution procedure is developed using the Torabi and Hassini method to solve the model and to provide a systematic framework that facilitates the fuzzy decision-making process while enabling the DM to adjust the decision and obtaining a more preferred satisfactory solution. The proposed solution procedures obtain a promising result which produces more balanced feasible solutions and provide decision support to identify critical objective in both decentralized and centralized SCN.

Moreover, as a supplementary consideration, we consider daily planning for three echelon SCN considering inventory conditions. To cope with the problem, we applid a practical hybrid meta-heuristic method that supports decision making at a tactical and operational level. Its solution procedure is developed by means of two modified heuristic methods known as the saving method and tabu search together with the graph algorithm of minimum cost flow problem. Finally, to enhance usability of the method, visualization of result is also realized by virtue of Google map API. Numerical experiments are carried out to validate effectiveness of the proposed approach.

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Chapter 1

INTRODUCTION

1.1. Background

In today's competitive environment characterized by low profit margins and high responsiveness to consumer demand for high quality products and shorter lead-times, companies are forced to manage their competitive advantage and opportunity to optimize their business processes. Manufacturing enterprises along with their distribution systems face dynamic challenges that require not only well-planning capacity, but also robust SC networks with coordination mechanisms that allow the members involved in such networks to address and respond to any changes in a short notice. From radical volume changes in customer demand, to variations in prices of raw material and finished products due to currency fluctuations in the global marketplace, to increases in transportation costs due to speculation in the price of crude oil, any number of factors can have a serious effect on corporate revenue projections. In particular, when inventory is stuck in the various stages of the supply chain, the company may be forced to operate at critical cash flow levels. As known, high inventory levels increase the responsiveness of the supply chain but decrease its cost efficiency because of the cost of holding inventory. In this situation, the ability to intelligently address critical issues through effective supply chain inventory and distribution strategies not only keeps the wheels of business turning, but it also gives the company a relative advantage over its competitors in being able to address supplier concerns and consumer needs in a way that slower, less agile manufacturers are unable to do. Hence, a relevant problem in SC network is to determine the appropriate levels of inventory at the various stages involved in a supply chain.

Of the various activities involved in SC network, purchasing is one of the most strategic functions because it provides opportunities to reduce costs across the entire supply chain. An essential task within the purchasing function is supplier selection, given that the cost of raw materials and component parts represents the largest percentage of the total product cost in most industries. For instance, in high technology firms, purchased materials and services account for up to 80% of the total product cost [1]. In contemporary supply chain management, companies maintain long term partnership with suppliers, and use fewer, but more reliable suppliers. The performance of potential suppliers is evaluated against multiple criteria rather than considering a single factor [2].

Given the prevalence of both inventory decisions and supplier selection in a supply chain, this study addresses both problems separately by studying a multi-objective inventory control problem and supplier selection problem in a typical two-echelon SC under uncertainty.

1.2. Research Scope and Objectives

Investment in inventory should neither be excessive nor inadequate. It should just be optimum. Maintaining optimum level of inventory is the main aim of inventory control system. Excessive investment in inventory slips the economical efficiency. At the same time, insufficient investment in inventory creates stock-out problems, interruption in production and selling operation. Therefore, the firm may loose the customers as they shift to the competitors.

While inventory has always been important, establishing and maintaining long term partnership with suppliers has also become important over the past several decades. Selecting the right supplier not only gives the companies the opportunity to reduce material cost, but also helps the companies to receive necessary products in a timely and effective manner to help maintain competitive advantage.

Based on the above description, this research addresses inventory control and supplier selection problem as follows:

In the first part, we develop multi-objective inventory control problem in two echelon supply chain under uncertainty in demand and lead time and proposes two inventory replenishment strategies, beside conventional strategy, with alternative supply possibilities to fulfill the shortage which involve different level of coordination mechanism between manufacturers and retailers. A multi-objective Differential Evolution (MODE) is introduced to solve the problem and multi-objective analysis is carried out to evaluate the performance of the system by simultaneously minimizing total cost and loss rate of the supply chain. The aim is to examine the situation when such coordination is profitable for all members in the system.

In the second part, we study a multi-objective supplier selection to determine the order quantity in a multi-sourcing environment. Specifically, this research focuses on fuzzy multi-objective linear programming (fuzzy MOLP) for solving supplier selection problem. Both quantitative and qualitative criteria are considered during the selection process and the fuzzy approach is utilized to cope with uncertainty issue. This research introduces an enhanced two-phase fuzzy MOLP to help obtain more reasonable compromise solutions.

In the third part, a periodic review inventory model in a typical SC system with multiple-manufacturer, multiple-retailer is considered. The aim of this paper is to develop a multi-objective periodic review inventory model in uncertain environment by simultaneously incorporating uncertainty in critical parameters. Unlike the research in the first part, which tackles the uncertainty using a stochastic approach, this research applies a fuzzy approach in coding the imprecise nature of demand, lead time and cost parameters. The problem is to determine ordering policy of raw material and the safety stock level of each manufacturer, and the order allocation and target stock level of each retailer that yield satisfactory minimum total cost while maintaining low loss rates. Several alternative solutions are obtained by solving a proposed multi-objective possibilistic mixed integer programming (MOPMIP) inventory model.

Towards future real world applications, it is of special importance to concern operational problems besides strategic ones considered in the above. Noticing such circumstance, and to enrich the prospects of this thesis, we also present a daily optimization of three echelon logistics as a supplemental concern. Developing a hybrid approach for efficient solution, we analyze an issue of inventory associates with demand deviations.

In detail, the main objectives of the proposed research are summarized as follow:

1. Develop a multi-objective inventory control model for two echelon supply chain under uncertainty utilizing three different scenarios of replenishment to fulfill the shortage and apply multi-objective Differential Evolution to yield several compromised solutions.
2. Develop solution procedures by enhancing a two-phase approach to solve the multi-objective supplier selection in a fuzzy environment incorporating both quantitative and qualitative criteria simultaneously.
3. Propose an integrated solution procedure of multi-objective possibilistic mixed integer programming (MOPMIP) inventory model to facilitate the fuzzy decision-making process in a multi-manufacturer multi retailer supply chain.

1.3. Overview of Thesis

This thesis is composed of seven chapters. The first chapter describes the introduction. It includes background, objectives of the thesis and overview of the thesis. Chapter two is concerned with literature review. This review includes the supply chain concepts, uncertainty in supply chain, inventory in supply chain, supplier selection, and the concept of multi-objective optimization. Chapter three presents a multi-objective Analysis of Periodic Review Inventory Problem with Coordinated Replenishment in Two-echelon Supply Chain System. Chapter four studies an enhanced two-phase fuzzy programming model for multi-objective supplier selection problem. Chapter five focuses on the application of possibilistic programming to solve fuzzy multi-objective inventory problem in two-echelon supply chain system. The conclusion and recommendation for further study are briefly discussed in Chapter six. Lastly, we present a hierarchical approach to optimize a daily logistics problem associated with inventory control against demand deviations in Appendix section.

Chapter 2

LITERATURE REVIEW

2.1. Supply Chain

The study about supply chains has grown very fast during this decade. Even so, there is no explicit description of supply chain management or its activities in the literature [3]. Each research defines the term supply chain, its processes and the complexities of the supply chain in different ways. The literature in this section starts by giving the definition of the supply chain and supply chain management and then describes the main process and the levels of the supply chain system.

2.1.1. Definition of Supply chain

Supply chains represent a coordinated network of firms interacting to provide a product or service to the end customer. They operate across functions within organizations, company boundaries, and national borders. A diagram illustrating the basic components of a supply chain is presented in Figure 2.1. Most of the supply chains have three basic components: suppliers, producers, and customer.

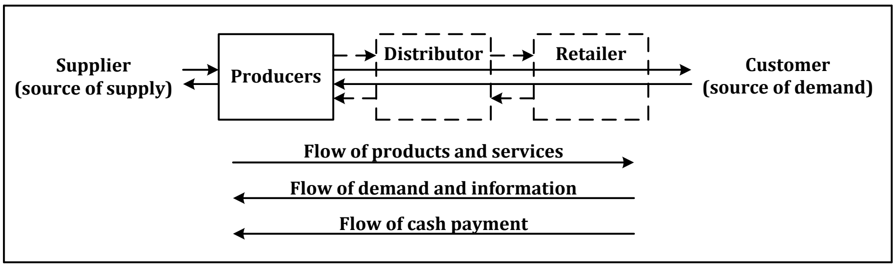


Figure 2.1. Supply chain

Supply chains often contain distributors and retailers along with service and support functions. The components of the supply chain must interact in a coordinated manner to achieve the ultimate goals: the delivery of goods and services resulting in the creation of customer satisfaction. Products and services generally flow from sources of supply to sources of demand, while information and cash payments generally flow in the reverse direction [4].

For many reasons, an interest in logistic and supply chain management has grown explosively in the last few years. Supply chain management is considered to be an extension of traditional logistics. Whereas logistics investigates the flow of information, materials, capital and manpower in the internal supply chain owned by a single firm; supply chain management deals with the coordination of logistic processes with in the external supply chain. The main goal of both traditional logistics and supply chain management is to deliver superior customer value at less cost to the supply chain as a whole. Unlike traditional logistics, supply chain management involves the coordination of independently managed companies who seek to maximize their own profits. Although overall performance of the supply chain depends on the company's joint performance, the operational goals may conflict and result in inefficiency for the entire chain. Therefore, one of the main issues in supply chain management is to find suitable mechanisms for coordinating the logistical processes that are controlled by various independent companies in order to achieve overall minimal cost and maximum profit.

Other interesting definitions of supply chain management are described by the following research. Simchi-Levi et al. [5] defined supply chain management as a set of approaches utilized to efficiently integrate suppliers, manufacturers, warehouses, and stores, so that merchandise is produced and distributed at the right quantities, to the right locations, and at the right time, in order to minimize system wide costs while satisfying service level requirements.

Scott and Westbrook [6] and New and Payne [7] described supply chain management as a chain linking each element of the manufacturing and supply process from raw materials through to the end customer, encompassing several organizational boundaries. According to this broad definition, supply chain management encompasses the entire value of the chain and addresses materials and supply management from the extraction of raw materials until the end of its useful life. Supply chain management focuses on how firms utilize their supplier's processes, technology, and capability to enhance competitive advantage and the coordination of the manufacturing, logistics, and materials management functions within and organization. When all strategic organizations in the value chain 'integrate' and act as a single unified entity, performance is enhanced throughout the system of suppliers.

2.1.2. Supply Chain Process

As briefly described earlier, a supply chain is an integrated manufacturing process wherein raw materials are converted into final products and then delivered to the customer. A supply chain is comprised of two basic, integrated processes: 1) the production planning and inventory control process, and 2) the distribution and logistics process.

1. The production planning and control process encompasses manufacturing and storage sub-processes, and their interface. In detail, production planning describes the design and management of the entire manufacturing process, including raw material scheduling and acquisition, manufacturing process design and scheduling and material handling design and control. Inventory control describes the design and management of storage policies and procedures for raw materials, work-in-process and final products inventory.

2. The distribution and logistics process determines how products are retrieved and transported from the warehouse to the retailer. These products may be transported to retailers directly, or may first be moved to distribution facilities, which, in turn, transport products to the retailers. This process includes the management of inventory retrieval, transportation, and final product delivery.

Both processes interact with one another to produce an integrated supply chain [8]. These processes are illustrated in Figure 2.2, providing the basic framework for the conversion and movement of raw materials into final products.

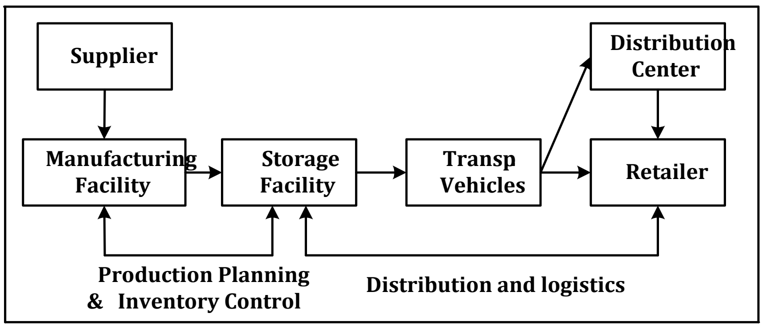


Figure 2.2. Supply chain process

2.1.3. Supply Chain System

The supply chain system as described by Harland [9] can be divided into 4 levels according to the scope of study of each researcher so that the term 'supply chain' represents different concepts relating to different spans of influence. The levels of supply chain system are illustrated in Figure 2.3.

1. Internal chain: the first level is the internal chain, which refers to the processes inside a manufacturing organization starting from ordering and receiving materials through the transformation processes of production, to the dispatch and physical distribution of the product to the customers.

2. Dyadic Relationship: the second level of supply chain system is called dyadic relationship, and is concerned with the relationship of two echelons in the supply chain, including the flow of material and information, purchasing procurement, stock level etc. Most of the research in a supply chain system focuses on this level.

3. External chain: the third level in a supply chain system is called an external chain. This views supply chains more holistically as the total chain of exchange from original source of raw material,

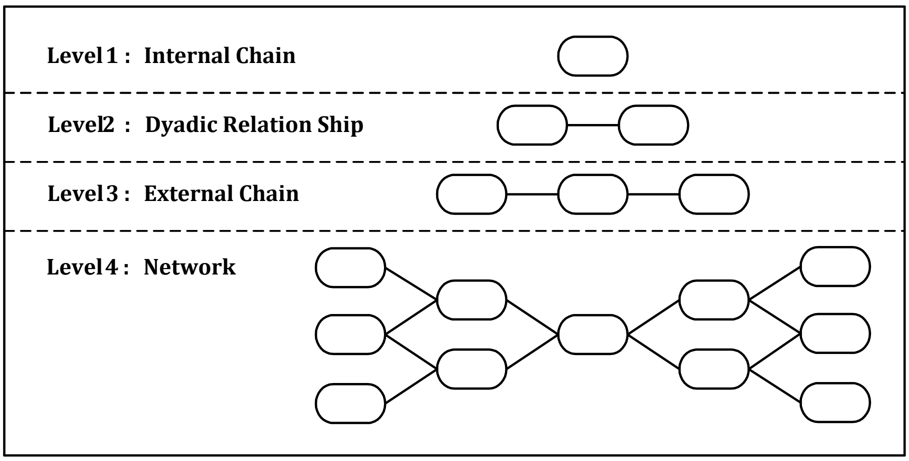


Figure 2.3. Levels of the supply chain

through the various firms involved in extracting and processing raw materials, manufacturing, assembling, distributing and retailing to ultimate end customers.

4. Network level: this level has undergone increased attention on the total focal firm network, not only concerned in a single chain. For example, it is the network of relationships that a firm has with its suppliers, its supplier's supplier and so on in upstream, and its customers and its customer's customer and so on in downstream.

2.2. Uncertainty in the supply chain system

Uncertainty rules the supply chain. Uncertainties in supply, process and demand are recognized to have a major impact on the supply chain. Uncertainty propagates throughout the network and leads to inefficient processing and non-value adding activities. Sales deviate from forecast, components are damaged in transit, fabrication yields fail to meet plan, shipments are held up in customs, are the most common events as direct results of uncertainty.

2.2.1. Types of uncertainty

Supply chain uncertainty can be classified into four general types: process, supply, demand, and control uncertainty. Below is the description of each type of uncertainty as cited from Geary et al. [10].

Process uncertainty. Process uncertainty affects a company's internal ability to meet a production delivery target. The amount of process uncertainty can be established by understanding each work process's yield ratios and lead time estimates for operations. Also, if the particular product delivery process is competing against other value streams for resources, then the interaction between these must be studied and codified.

Supply uncertainty. Supply uncertainty results from poorly performing suppliers due to their inability to meet company's requirements and thereby handicapping value-added processes. It can be evaluated by looking at supplier delivery performance, time series of orders placed or call-offs and deliveries from customers, actual lead times, supplier quality reports, and raw material stock time series.

Demand uncertainty. Demand uncertainty can be thought of as the difference between the actual end-marketplace demand and the orders placed with a company by its customers. Demand uncertainty can also be quantified by measuring how well companies meet customer demand. For example, poor on-time delivery or fill rates are often a result of demand uncertainty, though this is not always the case. If a customer suddenly places a weekly order that is twice the typical order size, it may be the result of a shift in underlying demand or it may just be that the customer has modified safety stocks or ordering rules.

Control uncertainty. Control uncertainty is associated with information flow and the way an organization transforms customer orders into production targets and supplier raw material requests. The level of control uncertainty can be determined by comparing customer requirements, supplier requests to deliver, and production targets over the same time periods. Control uncertainty is driven by the algorithms an control systems that are used to transfer the customer orders into production targets and supplier raw material requests. In a pure demand-pull environment, the linkage between supply and demand is clear and control uncertainty is eliminated. However, companies typically use order batching and lot sizing, which obscures the linkage between demands placed and true requirements.

Each of these uncertainties creates a drag on operational performance. However, supply chain professionals are often so busy dealing with the fallout from uncertainty (such as stock-outs, missed shipments, and oversupply) that they do not have time to attack the root cause of the problem. The issue has been complicated even further over the course of the last decade by the movement away from the vertically integrated supply chain. Now, rather than confronting the uncertainty generated just by activities within the operational domain of a single organization, we must manage uncertainty across a host of supply chain participants. Outsourcing, the virtual organization, and modular manufacturing all contribute to supply chain uncertainty issues. All of this makes it more important to understand the relationship between supply chain performance and uncertainty

2.2.2. Modeling uncertainty in the supply chain

With the growing attention paid in recent years to supply chain uncertainty, it is worth examining in more detail different models employed in the literatures to cope with uncertainty. There have been three broad philosophies on which several methods for optimization under uncertainties can be categorized: stochastic programming, fuzzy mathematical programming and chance constrained programming [11]. In this thesis, only the first two-approach will be discussed.

1. Stochastic programming model

Stochastic programming is a typical method of generating an operational plan within an uncertain environment when the precise probability distribution of future uncertainty is known in advance. Stochastic programming formulations assume that the probability distributions governing the uncertain data are known or can be estimated [12]. This means that historical record for the uncertain data is available, and this data is analyzed using statistical approach to approximate its future trend.

MirHassani et al. [13] considered a two-stage model for multi-period capacity planning of supply chain networks. Here the first stage decisions, comprised of openings and closings of the plants and distribution centers and setting their capacity levels, are to be decided prior to the realization of future demands. Then, based upon the particular demand scenario realized, the production and distribution decisions are to be decided optimally. The overall objective is to minimize the cost of the first-stage strategic decisions and the expected production and distribution costs over the uncertain demand scenarios. The authors used Benders decomposition to solve the resulting stochastic integer program, and presented computational results on supply chain networks involving up to 8 plant sites, 15 distribution centers, 30 customer locations, and with 100 scenarios.

Georgiadis et al. [14] considered a two-stage stochastic programming model for supply chain network design under demand uncertainty. The authors developed a large-scale mixed-integer linear programming model for this problem, and presented a case study using a European supply chain network involving 14 products, 18 customer locations, 6 distribution center locations, and 3 demand scenarios.

Alonso-Ayuso et al. [15] proposed a branch-and-fix heuristic for solving two-stage stochastic supply chain design problems. Computational results on networks involving 6 plants, 12 products, 24 markets, and 23 scenarios were presented.

2. Fuzzy programming model

Fuzzy mathematical programming is proliferated by Zimmermann [16, 17] by formulating mathematical programming model that takes into account (a) the decision maker's expectations of a target range of objective values and (b) soft constraints based on decision making in a fuzzy environment. In this approach, uncertain parameters are treated as fuzzy numbers and constraints are treated as fuzzy sets. The degree of satisfaction of a constraint is defined in terms of a normalized membership function of the constraint and a small extent of constraint violation is allowed while objective functions may be either a fuzzy goal or a crisp function. The advantage of fuzzy approach over the other two approaches mentioned earlier is that fuzzy approach neither assumes that the uncertain parameters have to follow any statistical distribution nor allows the final deterministic equivalent formulation of the uncertain model to blow up in size with increase in number of uncertain parameters. The disadvantage of the fuzzy approach lies in its inability to represent the exact nature of the uncertainty and the results could depend on the fuzzification approach.

Mitra et al. [11] formulated the mid-term planning problem in a multi-site, multi-product, multi-period supply chain under uncertainty using the fuzzy mathematical programming approach. They demonstrate that the fuzzy approach is quite generic, relatively simple to use and can be adapted for bigger size planning problems, as the equivalent deterministic problem does not blow up in size with increase in number of uncertain parameters while using fuzzy approach.

Liu and Sahinidis [18] solved a single objective capacity planning problem under uncertainty using fuzzy and two stage stochastic programming approaches and compared the performance of the two. Selim et al. [19] used fuzzy goal programming approaches in handling the multi-objective collaborative production–distribution planning problems in both centralized and decentralized supply chain design structures to make a comparative analysis between them.

Chen et al. [20] studied a multi-objective supply chain design problem for locating warehouses using two-phase fuzzy approach where they have used scenario-based approach to represent uncertainty in demand. Liang [21] developed an interactive fuzzy multi-objective linear programming method to simultaneously minimize the total distribution costs and the total delivery time with reference to fuzzy available supply and total budget at each source, and fuzzy forecast demand and maximum warehouse space at each destination.

2.3. Inventory in the Supply Chain System

Inventory is the stock of any resource used in a company. An inventory system is the set of policies and controls that monitor levels of inventory and determine what levels should be maintained, when stock should be replenished, and how large orders should be.

By convention, manufacturing inventory generally refers to items that contribute to or become part of a company's product output. Manufacturing inventory is typically classified into raw materials, finished products, component parts, supplies, and work-in-process. In distribution, inventory is classified as in-transit, meaning that it is being moved in the system, and warehouse, which is inventory in a warehouse or distribution center. Retail sites carry inventory for immediate sale to customers. In services, inventory generally refers to the tangible goods to be sold and the supplies necessary to administer the service.

The basic purposes of inventory analysis are to specify (1) when items should be ordered and (2) how large the order should be. Many firms are tending to enter into longer-term relationships with vendors to supply their needs for perhaps the entire year. This changes the "when" and "how many to order" to "when" and "how many to deliver."

Inventory decisions involve high risk and high impact for the supply chain management. Inventory committed to support future sales, drives a number of anticipatory supply chain activities. Without a proper inventory assortment lost sales and customer dissatisfaction may occur. Likewise, inventory planning is critical to manufacturing. Material or component shortages can shut down a manufacturing line or force modification of a production schedule, which creates added cost and potential finished goods shortage. Just as a shortage can disrupt planned marketing and manufacturing operations, inventory overstocks also create operating problems. Overstocks increase cost and reduce profitability as result of increasing warehousing, working capital, insurance, taxes, and obsolescence. This section reviews the inventory management according to different configuration structure of supply chain as follow:

2.3.1. Inventory in the Dyadic Supply Chain

Newhart et al. [22] designed an optimal supply chain using a two- phase approach. The first phase combines mathematical program and heuristic model with the objective of minimizing the number of distinct product types held in inventory throughout the supply chain. The second phase is a spreadsheet based inventory model, which determines the minimum amount of safety stock required to absorb demand and lead time fluctuations.

Pyke and Cohen [23] developed a heuristic algorithm for determining reorder at warehousing and orders up to levels S for retailer. The system is a three level supply chain, consisting of one product, one manufacturer, one warehousing and one retailer. Warehouse uses (Qn, R) system where retailer uses periodic review with order up to level (T, S). The model minimizes total cost, subject to a service level constraint, and holds the set up times, processing times, and replenishment lead times constant.

Pyke and Cohen [24] furthered their study on integrated production and distribution for multi-products in the three echelons supply chain system. The system consists of a factory, a finished good stockpile and a single retailer. The finished good stockpile uses a (Q, R) system to control inventory, factory orders at Q when stock reach reorder point R and a retailer uses a base stock inventory with an order up to level S or (T, S) policy. The system allows the retailer to make a second order if shortage has occurred. They developed an algorithm to determine order up to level at the retailer, normal and expedite replenishment reorder point and normal and expedite replenishment batch size for each product.

Altiok and Ranjan [25] considered a production and distribution system. The system experiences demand for finished products according to a compound Poisson process. The inventory levels for inventories are controlled according to a continuous review (R, r) inventory policy. Backorders are allowed in their study.

Ishii et al. [26] developed a deterministic model, known as a demand process, for determining the base stock levels and lead-times associated with the lowest cost solution and integrated with the lowest cost solution for an integrated supply chain on a finite horizon. The stock levels and lead-times are determined in such a way as to prevent stock out, and to minimize the amount of obsolete inventory at each stock point.

Khouja et al. [27] tried to solve the economic lot size-scheduling problem (ELSP) for multi-products system by using Genetic Algorithm (GA). They used a GA to solve the optimal floating cycle time and economic lot size or integer multipliers of a basic period for each product. They compared the result of using GA with the result from using dynamic programming. Dynamic Programming (DP) allows for a time-varying lot size approach with a fixed cycle time, but GA optimizes floating cycle time and fixed economic lot size for the whole cycle time. They concluded that the resulting solutions from GA were better than those obtained using DP.

2.3.2. Inventory in the Supply Chain network

Ganeshan [28] presented a near-optimal (*s, Q*) type of inventory-logistics cost minimizing model for a production/distribution network with multiple suppliers supplying a distribution center, which in turn distributes to a large number of identical retailers. The decisions in the model were made through a comprehensive distribution-based cost framework that includes the inventory, transportation, and transit components of the supply chain.

Gjerdrum et al. [29] studied the replenishment control system in a supply chain network. The agent types in this supply chain network consists of two factories, two warehouses, external logistic, internal logistic, spot market and transportation. The objective of this supply chain network system is to reduce operating cost, while maintaining a high level of customer order fulfillment.

Miranda and Garrido [30] studied three echelon supply chain network in which a single plant supplied products to multi-regional warehouses, and distributed products to multi-retailers or customers. They proposed a simultaneous approach to incorporate inventory control decisions which are economic order quantity and safety stock. They presented a nonlinear mixed integer model and a heuristic solution approach, based on Lagrangian relaxation and the subgradient method. They found that the potential cost reduction, compared to the traditional approach, increases when the holding cost and/or the variability of demand are higher.

Seferlis and Giannelos [31] studied the four-echelon supply chain network that consisted of two production modes, two warehouse nodes, four distribution centers and sixteen retailer nodes. The optimization-based control scheme aimed at adjusting the decision variables in the supply chain (e.g. transportation load, production inventory) to satisfy the customer orders with the least operating cost over a specified rolling time horizon using a detailed different model of the system. Simulation results exhibited good dynamic performance under both stochastic and determination variation.

2.4. Suppliers Selection

Supplier selection is the process by which companies identify, evaluate, and contract with suppliers. The supplier selection process deploys a tremendous amount of a company's financial resources. In return, companies expect significant benefits from contracting with suppliers offering high value.

Several factors make new suppliers important. First, there may exist new suppliers that are superior in some way to a company's existing suppliers. For example, a new supplier may have developed a novel production technology or streamlined process which allows it to significantly reduce its production costs relative to predominate production technology or processes. Or, a new supplier may have a structural cost advantage over existing suppliers, for example, due to low labor costs or favorable import/export regulations in its home country. Second, existing suppliers may go out of business, or their costs may be increasing. Third, the buyer may need additional suppliers simply to drive competition, reduce supply disruption risks, or meet other business objectives such as supplier diversity. In recognition of these reasons, buyers and their internal customers may be obliged by company policy to locate a minimum number of viable, potential suppliers for every product or service procured.

Finding a viable new supplier is challenging due to the need to verify the supplier's ability to meet the buyer's requirements [32]. Supplier non-performance on even the most basic level, and for the most-simple commodity, can have dire consequences for the buyer. Boeing's 787 Dreamliner production schedule was significantly affected by shortages of fasteners, essentially bolts that secure sections of the fuselage together [33]. In consumer products many product safety issues have been traced back to suppliers failing to meet a buyer's requirements, resulting in dangerous lead paint in toys [34], unsafe car tires [35], and pet food containing poisonous chemicals [36].

Production delays due to parts shortages and recalls of faulty products produced by noncompliant suppliers have cost buyer firms millions of dollars through recalls, warranty costs, and associated inventory adjustments, and have inflicted untold damage on their reputations and future sales potential. New Jersey based tire importer Foreign Tire Sales traced field failures of its tires to an unauthorized design change made by its supplier, whose design engineer decided to omit gum strips, apparently unaware of their role in preventing tread separation [35]. A surprised Foreign Tire Sales was forced by U.S. government authorities to recall a quarter of a million tires, and risked bankruptcy as a result [37].

2.4.1. Supplier Selection Criteria

Supplier selection decisions are complicated by the fact that various criteria must be considered in the decision making process. The analysis of criteria for selection and measuring the performance of suppliers has been the focus of many scientists and purchasing practitioners since 1960's.

Supplier selection criteria for a particular product or service category should be defined by a "cross-functional" team of representatives from different sectors within the company. In a manufacturing company, for example, members of the team typically would include representatives from purchasing, quality, engineering and production. Team members should include personnel with technical/applications knowledge of the product or service to be purchased, as well as members of the department that uses the purchased item.

An interesting work, which has been adopted as reference for the majority of papers dealing with supplier problem, was presented by Dickson [38]. Dickson's study was based on questionnaires sent to 273 purchasing agents and managers selected form the membership list of the National Association of Purchasing managers. The list included purchasing agents and managers from the United States and Canada. From the returned 170 questionnaires, the total of 23 criteria was regarded to be the most considered criteria for supplier selection. Indeed, the 23 criteria are ranked with respect to their importance observed in the beginning of the sixties. At the time (1966), the most significant criteria were "quality" of the product, the "on-time delivery", the "performance history" of the supplier and the warranty policy used by the supplier. The complete list of there criteria can be found in Table 2.1.

In [39], the authors present a classification of all the articles published since 1966 according to the treated criteria. Based on 74

Table 2.1. Dickson' 23 criteria for supplier selection

Rank	Criteria	Rating	Evaluation
1	Quality	3.508	Extreme importance
2	Delivery	3.147	
3	Performance history	2.998	
4	Warranty and claim policies	2.849	
5	Production facility and capacity	2.775	Considerable importance
6	Price	2.758	
7	Technical capability	2.545	
8	Financial position	2.514	
9	Procedural compliance	2.488	
10	Communication system	2.426	
11	Reputation and position in industry	2.412	
12	Desire of business	2.256	
13	Management and organization	2.216	
14	Operating controls	2.211	
15	Repair service	2.187	Average importance
16	Attitude	2.120	
17	Impression	2.054	
18	Packaging ability	2.009	
19	Labor relations record	2.003	
20	Geographical location	1.872	
21	Amount of past business	1.597	
22	Training aids	1.537	
23	Reciprocal arrangement	0.006	Slight importance

papers, they observed that “price”, ”delivery”, ”quality” and “production capacity and location” are the criteria most often treated in the literature.

Overall, the 23 criteria presented by Dickson still cover the majority of the criteria presented in the literature until today. On the other hand, the evolution of the industrial environment modified the degrees of the relative importance of these criteria. For example, Weber [39] insists on the high importance of the geographical position of the supplier in Just-in-Time environment, whereas this criterion appeared in the 20th position in 1966. Also, the criterions in the 10th, 12th, 13th position (communication system, desire of business, management and organization), of the Dickson’s study, are very important for the actual industrial environment. Indeed, the actual situation requires a perfect coordination and a durable cooperation between various actors of the supply chain.

2.4.2. Supplier Selection Methods

Several well-known supplier selection methods have been developed and classified by numerous scholars over the years. Certain methods have been popular selection choices for years, while other methods have only emerged recently.

As cited from Ho et al. [40], the classification of supplier selection methods are described briefly in as follow.

1. Data envelopment analysis (DEA)

Braglia and Petroni [41] applied DEA to measure the efficiencies of alternative suppliers. Nine evaluating factors were proposed to measure each supplier rating. To avoid selecting a sub-optimal or ‘‘false positive” supplier, both cross-efficiency and Maverick index were measured.

Narasimhan et al. [42] applied DEA model to evaluate alternative suppliers for a multinational corporation in the telecommunications industry. Eleven evaluating factors were considered in the model, in which there are six inputs related to the supplier capability, and five outputs related to the supplier performance. Based on the performance score, the suppliers were classified into four categories: high performers and efficient, high performers and inefficient, low performers and efficient, and low performers and inefficient.

Ross et al. [43] used DEA to evaluate the supplier performance with respect to both buyer and supplier performance attributes. Three sensitivity analyses were carried out. The first analysis was to compute the supplier efficiency scores without considering the evaluation team's weights and bounds. The second analysis considered the evaluation team's preferences on the supplier performance attributes, whereas the third analysis considered the buyer's preferences on the supplier performance attributes.

Wu et al. [44] presented a so-called augmented imprecise DEA for supplier selection. The proposed model was able to handle imprecise data (i.e., to rank the efficient suppliers) and allow for increased discriminatory power (i.e., to discriminate efficient suppliers from poor performing suppliers). A web-based system was developed to allow potential buyers for supplier evaluation and selection.

2. Mathematical programming

Hong et al. [45] presented a mixed-integer linear programming model for the supplier selection problem. The model was to determine the optimal number of suppliers, and the optimal order quantity so that the revenue could be maximized. The change in suppliers' supply capabilities and customer needs over a period of time were considered.

Ghodsypour and O'Brien [46] formulated a mixed integer non-linear programming model to solve the multi-criteria sourcing problem. The model was to determine the optimal allocation of products to suppliers so that the total annual purchasing cost could be minimized. Three constraints were considered in the model.

Karpak et al. [47] constructed a goal programming (GP) model to evaluate and select the suppliers. Three goals were considered in the model, including cost, quality, and delivery reliability. The model was to determine the optimal amount of products ordered, while subjecting to buyer's demand and supplier's capacity constraints.

Narasimhan et al. [48] constructed a multi-objective programming model to select the optimal suppliers and determine the optimal order quantity. Five criteria were proposed to evaluate the performance of suppliers. Before solving the model to optimality, the relative importance weightings of five criteria were derived in advance. The authors suggested that AHP could be one of the possible ways for generating the weightings.

3. Case-based reasoning

Choy and Lee [49] presented a generic model using the CBR technique for supplier selection. Various evaluating criteria were grouped into three categories: technical capability, quality system, and organizational profile. The model was implemented in a consumer products manufacturing company, which had stored the performance of past suppliers and their attributes in a database system. The proposed model would then retrieve or select a supplier who met the specification predefined by the company most.

Choy et al. [50] applied the CBR-based model to aid decision makers in the supplier selection problem again. The approach was very similar to that proposed in Choy and Lee [51], including the supplier selection workflow. In addition, the model was deployed to the same company.

4. Analytical hierarchy process (AHP)

Muralidharan et al. [52] proposed a five-step AHP-based model to aid decision makers in rating and selecting suppliers with respect to nine evaluating criteria. People from different functions of the company, such as purchasing, stores, and quality control, were involved in the selection process.

Akarte et al. [53] developed a web-based AHP system to evaluate the casting suppliers with respect to 18 criteria. In the system, suppliers had to register, and then input their casting specifications. To evaluate the suppliers, buyers had to determine the relative importance weightings for the criteria based on the casting specifications, and then assigned the performance rating for each criterion using a pairwise comparison.

Chan [54] developed an interactive selection model with AHP to facilitate decision makers in selecting suppliers. The model was so-called because it incorporated a method called chain of interaction, which was deployed to determine the relative importance of evaluating criteria without subjective human judgment. AHP was only applied to generate the overall score for alternative suppliers based on the relative importance ratings.

5. Fuzzy set theory

Chen et al. [55] presented a hierarchy model based on fuzzy-sets theory to deal with the supplier selection problem. The linguistic values were used to assess the ratings and weights for the supplier evaluating factors. These linguistic ratings could be expressed in trapezoidal or triangular fuzzy numbers. The proposed model was capable of dealing with both quantitative and qualitative criteria.

Sarkar and Mohapatra [56] suggested that performance and capability were two major measures in the supplier evaluation and selection problem. The authors used the fuzzy set approach to account for the imprecision involved in numerous subjective characteristics of suppliers. A hypothetical case was adopted to illustrate how the two best suppliers were selected with respect to four performance-based and ten capability-based factors.

Florez-Lopez [57] picked up 14 most important evaluating factors from 84 potential added-value attributes, which were based on the questionnaire response from US purchasing managers. To obtain a better representation of suppliers' ability to create value for the customers, a two-tuple fuzzy linguistic model was illustrated to combine both numerical and linguistic information. Besides, the proposed model could generate a graphical view showing the relative suitability of suppliers and identifying strategic groups of suppliers.

6. *Integrated approaches*

Sevkli *et al.* [58] applied an integrated AHP–DEA approach for supplier selection. In the approach, AHP was used to derive local weights from a given pairwise comparison matrix, and aggregate local weights to yield overall weights. Each row and column of the matrix was assumed as a decision making unit (DMU) and an output, respectively. A dummy input that had a value of one for all DMUs was deployed in DEA to calculate the efficiency scores of all suppliers. However, the authors pointed out that the approach was relatively more cumbersome to apply than the individual AHP.

Kull and Talluri [59] utilized an integrated AHP – Goal Programming approach to evaluate and select suppliers with respect to risk factors and product life cycle considerations. In the proposed model, AHP was used to assess suppliers along the risk criteria, and to derive risk scores. The GP model was then constructed to evaluate alternative suppliers based on multiple risk goals and various hard constraints.

Xia and Wu [60] incorporated AHP into the multi-objective mixed integer programming model for supplier selection. The model applied AHP to calculate the performance scores of potential suppliers first. The scores were then used as coefficients of one of the four objective functions. The model was to determine the optimal number of suppliers, select the best set of suppliers, and to determine the optimal order quantity.

Chan and Kumar [61] also used a fuzzy AHP for supplier selection as the case with Kahraman et al. [50]. In the proposed approach, triangular fuzzy numbers and fuzzy synthetic extent analysis method were used to represent decision makers' comparison judgment and decide the final priority of different criteria.

Amid et al. [62] developed a fuzzy multi-objective linear programming model for supplier selection. The model could handle the vagueness and imprecision of input data, and help the decision makers to find out the optimal order quantity from each supplier. Three objective functions with different weights were included in the model. An algorithm was developed to solve the model.

2.5. Multi-objective Optimization

A multi-objective problem (MOP) deals with more than one objective function. Most real world problems involve the simultaneous optimization of two or more (often conflicting) objectives. The solution of such problems (called "multi-objective") is different from that of a single-objective optimization problem. The main difference is that multi-objective optimization problems normally have not one but a set of solutions which are all equally good.

2.5.1. Multi-objective Optimization Problem

As cited from Shimizu et al. [63], a MOP can be described as a triplet like (*x, f, x*), similar to the usual single-objective optimization. However, it should be noticed that the objective function in this case is not a scalar but a vector. Consequently, the MOP is written, in general, by

$$[\mathit{Problem}]\ \min f(x) = \{f_1(x), f_2(x), \ldots, f_N(x)\}$$
$$\text{subject to } x \in X,$$

where *x* denotes an *n*-dimensional decision variable vector, *X* a feasible region defined by a set of constraints, and *f* an *N*-dimensional objective function vector, some elements of which conflict and are incommensurable with each other.

The conflicts occur when one tries to improve a certain objective function, at least one of the other objective functions deteriorates. As a typical example, if one weighs on the economy, the environment will deteriorate, and *vice versa*. On the other hand, the term incommensurable means that the objective functions lack a common scale to evaluate them under the same standard, and hence it is impossible to incorporate all objective functions into a single objective function. For example, environmental impact cannot be measured in terms of money, but money is usually used to account economic affairs.

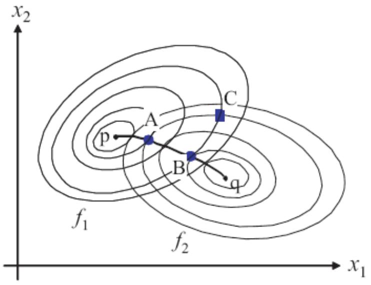


Figure 2.4. Optimal solution in decision space
(Source: Shimizu et al.[63])

To grasp the entire idea, let us illustrate the feature of MOP schematically. Figure 2.4 describes the contours of two objective functions $f1$ and $f2$ in a two-dimensional decision variable space. There, it should be noted that it is impossible to reach the minimum points of the two objective functions p and q simultaneously.

Here, let us make a comparison between three solutions, A, B and C. It is apparent that A and B are superior to C because $f1(A) < f1(C)$, and $f2(A) = f2(C)$, and $f1(B) = f1(C)$, and $f2(B) < f2(C)$. We call A and B as non-dominated solution. Thus we can rank the solutions from these comparisons. However, it is not true for the comparison between A and B. We cannot rank these as just the magnitudes of the objective values because $f1(A) < f1(B)$, and $f2(A) > f2(B)$. Likewise, a comparison between any solutions on the curve, p − q, which is a trajectory of the tangent of both contour curves is impossible. These solutions are known as Pareto optimal solutions. Such a Pareto optimal solution (POS) becomes a rational basis for MOP since any other solutions are inferior to every POS. It should be also recalled, however, that there exist infinite POSs that are impossible to rank. Hence the final decision is left unsolved.

To understand intuitively the POS as a key issue of MOP, it is depicted again in Figure 2.5 in the objective function space when N =

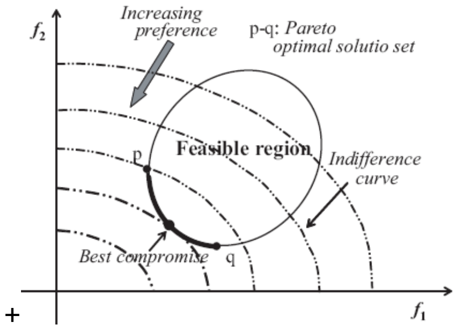


Figure 2.5. Idea of solution procedure in objective space
(Source: Shimizu et al.[63])

2. From this, we also know that there exist no solutions that can completely outperform any solution on the POS set (also called Pareto front). For any solution belonging to the POS set, if we try to improve one objective, the rest of the objectives are urged to degrade.

It is also apparent that it never provides a unique or final solution for the problem under consideration. For the final decision under multi-objectives, therefore, we have to decide a particular one among an infinite number of POSs. For this purpose, it is necessary to reveal a certain value function of decision maker (DM) either explicitly or implicitly. This means that the final solution will be derived through the tradeoff analysis among the conflicting objectives by the DM. In other words, the solution process needs a certain subjective judgment to reflect the DM's preference in addition to the mathematical procedures [63].

2.5.2. Multi-objective versus single-objective Optimization

Besides having multiple objectives, there are a number of fundamental differences between single-objective and multi-objective optimization.

In single objective optimization, there is one goal – the search for the optimum solution. Although the search space may have a number of local optimal solutions, the goal is always to find the global optimal solution. However, in multi-objective optimization, there are clearly two goals. Progressing toward the optimal front is certainly an important goal. However, maintaining a diverse set of solutions in the Pareto front is also essential [64]. An algorithm that finds a closely packed set of solution in Pareto optimal front satisfies the first goal of convergence of the solutions, but does not satisfy maintenance of a diverse set of solutions. Since all objective are important, the diverse set of the obtained solutions close to the Pareto front provide a variety of optimal solutions, trading objective differently.

Since both goals are important, an efficient multi-objective optimization algorithm must work on satisfying both of them. It is important to realize that both of these tasks are somewhat orthogonal to each other. The achievement of one goal does not necessarily achieve the other goal. Explicit or implicit mechanisms to emphasize convergence near the optimal Pareto front and the maintenance of a diverse set of solutions must be introduced in an algorithm. Because of these dual tasks, multi-objective optimization is more difficult than single objective optimization.

Another difficulty is that multi-objective optimization involves two search space, instead of one. In single objectives optimization, there is only one search space – the decision variable space. An algorithm works in this space by accepting and rejecting solutions based on their objective function values. Here in addition to the decision variable space, there also exists the objective or criterion space. Although these two spaces are related by a unique mapping between them, often the mapping is non-linear and the properties of the two search spaces are not similar. For example, proximity of two solutions in one space does not mean proximity in the other space. Thus, while achieving the second task of maintaining diversity in the obtained set of solutions, it is important to decide the space in which the diversity must be achieved.

In any optimization algorithm, the search is performed in the decision variable space. However the proceeding of an algorithm in the decision variable space can be traced in the objective space. In some algorithms, the resulting proceedings in the objective space are used to steer the search in the decision variable space. When this happens, the proceedings in both spaces must be coordinated in such away that the creation of new solution is complimentary to the diversity needed in the objective space. This, by no means, is an easy task and depends on the mapping between the decision variables and the objective function values.

2.5.3. Search and decision making

In solving an MOP, two conceptually distinct types of problem difficulty can be identified [65]: search and decision making. The former refers to the optimization process in which the feasible set is sampled for Pareto optimal solutions. Even in single-objective optimization, large and complex search spaces can make search difficult and preclude the use of exact optimization methods like linear programming [66]. The latter addresses the problem of selecting a suitable compromise solution from the Pareto-optimal set. The decision maker is necessary to make the often difficult trade-offs between conflicting objectives.

Depending on how optimization and the decision process are combined, multi-objective optimization methods can be broadly classified into three categories [67, 68]:

- **Decision making before search:** The objectives of the MOP are aggregated into a single objective which implicitly includes preference information given by the decision maker.
- **Search before decision making:** Optimization is performed without any preference information given. The result of the search process is a set of (ideally Pareto-optimal) candidate solutions from which the final choice is made by the decision maker.
- **Decision making during search:** The decision maker can articulate preferences during the interactive optimization process. After each optimization step, a number of alternative trade-offs is presented on the basis of which the decision maker specifies further preference information, respectively guides the search.

The aggregation of multiple objectives into one optimization criterion has the advantage that the classical single-objective optimization strategies can be applied without further modifications. However, it requires profound domain knowledge which is usually not available. For example, in computer engineering design space exploration specifically aims at gaining deeper knowledge about the problem and the alternative solutions.

Performing the search before decision making overcomes this drawback, but excludes DM's preference articulation which might reduce the search space complexity. Another problem with this and also the third algorithm category might be the visualization and the presentation of non-dominated sets for higher dimensional MOPs. Finally, the integration of search and decision making is a promising way to combine the other two approaches, uniting the advantages of both [68].

2.5.4. Concept of domination

Most multi-objective optimization algorithms use the concept of domination. In these algorithms, two solutions are compared on the basis of whether one dominates the other solution or not. We assume that there are M objective functions. In order to cover both minimization and maximization of objective functions, we use the operator $\triangleleft$ between solution i and j as $i \triangleleft j$ to denote that solution i is better than solution j on a particular objective. Similarly, $i \triangleright j$ for a particular objective implies that solution i is worse than solution j on this objective. For example, if an objective function is to be minimized, the operator $\triangleleft$ would be mean the "<" operator, whereas if the objective function is to be maximized, the operator $\triangleleft$ would mean the ">" operator. The following definition covers mixed problems with the minimization of some objective functions and maximization of the rest of them.

A solution $\mathbf{x}^{(1)}$ is said to dominate the other solution $\mathbf{x}^{(2)}$, if both condition 1 and 2 are true:

1. The solution $\mathbf{x}^{(1)}$ is no worse than $\mathbf{x}^{(2)}$ in all objectives, or $f_j(\mathbf{x}^{(1)}) \not\triangleright f_j(\mathbf{x}^{(2)})$ for all j = 1,2,…,M.
2. The solution $x^{(1)}$ is strictly better than $x^{(2)}$ in at least one objective, or $f_j(\mathbf{x}^{(1)}) \triangleleft f_j(\mathbf{x}^{(2)})$ for at least one $j \in \{1,2,\ldots,M\}$.

If any of the above condition is violated, the solution $\mathbf{x}^{(1)}$ does not dominate the solution $\mathbf{x}^{(2)}$. If $\mathbf{x}^{(1)}$ dominates the solution $\mathbf{x}^{(2)}$, it is also customary to write any of the following:

- $\mathbf{x}^{(2)}$ is dominated by $\mathbf{x}^{(1)}$;

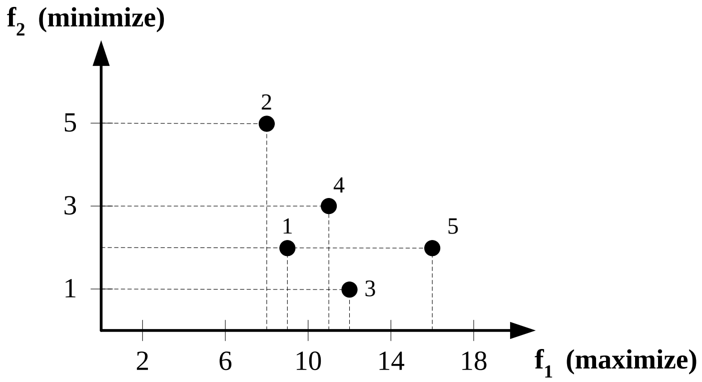


Figure 2.6. Illustration of domination concept

- $\mathbf{x}^{(1)}$ is non-dominated by $\mathbf{x}^{(2)}$, or;
- $\mathbf{x}^{(1)}$ is non-inferior to $\mathbf{x}^{(2)}$.

Let us consider a two-objective optimization with five different solutions shown in the objective space, as illustrated in Figure 2.6. Let us also assume that the objective function 1 is needs to be maximized while the objective function 2 needs to be minimized. Five solutions with different objective function values are shown in this figure. Since both objective functions are of important to us, it is usually difficult to find one solution which is the best with respect with both objectives. However, we can use the above definition of domination to decide which solution is better among any two given solutions in term of both objectives. For example, if solution 1 and 2 are to be compared, we observe that solution 1 is better than solution 2 in objective function 1 and solution 1 is also better than solution 2 in objective function 2. Thus, both the above conditions are satisfied and we may write the solution 1 dominates solution 2. We take another instance of comparing solution 1 and solution 5. Here, solution 5 is better than solution 1 in the first objective and solution one is no worse (in fact they are equal) than solution 1 in the second objective. Thus, both the above conditions for domination are also satisfied and we may write that solution 5 dominates solution 1. Moreover, if we compare solution 1 and solution 4, we can see that solution one is better than solution 4 in objective function 1, but solution 1 is worse than solution 4 in objective function 2. Thus, the above conditions are violated. In this case, we say that solution 1 and solution 4 are non-dominated solutions.

Chapter 3

MULTI-OBJECTIVE PERIODIC REVIEW INVENTORY WITH COORDINATED REPLENISHMENT IN TWO-STAGE SUPPLY CHAIN TROUGH DIFFERENTIAL EVOLUTION

3.1. Introduction

In today's globalization, every supply chain is expected to minimize the system wide cost including inventory cost along the supply chain while minimizing loss rate to meet customer demand as much as possible. This is because recent innovative technologies have shortened the product life cycle and increased the demand variability. The excess inventory in the supply chain block the cash flow and indeed gives an adversely effect on the enterprise.

It is difficult to determine an optimal inventory policy for a multi-echelon supply chain system due to the interaction among the different levels with different goals. Moreover, such policy depends on the structure of the system and should be based on the states of the whole system. Even if such a policy can be identified, it usually has a very complex structure and is not suitable for implementation. Therefore it is reasonable to consider simple, cost-effective heuristic policies, which can be readily applicable in practice [69].

Among inventory control policies, periodic review inventory system is commonly implemented in practice. In the survey of Simchi-Levi et al. [70], material managers indicate the effectiveness of periodic review systems for reducing inventory levels in the supply chain. However, just as same as the others, one of the disadvantages of the periodic review is that the stock out is normally occurs before receiving the new replenishment due to the demand and lead time variations in the system.

To overcome this disadvantage, an idea of alternative supply in inventory system has been studied extensively in the literature. The majority of the papers in this area deal with either the concept of emergency supply modes [71, 72], or the concept of expedited supply modes [73]. Along with this idea, coordination and information sharing between members in the supply chain have recently become other key issues. Many companies undertake initiatives directed to re-engineering their supply chain to reduce costs while being more responsive to customer demand. Recent research carried out in this direction include Sinha and Sarmah [74], Ouyang [75], Zhou and Benton [76], Sarmah et al [77], and Gupta and Weerawat [78].

In this study, we note two inventory replenishment strategies in two-level supply chain with alternative supply possibilities which involve different level of coordination mechanism between manufacturers and retailers. Then, we compare the performance of these strategies with that of a traditional one where ordering from only one of manufacturers is allowed for each retailer.

Under normal circumstances, orders from a retailer are fulfilled by only one manufacturer which is designated to serve that retailer. However, in the case where the corresponding manufacturer cannot fully satisfy the order, a centralized decision can be made to assign another manufacturer in the chain to cover the shortage. This research also proposes another strategy which implies a higher level of coordination between manufacturer and retailer. In the case where another manufacturer cannot cover the shortage due to insufficient stock, the shortage is considered as backorder to the manufacturer which can serve faster. Under these circumstances, in this study, a multi-objective inventory analysis is proposed to evaluate the performance of the system by simultaneously minimizing total cost and loss rate of the supply chain. The aim is to examine the situation when such coordination is profitable for all members in the system.

3.2. System description

The supply chain operates under the make-to-stock environment, in which stochastic demand and lead-time are considered. The

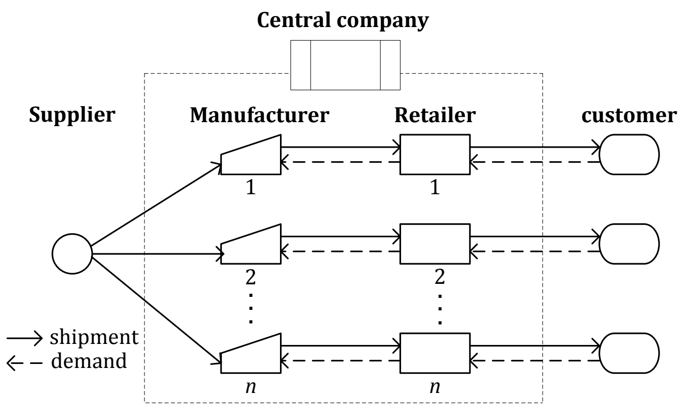


Figure 3.1. System Configuration with *n*-serial lines

system is controlled by a single major company which operates n-serial sub systems, as depicted in Fig. 3.1. Each serial subsystem consists of one manufacturer which serves one retailer.

In what follows, characteristic of the supply chain systems concerned here will be described briefly. For each member in the system, the following assumptions are introduced:

1. The manufacturer uses periodic review system with safety stock and lot sizing policy to control its inventory.
2. The retailer uses periodic review system with target stock level (T, S) to control its inventory.
3. Only a single product is considered in the model. Without loss of the generality, the manufacturer uses one unit of raw material to produce one unit of finished product.
4. End customer's demand and delivery lead-time are randomly generated based on the normal distribution.
5. Production rate of the manufacturer is assumed to be fixed and higher than the mean demands.
6. Unfulfilled demand at manufacturer is considered as backorder while unfulfilled demand at retailer is considered as loss.

The system model is described based on the following notation listed for major parameters.

Index

T	Number of planning horizon.
N	Number of serial lines.
t	Period (t = 1,2,…,T).
i	Manufacturer ($i \in N$)
j	Retailers ($j \in N$).

Parameters of Manufacturer

$FD_{i,t}$	Forecast demand of manufacturer *i* at period *t*
tp	Number of days in each period
PR_i	Production rate of Manufacturer *i*
$\widetilde{lm}_i$	Mean lead time of raw material delivery to manufacturer *i*
$lm_{i,t}$	Actual lead time of raw material delivery to manufacturer *i* at period *t*
$\widetilde{lr}_i$	Mean delivery lead time from manufacturer *i*
$lr_{i,t}$	Actual delivery lead time from manufacturer *i* at period *t*
$Qp_{i,t}$	Production quantity of manufacturer *i* during supplier's late delivery at period *t*
$Qpr_{i,t}$	Production quantity at manufacturer *i* at period *t*
$Bs_{i,t}$	Beginning stock level of raw materials of manufacturer *i* at period *t*
$Sr_{i,t}$	Amount of raw material left at manufacturer *i* after production during supplier's late delivery at period *t*
$Es_{i,t}$	Ending stock level of raw materials of manufacturer *i* at period *t*
$BSS_{i,t}$	Beginning safety stock level of manufacturer *i* at period *t*
$ESS_{i,t}$	Ending safety stock level of manufacturer *i* at period *t*
$Qm_{i,t}$	Ordering quantity of manufacturer *i* at period *t*
$Qf_{i,t}$	Quantity to fill back the safety stock of manufacturer *i* at period *t*
$Qa_{i,t}$	Available quantity of manufacturer *i* at period *t*
$Qb_{i,t}$	Backorder quantity of manufacturer *i* at period *t*
$Qsh_{i,t}$	shortage quantity of manufacturer *i* at period *t*
$Qsl_{i,t}$	Sales volume of manufacturer *i* at period *t*
$BI_{i,t}$	Beginning inventory level of manufacturer *i* at period *t*
$EI_{i,t}$	Ending inventory level of manufacturer *i* at period *t*

Parameters of Retailer

$D_{j,t}$	Total customer demand of retailer *j* at period *t*
$d_{j,t}$	Customer demand at retailer *j* before receiving replenishment at period *t*
$Br_{j,t}$	Beginning inventory level of retailer *j* at period *t*
$Io_{j,t}$	Inventory level left at retailer *j* during manufacturer's lead time at period *t*
$Qs_{j,t}$	Shortage quantity at retailer *j* during manufacturer's lead time at period *t*
$Qre_{j,t}$	Replenishment quantity received by retailer *j* at period *t*
$Ir_{j,t}$	Ending inventory level of retailer *j* at period *t*
$Qsh_{j,t}$	Shortage quantity of retailer *j* at period *t*
$Qor_{j,t}$	Ordering quantity of retailer *j* at period *t*
$Qse_{j,t}$	Sales volume of retailer *j* at period *t*

Cost Parameters

Com_i	Ordering cost of manufacturer *i*
Cp_i	Unit purchasing cost of manufacturer *i*
Cpr_i	Unit production cost of manufacturer *i*
Chr_i	Unit holding cost of raw material of manufacturer *i*
Chf_i	Unit holding cost of finished product of manufacturer *i*
Cb_i	Unit backordering cost of manufacturer *i*
Ctr_i	Unit transportation cost of manufacturer *i*
Cpu_j	Unit purchasing cost of retailer *j*
Cho_j	Unit holding cost of finished product of retailer *j*
Cs_j	Unit shortage cost of finished product of retailer *j*

Decision Varibales

LS_i	Lot sizing policy of manufacturer *i*
SS_i	Safety stock level of manufacturer *i*

R_j Target stock level of retailer j

Manufacturer

The inventory level of the manufacturer is reviewed at every period t, over totally T periods (planning horizon). Each period consists of tp days. The manufacturer receives raw materials from an outside supplier which has unlimited capacity, transforms it to the finished product and then distributes the product to corresponding retailer. However, under uncertainty in the delivery lead-time, the supplier may delay the supply of raw materials to the manufacturer. Therefore, the manufacturer has to select the appropriate material ordering policy and hold some safety stock of finish product.

The ordering quantity of the manufacturer is directly influenced by the lot sizing policy (LS_i) which is adopted for ordering raw material. For instance, the first policy is to place an order in every period. The second policy is to place an order at the first period and combine the orders of remaining periods together, and so on. After the best pattern of LS_i is selected, the manufacturer checks current inventory level at the beginning of the period. If the inventory level is less than the sum of the forecasted demand, the quantity to fill back the safety stock and the backorder quantity, then the manufacturer will place an order. Otherwise no order will be issued (Eq. 3.1).

$$Qm_{i,t} = \max\left\{0,\ FD_{i,t} + Qf_{i,t-1} + Qb_{i,t} - BI_{i,t} - Bs_{i,t}\right\} \tag{3.1}$$

It is assumes that we always starts reviewing the inventory at time t. Then the manufacturer start producing the product at the lead-time contract $t + \widetilde{lm}_i$. When late delivery occurs ($lm_{i,t} > \widetilde{lm}_i$), the manufacturer still can start the production at time $t + \widetilde{lm}_i$ if there is beginning raw material on hand. Otherwise, the manufacturer has to wait until it receives replenishment from the supplier at time $t + lm_{i,t}$. The production quantities during late delivery of supplier and amount of raw material left after production during supplier's late delivery are calculated using equations (3.2) and (3.3), respectively. Consequently, we can determine the total production quantity (Eq. (3.4)) and ending stock level of raw material as shown in equation Eq. (3.5).

Ending inventory level ($EI_{i,t}$) is the amount of finished product left after fulfilling retailer's demand and the use of safety stock. The safety stock of the manufacturer is used only when the order quantity of the retailers is greater than the sum of the production quantity ($Qpr_{i,t}$) and amount of beginning inventory of finished products ($BI_{i,t}$). The $EI_{i,t}$ and $ESS_{i,t}$ are calculated using Eq. (3.6) and Eq. (3.7), respectively.

$$Qp_{i,t} = \begin{cases} \left(lm_{i,t} - l\tilde{m}_i\right) \times PR_i & \text{if } \; lm_{i,t} > l\tilde{m}_i \text{ and } \; Bs_{i,t} > \left(lm_{i,t} - l\tilde{m}_i\right) \times PR_i \\ Bs_{i,t} & \text{if } \; lm_{i,t} > l\tilde{m}_i \text{ and } Bs_{i,t} \le \left(lm_{i,t} - l\tilde{m}_i\right) \times PR \\ 0 & \text{if } \; lm_{i,t} \le l\tilde{m}_i \end{cases} \tag{3.2}$$

$$Sr_{i,t} = \begin{cases} Bs_{i,t} - & \text{if } \; lm_{i,t} > l\tilde{m}_i \text{ and} \\ \quad \left(lm_{i,t} - l\tilde{m}_i\right) \times PR_i & \qquad Bs_{i,t} > \left(lm_{i,t} - l\tilde{m}_i\right) \times PR_i \\ 0 & \text{if } \; lm_{i,t} > l\tilde{m}_i \text{ and} \\ & \qquad Bs_{i,t} \le \left(lm_{i,t} - l\tilde{m}_i\right) \times PR_i \\ Bs_{i,t} & \text{if } \; lm_{i,t} \le l\tilde{m}_i \end{cases} \tag{3.3}$$

$$Qpr_{i,t} = \begin{cases} Qp_{i,t} + \left((tp - lm_{i,t}) \times PR_i\right) & \text{if } Bs_{i,t} > 0 \text{ and} \\ & \left(Sr_{i,t} + Qm_{i,t}\right) > \left(tp - lm_{i,t}\right) \times PR_i \\ Qp_{i,t} + Sr_{i,t} + Qm_{i,t} & \text{if } Bs_{i,t} > 0 \text{ and} \\ & \left(Sr_{i,t} + Qm_{i,t}\right) \le \left(tp - lm_{i,t}\right) \times PR_i \\ \left(tp - lm_{i,t}\right) \times PR_i & \text{if } Bs_{i,t} = 0 \text{ and} \\ & Qm_{i,t} > \left(tp - lm_{i,t}\right) \times PR_i \\ Qm_{i,t} & \text{if } Bs_{i,t} = 0 \text{ and} \\ & Qm_{i,t} \le \left(Tp_i - lm_{i,t}\right) \times PR_i \end{cases} \tag{3.4}$$

$$Es_{i,t} = \begin{cases} \left(Sr_{i,t} + Qm_{i,t}\right) - & \text{if } Bs_{i,t} > 0 \text{ and} \\ \quad \left(\left(Tp_i - lts_{i,t}\right) \times PR_i\right) & \left(Sr_{i,t} + Qm_{i,t}\right) > \left(Tp_i - lts_{i,t}\right) \times PR_i \\ Qm_{i,t} - \left(Tp_i - lts_{i,t}\right) \times PR_i & \text{if } Bs_{i,t} \le 0 \text{ and} \\ & Qm_{i,t} > \left(Tp_i - lts_{i,t}\right) \times PR_i \\ 0 & \text{if otherwise} \end{cases} \tag{3.5}$$

$$EI_{i,t} = \begin{cases} Qpr_{i,t-1} + BI_{i,t} & \text{if } BSS_{i,t} = SS_i \text{ and} \\ \quad -(Qor_{j,t} + Qb_{i,t}) & Qpr_{i,t-1} + BI_{i,t} > Qor_{j,t} + Qb_{i,t} \\ Qpr_{i,t-1} + BI_{i,t} - & \text{if } BSS_{i,t} < SS_i \text{ and} \\ \quad -(Qor_{j,t} + Qb_{i,t}) & Qpr_{i,t-1} + BI_{i,t} > +Qor_{j,t} + Qb_{i,t} \text{ and} \\ \quad -(SS_i - BSS_{i,t}) & Qpr_{i,t-1} + BI_{i,t} - (Qor_{j,t} + Qb_{i,t}) > \\ & (SS_i - BSS_{i,t}) \\ 0 & \text{otherwise} \end{cases} \tag{3.6}$$

$$ESS_{i,t} = \begin{cases} 0 & \text{if } Qor_{j,t} \geq Qa_{i,t} \\ Qa_{i,t} - Qor_{j,t} & \text{if } Qor_{j,t} > Qpr_{i,t-1} + BI_{i,t} \text{ and } Qor_{j,t} < Qa_{i,t} \\ BSS_{i,t} & \text{if } BSS_{i,t} = SS_i \text{ and } Qor_{j,t} \leq Qpr_{i,t-1} + BI_{i,t} \\ SS_i & \text{if } BSS_{i,t} < SS_i \text{ and } Qor_{j,t} \leq Qpr_{i,t-1} + BI_{i,t} \\ & \quad \text{and } Qpr_{i,t-1} + BI_{i,t} - Qor_{j,t} \geq SS_i - BSS_{i,t} \\ BSS_{i,t} + Qpr_{i,t-1} & \\ \quad + BI_{i,t} - Qor_{j,t} & \text{otherwise} \end{cases} \tag{3.7}$$

$$Qsl_{i,t} = \begin{cases} Qor_{j,t} + Qb_{i,t} & \text{if } Qa_{i,t} \geq Qor_{j,t} \\ Qa_{i,t} + Qb_{i,t} & \text{otherwise} \end{cases} \tag{3.8}$$

As shown in Eq. (3.6) and Eq. (3.7), the ending safety stock level ($ESS_{i,t}$) and the ending inventory level ($EI_{i,t}$) have different meanings. The $ESS_{i,t}$ is the amount of safety stock left at the end of each period while $EI_{i,t}$ is the number of finished products that is produced beyond the retailer's demand and is left from fulfilling the safety stock. The sales volume ($Qsl_{i,t}$) of the manufacturer is determined based on total order quantity of retailer (Eq. (3.8)). When the total order quantity of the retailer exceeds the available quantity on hand, the shortage quantity ($Qsh_{i,t}$) will be backordered the next period ($Qb_{i,t}$).

Retailer

The retailer periodically places the order to a corresponding manufacturer to raise up its inventory to the target stock level. The order quantity ($Qor_{j,t}$) is determined by comparing the ending stock level ($Ir_{j,t}$) at period t with the desired target stock level (R_j) , which is equal to (R_j - $Ir_{j,t}$) . The target stock level is not only for covering the end customer's demand but also to cover the effect of end customer demand's fluctuation as well as the late delivery and unfulfilled quantity of products from the manufacturer.

After placing the order to the corresponding manufacturer, the retailer receives replenishment after some lead time. At the beginning of the period, each retailer uses beginning inventory of finished product ($Br_{j,t}$) to fulfill end customer demand during replenishment lead time. Due to uncertainty in the system, sometimes the retailer may not receive a full replenishment from corresponding retailer. When this situation occurs, the manufacturer promises to deliver the remaining quantity the next period. The inventory that is left and the amount of shortage during this time are shown in equation (3.9) and (3.10). Consequently, ending inventory, total shortage quantity and sales volume of retailer after receiving replenishment can be calculated using equation (3.11), (3.12) and (3.13), respectively.

$$Io_{j,t} = \max\left\{Br_{j,t} - d_{j,t}\,,\, 0\right\} \tag{3.9}$$

$$Qs_{j,t} = \max\left\{d_{j,t} - Br_{j,t}\,,\, 0\right\} \tag{3.10}$$

$$Ir_{j,t} = \begin{cases} Io_{j,t} + Qre_{j,t} - (D_{j,t} - d_{j,t}) & \text{if} \quad Io_{j,t} + Qre_{j,t} > D_{j,t} - d_{j,t} \\ 0 & \text{otherwise} \end{cases} \tag{3.11}$$

$$Qsh_{j,t} = \begin{cases} Qs_{j,t} + (D_{j,t} - d_{j,t}) & \text{if} \quad Io_{j,t} + Qre_{j,t} < D_{j,t} - d_{j,t} \\ \quad -(Io_{j,t} + Qre_{j,t}) & \\ Qs_{j,t} & \text{otherwise} \end{cases} \tag{3.12}$$

$$Qse_{j,t} = \begin{cases} D_{j,t} & \text{if} \quad Qsh_{j,t} = 0 \\ D_{j,t} - Qsh_{j,t} & \text{otherwise} \end{cases} \tag{3.13}$$

Any stock-out that the retailer faces is considered as a total lost due to the fact that in today high competitive market, the customers have a plenty of choices to acquire products, especially for retailers such as department stores, supermarkets or conventional stores. Consequently, the situation in which the customers buy the same product from a second shop when there is the stock-out occurs at the first shop is quite common in the real world business.

This study considers two objective functions to evaluate the system performance. The first objective minimizes system total cost (Z_{TCS}) consisting of total cost of manufacturers (TCM_i) and total cost of retailers (TCR_j). The second objective function minimizes loss rate of supply chain (Z_{LRS}) calculated from total shortage of retailers. These two objectives require a trade-off in solution as they are conflicting with each other. As the system faces uncertainty, one way to maintain the responsiveness (minimum loss rate) to the customer demand is holding inventory in higher volume. However, this causes an increase in system total cost as an excess inventory blocking system cash flow. On the contrary, holding lower inventories give the opposite consequence.

3.3. Replenishment Strategy

The details of each replenishment strategy will be described in this section.

3.3.1. Replenishment Strategy 1 (S1)

The inventory flow of strategy 1 is shown in Fig.1. It is assumed that manufacturer 1 is the only source of supply for retailer 1, manufacturer 2 is the only source of supply of retailer 2 and so forth. If a retailer places an order to its corresponding manufacturer and that manufacturer holds insufficient quantity, the retailer's order is partially backordered with the corresponding manufacturer. Then, the unfulfilled quantity is delivered by the corresponding manufacturer the next period. In the rest of this paper, this strategy is referred to as a traditional strategy which is common for the inventory systems with single manufacturer and single retailer. In general, the objective function of the multi-objective optimization problem for *p* objectives can be described as minimizing F = {$F_1, F_2, F_3, \ldots, F_p$}. In the present problem, we give the objective function as follows:

$$\text{Minimize}\ \{F_1, F_2\} = \{Z_{\text{TCS}}, Z_{\text{LRS}}\} \tag{3.14}$$

where Z_{TCS} is given by

$$Z_{TCS} = \sum_{i=1}^{I} TCM_i(\text{S1}) + \sum_{j=1}^{J} TCR_j(\text{S1}) \tag{3.15}$$

$$TCM_i(\text{S1}) = \left\{ \begin{array}{l} \sum_{t=1}^{T} Com_{i,t} + \sum_{t=1}^{T} Cp_i \times Qm_{i,t} + \sum_{t=1}^{T} Cpr_i \times Qpr_{i,t} + \\ \sum_{t=1}^{T} Chr_i \times Es_{i,t} + \sum_{t=1}^{T} Chf_i \times \left(ESS_{i,t} + EI_{i,t}\right) + \\ \sum_{t=1}^{T} Cb_i \times Qb_{i,t} \times tp + \sum_{t=1}^{T} Ctr_i \times Qsl_{i,t} \end{array} \right\} \tag{3.16}$$

$$TCR_{\text{i}}(\text{S1}) = \sum_{t=1}^{T} Cpu_j \times Qre_{i,t} + \sum_{t=1}^{T} Cho_j \times Ir_{j,t} + \sum_{t=1}^{T} Cs_j \times Qsh_{j,t} \tag{3.17}$$

and Z_{LRS} is given by

$$Z_{LRS} = \sum_{j=1}^{J} \sum_{t=1}^{T} \left(\frac{Qsh_{j,t}}{D_{j,t}} \right) \tag{3.18}$$

3.3.2. Replenishment Strategy 2 (S2)

Under circumstance of strategy 1, manufacturers only fulfill the demands of their corresponding retailers. However, under strategy 2, a retailer may receive an alternative supply from another manufacturer in the chain if the corresponding manufacturer fails to meet the demand. This alternative supply is illustrated in Fig. 3.2.

When a certain retailer *n* does not receive full replenishment from manufacturer *n* as its corresponding manufacturer, the central decision maker will check the remaining inventory of the finished product of other manufacturers (say manufacturer *k*) after supplying their corresponding retailer and then assign one of them to serve retailer *n*. The required quantity is backordered to manufacturer *n* if no other manufacturers can supply all quantity of shortage.

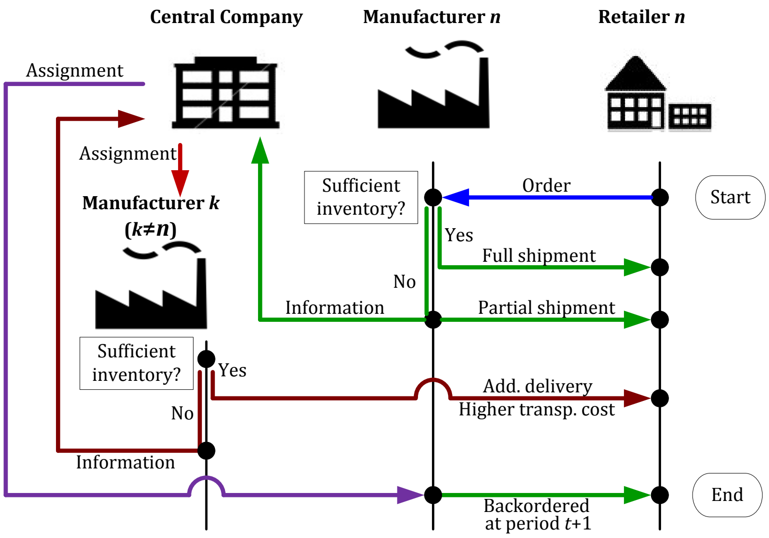


Figure 3.2. Replenishment Strategy 2

Since each retailer can possibly receive a product from more than one manufacturer, a new transportation cost from manufacturer to the retailer should be added to the first objectives function. Thus for each manufacturer, there are two types of transportation cost that are incurred which correspond to the transportation cost to regular retailer and to other retailer, where the latter is more costly due to non-regular delivery. On the other hand, the other objective function remains the same.

$$TCM_i(S2) = TCM_i(1) + \sum_{i=1}^{T} Cta_i \times Qsa_{i\to l,t} \tag{3.19}$$

$$TCR_j(S2) = TCR_j(1) + \sum_{i=1}^{T} Cpu_j \times Qsa_{k\to j,t} \tag{3.20}$$

where

$Qsa_{i\to l,t}$	Sales volume of manufacturer *i* to retailer *l* at period *t*, $l \neq j$ where $l, j \in J$ (unit).
Cta_i	Unit transportation cost of manufacturer *i* to other retailer ($).

3.3.3. *Replenishment Strategy 3* (S3)

This strategy works in the same way as strategy 2 except for the situation where one manufacturer experiences a shortage while the other manufacturers hold inadequate inventory to fulfill this shortage.

Unlike strategy 2, in which the shortage is backordered partially to the corresponding manufacturer when the stock-out occurs, this strategy proposes different coordination mechanism. The central decision maker examines the supplier's lead time for the upcoming de-

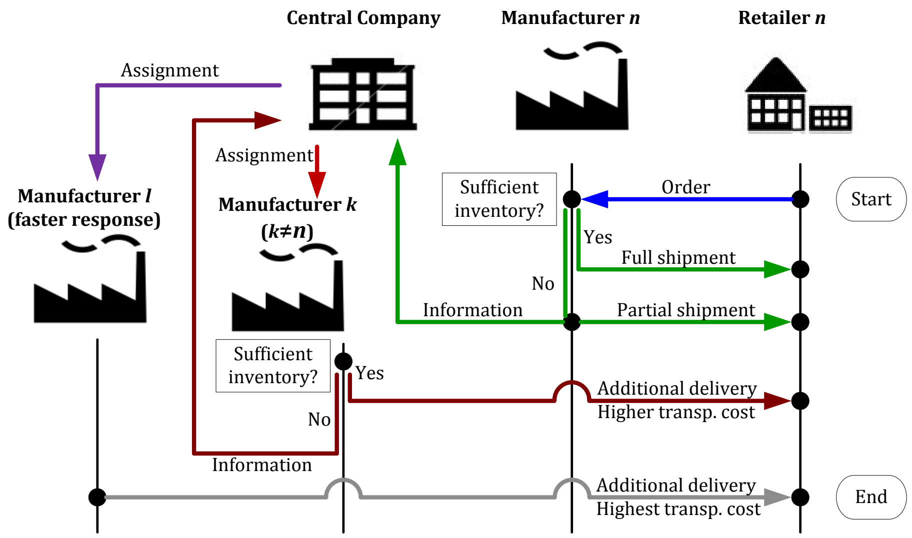


Figure 3.3. Replenishment Strategy 3

livery and the current inventory status of finished product of all manufacturers. This information is used to determine the time required to produce the products to fulfill the shortage. Supplier's lead time affects the starting time of production and the inventory status determines the quantity of product to be produced. Lastly, a manufacturer which has a shorter lead time is assigned to fulfill the shortage and the backordered quantity is delivered as soon as production is finished.

Accordingly, the new transportation cost for additional replenishment is added to the cost of manufacturers while others remain the same as strategy 2 after adjusting the backorder cost at manufacturer (Refer to Fig.3.3).

$$TCM_i(S3) = \begin{Bmatrix} TCM_i(S2) + \sum_{i=1}^{T} Cpr_i \times Qpx_{i,t} + \sum_{i=1}^{T} Ctx_i \times Qpx_{i,t} \\ + \sum_{i=1}^{T} Cb_i \times Qb_{i,t} \times tf_{i,t} \end{Bmatrix} \tag{3.21}$$

$Qpx_{i,t}$	Non-regular production quantity of manufacturer *i* at period *t* to fulfill shortage (unit).
Ctx_i	Unit transportation cost of manufacturer *i* to fulfill shortage quantity of manufacturer i, where $ctr_i < cta_i < ctx_i$ ($).
$tf_{i,t}$	Total time to produce backorder at manufacturer i at period t (days).

It should be noted in Eq. 3.21 that for a manufacturer which is suffered from stock-out, there is no cost component of transportation ($\sum_{i=1}^{T} ctx_i \times Qpx_{i,t} = 0$) because the non-regular production quantity is designated to fulfill its own requirement. On the other hand, the cost component of backorder is not applied ($\sum_{i=1}^{T} cb_i \times Qb_{i,t} \times tf_{i,t} = 0$) for manufacturers which are assigned as backup resource.

3.4. Multi-objective Differential Evolution (MODE)

Differential Evolution (DE) is a recent optimization technique in the family of evolutional algorithms. It is proposed as a variant of genetic algorithms to achieve the goal of robustness in optimization

Generate initial population M
Set $G = 0$
While the stopping criteria is not satisfied **do**
    For each individual i in the population
        Generate random integer, $x_1, x_2, x_3 \in (1, M)$ with $x_1 \neq x_2 \neq x_3 \neq i$
        For each parameter j

$$u_{ji,G+1} = \begin{cases} x_{3,G} + F(x_{2,G} + x_{1,G}) & \text{if} \quad rand(j) \leq CR \quad or \quad j = rnbr(a) \\ x_{ji,G} & \text{if} \quad rand(j) > CR \quad or \quad j \neq rbnr(a) \end{cases}$$

        End For
        Replace x_i with u_i, if u_i is better. Otherwise x_i is remained
    End For
G += 1
End While

Figure 3.4. Pseudo code of DE (Strategy: DE/rand/1/bin)

and faster convergence [79, 80]. DE uses a self-organizing scheme to take the different vector of two or more vector to create a mutant vectors. So that a few input is required from the user and it eases to implement DE to solve the problem. The pseudo code of DE can be seen in Figure 3.4.

One of the most commonly applied strategies of DE to solve the problem is “DE/rand/1/bin”. Notation “rand/1” means one different set of vector (from 2 vectors) is randomly chosen in the populations to be mutated. Then “bin” means the independent binomial experiment is used for crossover schemes.

The detailed of DE’s algorithm is summarized as follow:

1. Randomly generate the initial population to yield target vector ($x_{i,G}$) by using Eq. (3.22).

   $$x_{i,G}(i = 1,2,..., M) \tag{3.22}$$

   where M = population size
2. Apply mutation to generate the mutant vector by adding the weight difference between target vectors to the third target vector as show in Eq. (3.23).

   $$v_{i,G+1} = x_{3,G} + F(x_{2,G} - x_{1,G}) \tag{3.23}$$

   where F is a scaling factor which control controls the amplification of the differential variation ($x_{2,G} - x_{1,G}$)
3. Apply the crossover operation to generate the trial vector by mixing some elements of the target vector with the mutant vector through comparison between random value and crossover rate.

$$u_{ji,G+1} = \begin{cases} v_{ji,G+1} & \text{if} \quad \text{rand}(j) \le CR \quad \text{or} \quad j = rnbr(a) \\ x_{ji,G} & \text{if} \quad \text{rand}(j) > CR \quad \text{or} \quad j \ne rbnr(a) \end{cases} \tag{3.24}$$

where *rand*(*j*) is a random number, *CR* is crossover rate $\in$ [0, 1] and *rnbr*(*i*) is a randomly chosen index (1,2,…,*n*) which ensure that the trial vector gets at least one element from the mutant vector.

4. Perform the selection operation by comparing the target vector and the trial vector. If the trial vector is better than the target vector, the trial vector replaces the target vector at the next generation. Otherwise, the target vector is remained. Then check pre-specified stopping criteria. If it is satisfied, stop and return the overall best vector as a final solution. Otherwise, go back to step 2 by incrementing the generation number by 1.

In the single-objective DE, the selection process is straightforward. The vector which has optimal solution is chosen. In the multi-objective case, however, the selection process becomes more complicated. This is because the need of "Pareto optimal solutions". Previous research attempted to deploy DE to a multi-objective problem and showed that DE can be attractive alternative for multi-objective optimization [81, 82, 83, 84]. However, handling multi-objective DE poses certain difficulties in its implementation. Besides preserving a uniformly spread front of non-dominated solutions, it is also necessary to decide when to replace the parent (target vector) with the candidate solution (trial vector). Reddy and Kumar [85] proposed another methodology (MODE) to resolve these difficulties by combining Pareto Dominance principles with DE and using elitism in its

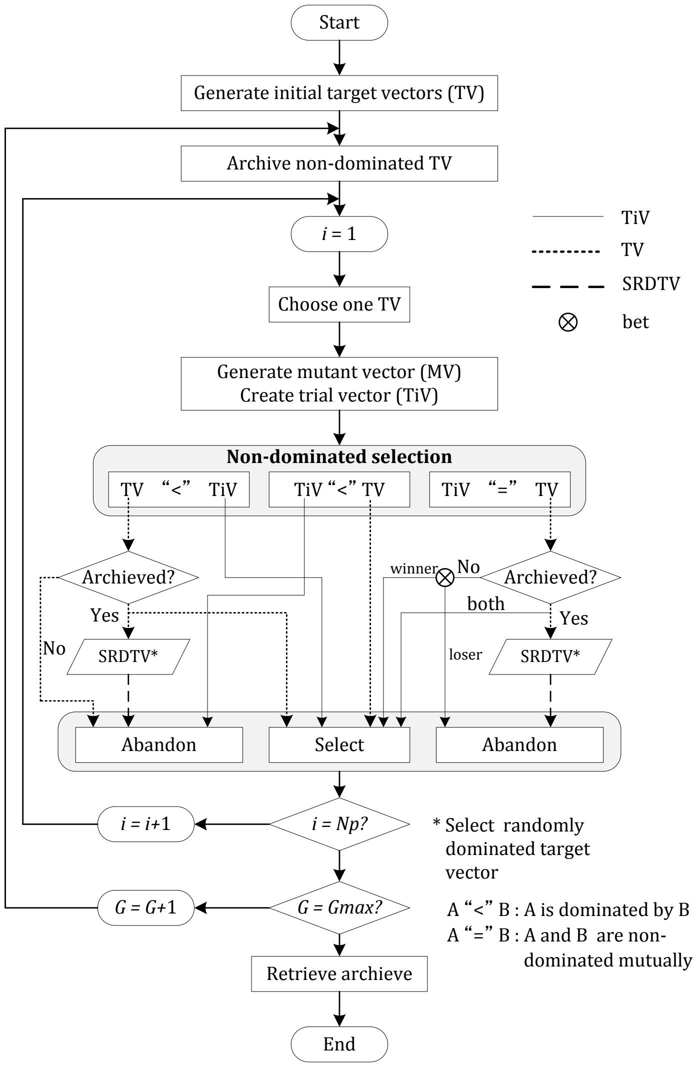


Figure 3.5. Flowchart of the proposed MODE

evolution. The main algorithm consists of initialization of population, evaluation, Pareto dominance selection, performing DE operations and repeating the search on population to reach the Pareto optimal solutions. One of the crucial points of this method is that the use of external archive to store the non-dominated solutions found so far over the generation.

In this study, we propose a new procedure with a different selection mechanism to discover the set of Pareto optimal solutions.

Since this procedure uses a single and fixed size population during the entire process, the algorithm becomes much simpler than the conventional one. All vectors are first evaluated and checked using domination relation to distinguish those into non-dominated and dominated classes. Thereafter, in order to select the new population for the next generation, a unique selection mechanism is applied between the target vector and the trial vector. The proposed MODE methodology is described as follows (See also Fig.3.5):

Step 1. Input the necessary DE parameters. Generate n-dimensional initial vectors (M) in the population randomly within the bounds of specified decision variables. Clear the archives.

Step 2. Evaluate each vector in the population.

Step 3. Perform non-dominated sorting. Apply the concept of dominance to identify vectors that become non-dominated vector in the current population, and archive them as non-dominated vectors.

Step 4. Perform mutation and crossover operations for every target vectors $x_{i,G}$ in the population as same as the single-objective DE, i.e.,

a. Select three different vectors randomly from the current population other than the target vector.
b. Calculate a mutant vector using Eq. (3.23).
c. Create a trial vector by mixing some element from target vector and mutant vector using crossover rate (eq.3.24).
d. Restrict the variables to its boundaries if any variable is outside the lower or upper bound.

Step 5. Evaluate each target vector

Step 6. Perform the selection operation based on the dominance concept according to the following cases:

Case 1 : The trial vector dominates the target vector

- Select trial vector as candidate parent for the next generation.
- Check the status of the target vector. If the target vector is previously non-dominated, keep it in the population by randomly removing one dominated target vector. Otherwise, remove the target vector from population.

Case 2 : The target vector dominates the trial vector

- Select the target vector as a candidate parent for the next generation.
- Remove the trial vector from the population.

Case 3 : Neither vector are dominated by the other

- Check the status of the target vector. If the target vector was previously non-dominated, keep it in the population by removing one dominated target vector and select a trial vector as the candidate parent.
- Otherwise, select randomly avector (target vector or trial vector) to be the candidate parent.

Step 7. Increment the generation counter, G to $G + 1$. Check the stopping criteria. If it is not satisfied, then go to step 3. Otherwise, return the non-dominated solutions.

3.5. Numerical Experiment

In practice, a single decision could hardly be formulated to handle problems characterized by different situations. The nature of the situation typically changes the characteristic of the problem causing the decision needs to be adjusted. The problem becomes more complicated when the decision maker faces several objectives, which is normally conflicting and need to be optimized simultaneously.

This research attempts to address such situation mentioned above. This numerical experiment evaluates the three replenishment strategies by solving a stock out problem for a given supply chain system and deciding the optimal inventory control policy for each strategy. Then we compare the performance of the system for three different uncertain situations and analyzed how the decision is adjusted for each of them. Since we approach the problem using multi-objective decision making, the comparison is carried out based on the Pareto solution set.

A numerical experiment was carried out for a system consisting of two-serial lines using the input parameters shown in Table 3.1. The experiment was performed according to the following steps:

1. Apply the proposed MODE to find a set of Pareto optimal solution of each proposed strategy by determining appropriate ordering policy and inventory level of each member.
2. Apply sensitivity analysis to Pareto front to see the effectiveness of the proposed strategy under different uncertain situations given by standard deviations of demand. Here the demand is selected as an uncertain parameter because variability affects greatly the whole system.
3. Examine the effect of each strategy for the appropriately selected compromised solution regarding the holding cost and backorder cost of manufacturers, and holding cost and shortage cost of retailers.

3.5.1. Coding and setting of lower/upper Bound

In this experiment, the decision variables consist of ordering policy of raw material (LS_i) and safety stock level (ss_i) of each manufacturer, and target stock level (S_i) of each retailer.

In order to generate initial population, lower and upper bound

Table 3.1. Parameters values for Numerical Experiment

Input parameters	**M1**	**M2**
T	6 period	
tp	7 days	
$FD_{i,t}$	250 unit / day	
σ_{FD_i}	25, 50, 100	25, 50, 100
$\overline{lm_i}$	3 days	
$lm_{i,t}$	Normal(3,1)	
PR_i	360 unit	400 unit
Input parameters	**R1**	**R2**
$D_{j,t}$	250 unit / day	
σ_{D_j}	25, 50, 100	25, 50, 100
$\overline{lr_i}$	3 days	
$lr_{i,t}$	Normal(3,1)	
Cost Parameters	**M1**	**M2**
Com_i	\$200 / order	
Cp_i	\$10 / unit	
Cpr_i	\$20 / unit	
Chr_i	0.15 * (Cp_i)	
Chf_i	0.20 * ($Cp_i + Cpr_i$)	
Cb_i	\$15 / unit	\$17 / unit
Ctr_i	\$13 / unit	\$15 / unit
Cta_i	\$20 / unit	
Ctx_i	\$30 / unit	
Cost Parameters	**R1**	**R2**
Cpu_j	\$77 / unit	
Cho_j	0.15 * (Cpu_i)	
Cs_j	\$20 / unit	
DE Parameters		
Np	300	
CR	0.5	
F	0.8	
G	5000	

of each decision variable should be set as follows:

For LS_i, the manufacturer has to decide whether to make the order at the beginning of every period or combine the order in a big batch. Therefore, the binary coding is applied to represent the value of LS_i. For example, with 6 periods planning horizons, 111100 means lot-for-lot policy is used for period 1, 2 and 3. For period 4 to 6, the order is combined and it is placed at period 4.

For ss_i and S_i, These decision variables are considered as the amount of safety stock at the manufacturer and the amount of target stock retailer, respectively. Thefore, the integer coding is used to represent these values.

Let $\overline{D}_j$, $\overline{FD}_i$, σ_{D_j} and σ_{FD_i} are the mean and standard deviation of the end customer demand and forecast demand, respectively, and, σ_{lm_i} and σ_{lr_i} are standard deviation of the delivery lead time of raw material and product, respectively.

- The lower bound of ss_i is set to 0 or no safety stock is hold at the manufacturer.
- The upper bound of ss_i is calculated by the using Eq. (3.25). In order to maintain the minimum loss rate (higher service level) and to make sure that all searching space is bounded, the upper bound of ssi is set at the value corresponding z = 4. (see [86] for further information).

$$z \times \sqrt{\left(\overline{lm}_i \times \sigma_{FD_i}^2\right) + \left(\overline{FD}_i^2 \times \sigma_{lm_i}^2\right)} \tag{3.25}$$

- The lower bound of S_i should be at least or equal to the expected demand during the review time plus delivery lead time contract, which is equal to $\overline{D}_j \times \left(tp + \overline{lr}_i\right)$.

- The upper bound of Si can be determined in the same way as done by [4], which is equal to:

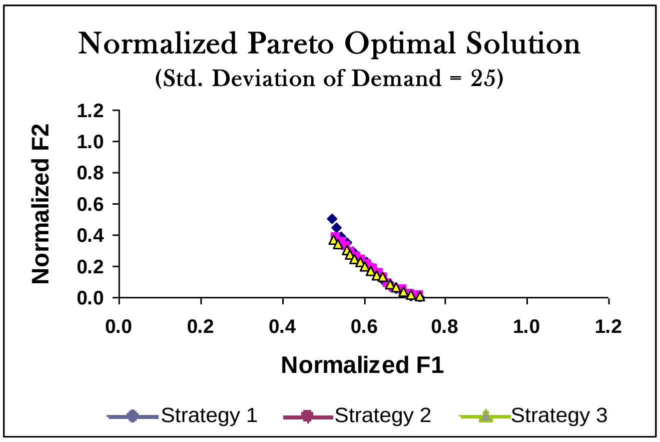
$$\bar{D}_j \times \left(tp + \bar{lr}_i\right) + \mathrm{z} \times \sqrt{\left(\bar{lr}_i \times \sigma_{D_j}^2\right) + \left(\bar{D}_j^2 \times \sigma_{lr_i}^2\right)} \qquad (3.26)$$

3.5.2. Results and analysis

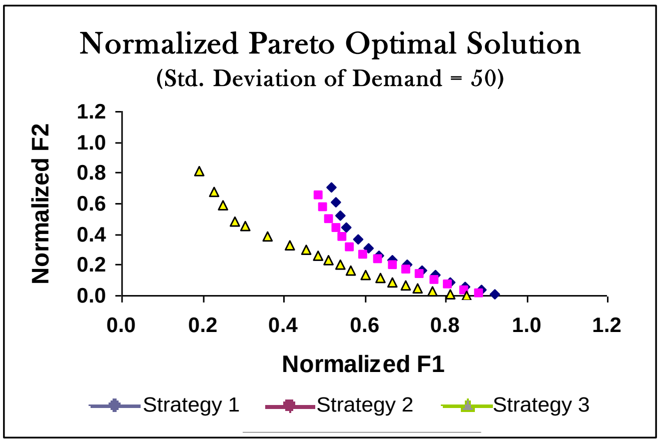
a. Pareto Optimal Solutions

Figure 3.6 shows Pareto optimal solution sets for each strategy under various standard deviations of demand. Each plot is normalized between 0.0 and 1.0 using the maximum and/or minimum values all over the computations. In every case, we can obtain favorable features of Pareto front using the developed MODE method.

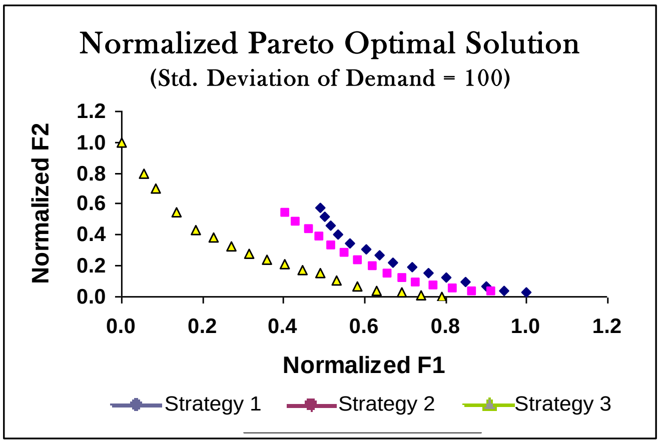
Under the small standard deviations of demand (σ = 25), strategies 2 and 3 have less influence to the system performance since only slight difference can be seen at Pareto front as shown in Fig. 3.6 (a). This is because when the demand is relatively steady, a shortage



(a). Std. Deviation of Demand = 25



(b). Std. Deviation of Demand = 50



(c). Std. Deviation of Demand = 100

Fig.3.6. Normalized Pareto Optimal Solution

such that the proposed coordination can be effectively applied is rarely occurred. In other words, each serial line can cope with its own market without cooperating with each other. In this case, the decision can be made not to introduce such coordination strategy in the system.

However, as variations of demand increase (σ = 50, 100), the different strategies produce remarkably distinct Pareto optimal solutions (Figures 3.6(b) and (c)). This indicates that strategies 2 and 3

Table 3.2. Objective Function Values and Decision Variable of Selected Pareto Solution

	Std. Dev. demand = 25		
	Strategy 1	**Strategy 2**	**Strategy 3**
TCSC ($-thousand)	2,372	2,363	2,368
LRSC (%)	5.23	4.88	4.57
DLS	1111	11011	1111
ss (unit)	961	821	767
S (unit)	1825	1890	2013
	Std. Dev. demand = 50		
	Strategy 1	**Strategy 2**	**Strategy 3**
TCSC ($-thousand)	2,403	2,381	2,359
LRSC (%)	6.31	6.19	3.81
DLS	10111	111	1011
ss (unit)	1058	825	529
S (unit)	1878	1838	2044
	Std. Dev. demand = 100		
	Strategy 1	**Strategy 2**	**Strategy 3**
TCSC ($-thousand)	2,404	2,373	2,254
LRSC (%)	6.05	5.28	4.75
DLS	1011	1011	1100
ss (unit)	1036	954	608
S (unit)	2072	2169	2568

are more suitable compared to strategy 1 since the Pareto optimal solution of both strategies move down toward the lower region and spread widely over the decision space. Eventually, this means strategy 3 is the one.

b. Uncertainty Effect on Each Objective Function

The final goal of multi-objective decision-making should be to present decision maker a unique solution known as preferentially optimal solution that will be derived through multi-objective optimization.

During the multi-objective optimization, we assume to take a posteriori approach that is search and then proceed to the actual decision-making in which the decision is made without any prior preference information. At the search stage, the result is a set of Pareto optimal solutions. The final choice will be made at the decision-making stage. To show how the uncertainty analysis is available for the preferential optimal solution, it is necessary to have a reference or a sample from the Pareto optimal front.

Presently, assuming that both goals are of equal importance (w1 = w2 = 0.5, for instance), we derive a reference solution from the

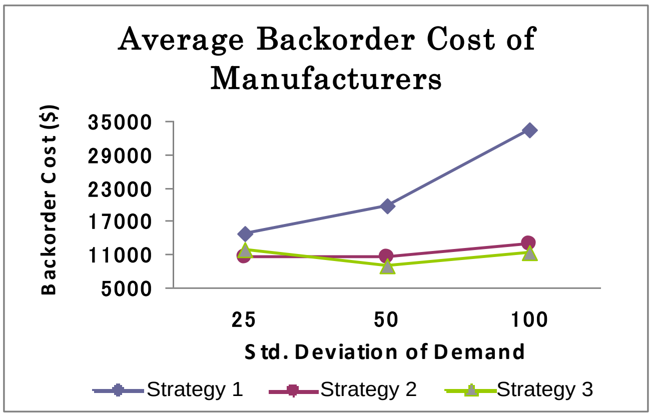


Figure 3.7. Comparison of Backorder cost of Manufacturer

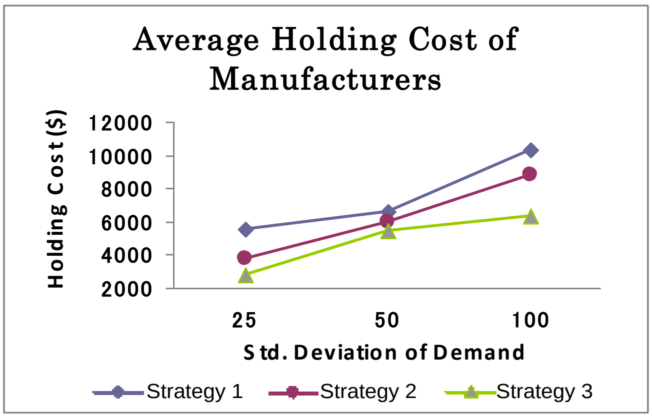


Figure 3.8. Comparison of Holding cost of Manufacturer

following objective functions:

$$\text{Minimize } 0.5Z_{TCSC} + 0.5Z_{LRSC}$$

As suggested by the strategies in Table 3.2, as the demand variation increases, decision can be made for both manufacturers to order raw material in a big batch and to hold moderate amount of safety stock rather than to order using lot for lot policy and to hold high amount safety stock. This decision avoid both manufacturers from experiencing frequent backorder. Figure 3.7 proves that strategies 2 and 3 produce lower backorder cost compared to strategy 1 while

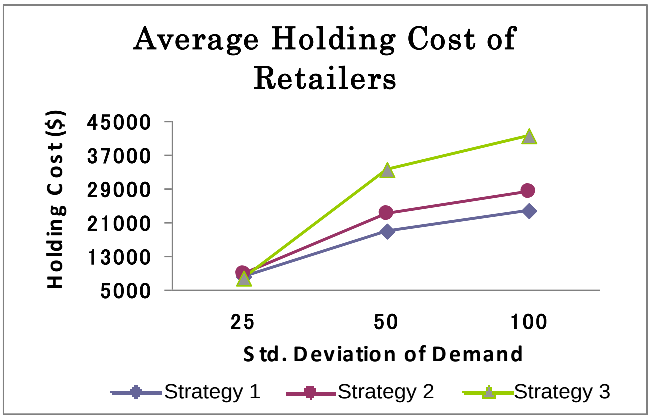


Figure 3.9. Comparison of Holding cost of Retailer

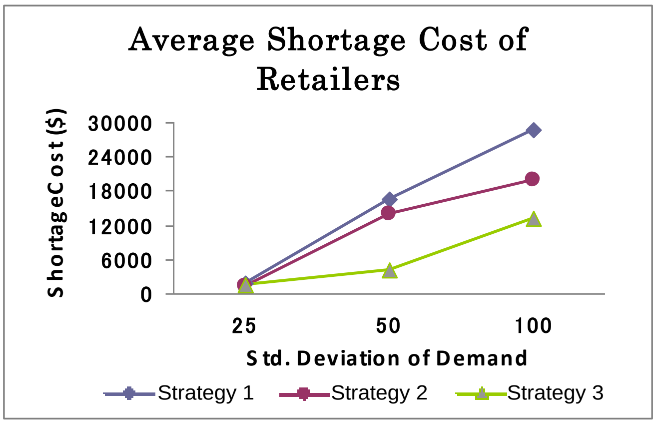


Figure 3.10. Comparison of Shortage cost of Retailer

strategy 3 outperforms strategy 2 in two cases (σ = 50, 100).

It can also be noticed from Table 3.2 that the optimal quantity of safety stock under strategy 3 is always the lowest in every cases. It is reflected in Figure. 3.8 where strategy 3 is superior in reducing the holding cost in most cases. Moreover, reduction in holding cost is driven by the fact that fulfilling the shortage quantity experienced by one manufacturer leads to reducing excess inventory of the donor manufacturer and hence reducing inventory in the system. However, retailers require setting slightly high target stock level to maintain the responsiveness to the customer demand. Even though this decision increases the average holding and shortage costs as shown in Figure. 3.9 and 3.10, respectively, this stock level is more effective to reduce the loss rate of the supply chain.

3.6. Conclusion

A multi-objective analysis of a periodic review inventory problem for two-echelon supply chain system was investigated. Three strategies of coordinated replenishment are proposed to manage inventory in efficient way while trying to improve the system performance by simultaneously minimizing total cost and loss rate of the supply chain. For this purpose, a multi-objective DE was adopted to the problem in question and applied for each of the three strategies. Finally, the most profitable situation was examined in which all members in the chain can achieve proportional satisfaction under these conflicting goals.

The result shows that the coordination strategy becomes more effective as the uncertainty increases in the system. By cooperating, manufacturers can avoid frequent backorder and reduce excess inventory in the system. Even though retailers are required to keep a bit high inventory level to maintain the good responsiveness to the customer demand, this stock level is more effective to reduce the loss rate of supply chain.

Future studies should be devoted to more general and complicated configurations of the supply chain system in real world. Relying on the ability of the proposed MODE revealed in this study, this seems to be straightforward. It is also meaningful to move on the multi-objective optimization to derive the preferentially optimal solution by revealing value system of the central decision maker.

Chapter 4

AN ENHANCED TWO-PHASE FUZZY PROGRAMMING MODEL FOR MULTI OBJECTIVES SUPPLIER SELECTION PROBLEM

4.1. Introduction

In global and competitive market, the need for establishing a longer-term relationship that fosters cooperation among suppliers and their customers has been highlighted. However, many purchasers find it difficult to determine which suppliers should be targeted as each of them has varying strengths and weaknesses in performance. Moreover, the importance of each criterion tends to vary from one purchaser to others. This problem becomes more complicated as the simultaneous evaluation is required in terms of qualitative and quantitative criteria. So, every decision must be integrated by trading off performances of different suppliers at each supply chain stage.

One of the main characteristic of supplier selection is that this task is characterized by an imprecision and incomplete of data which results in vagueness of information related to decision criteria. Stochastic models are usually based on representation of existing uncertainty by probability concepts and are, consequently, limited to tackling the uncertainties captured [87]. Moreover, the estimation of probability distribution is difficult to carry out in a fuzzy environment because of the imprecision of the data. This is why, Fuzzy set theory (FST) is suggested as an appropriate tool to handle this problem effectively.

A number of studies have been devoted to examining supplier selection methods. Quantitative techniques have become increasingly applied recently. A comprehensive review of numerous quantitative techniques used for supplier selection has been done by Weber et al. [1]. They found that linear weighting models, mathematical programming models and statistical/probabilistic approaches have been most common approaches.

Some researches used a single objective, such as cost, to evaluate suppliers. Kaslingam & Lee [88] developed an integer programming model to select suppliers and to determine order quantities with the objective of minimizing total supplying costs which include purchasing and transportation costs. Caudhry at al. [89] used linear and mixed binary integer programming to minimize aggregate price considering both all unit and incremental quantity discount.

As an extension of single objective techniques, multi-objective mathematical programming has been proposed to solve a more complex supplier selection problem. Weber et al. [90] combined multi-objective programming (MOP) and Data Envelope Analysis (DEA) to deal with non-cooperative supplier negotiation strategies where the selection of one supplier results in another being left out of the solution. Dahel [91] studied a multi-objective mixed integer programming model to select suppliers and allocate product to them in multi-product environment. Xia & Wu [92] improved the Analytical Hierarchy Process (AHP) using rough set theory and multi-objective mixed integer programming to determine the best suppliers and optimal quantity allocated to each of them in the case of multiple sourcing, multiple product with multiple criteria. Kokangul & Susuz [93] proposed an integration of analytical hierarchy process (AHP) and non-linear integer MOP to determine the best supplier and optimal order quantity among them that simultaneously maximize total value of purchase and minimize total cost of purchase. Chamodrakaz *et al.* [94] provided new approach of two-stage supplier selection problem. At the first stage, an initial screening is performed through the enforcement of hard constraint on the selection criteria, and in the second stage, final selection is performed using a modified variant of fuzzy preference programming (FPP). Eroll & Farell [95] used qualitative and quantitative factors in the supplier selection. A fuzzy QFD (Quality function Deployment) is used to translate linguistic input into qualitative data and then combine it with other quantitative data to develop a multi-objective mathematical programming model.

This research focuses on fuzzy multi-objective linear programming (fuzzy MOLP) to deal with the supplier selection problem. Kumar et al. [96] developed a fuzzy multi-objective integer programming approach for vendor selection problem subject to constraints including buyer's demand, vendors' capacity, and derived an optimal solution using max-min operator (Zimmermann's approach). To evaluate the performance of the model, they perform sensitivity analysis on the order allocation and objective function by changing the degree of uncertainty in vendor capacity. Amid et al. [97] solved fuzzy MOLP supplier selection problem by applying weighted additive method to facilitate an asymmetric fuzzy decision making technique. Since they found the performance of such a method to be inadequate to support decision making process, α-cut approach is then proposed to improve the resulted achievement level. Later on, Amid et al. [98] applied weighted max-min approach in supplier selection problem and compared the performance of the proposed approach with max-min operator and weighted additive model. They found that the ratio of achievement level of objectives matches the ratio of the objectives weight.

Although there are a number of publications adopting fuzzy programming models in supplier selection problem in the literature, most of them rely on the application of the existing methods and very few papers are concerned with the improvement in the methodological process of deriving the optimal solution. Kagnicioglu [99] proposed super-transitive approximation to determine the weights of objectives and constraint in formulating fuzzy MOLP model in supplier selection and solved the model using max-min operator and weighted additive model. Yucel & Guneri [100] proposed a new method of weights calculation in fuzzy MOLP supplier selection. Both researches mentioned above only focus on the process for weights calculation for fuzzy objective and constraints.

It has been verified that solving fuzzy MOLP using max-min operator may not result in an optimal solution (Tzeng & Tsaur [101]; Tzeng & Chen [102]; Li, [103]). Such a limitation has been resolved by Li et al. [103] who proposed two-phase approach to compute efficient solutions of fuzzy MOLP problems as the improvement of compromise approach of Wu & Guu [104]. They found that the performance of compromise approach decreases when the DM prefers to choose the minimum acceptable achievement level closer or equal to the most optimistic value. In their proposed method, the minimum acceptable achievement level is set to the solution of max-min operator. In this sense, the performance of compromise approach can be improved and, on the other hand, the disadvantage of max-min operator can be overcome. However, the two-phase approach will face the same obstacle if max-min operator outputs the result closer or equal to the most optimistic value, and hence, cannot provide the improvement. To tackle the above-mentioned shortcomings and to help obtain a more reasonable compromise solution, this paper proposes an enhanced two-phase approach of fuzzy MOLP by introducing additional variables which control the relaxation of resulted overall achievement level and apply it to solve supplier selection problem.

For that purpose, a supplier selection model is proposed in which net cost minimization, service level maximization and purchasing risk minimization are incorporated as fuzzy goals. The first two criteria are cited most often in ordering decision [105]. Purchasing risk is included as one objective to measure the risk of potential loss incurred if purchaser allocates a certain amount of product to purchase to a certain supplier. To this end, the Taguchi loss function (TLF) is used to quantify this risk. AHP is employed to determine the relative important between fuzzy goals and constraints.

4.2. Problem Formulation

In this section, we formulate a mathematical model of fuzzy MOLP supplier selection. The following notations are defined in order to describe the model.

i = index for supplier ($i = 1, 2, .., N$)

D = demand of buyer (unit)

B = total budget of buyer to purchase product ($)

x_i = order quantity to supplier *i* (unit)

p_i = unit price of supplier *i* ($)

f_i = service level of supplier *i* (% fulfillment)

r_i = purchasing risks of supplier *i* (% risk)

C_i = capacity of supplier *i* (unit)

The MOLP model for supplier selection is as follow:

$$\mathrm{Min}\ Z_1 = \sum_{i=1}^{n} p_i x_i \tag{4.35}$$

$$\mathrm{Max}\ Z_2 = \sum_{i=1}^{n} f_i x_i \tag{4.36}$$

$$\mathrm{Min}\ Z_3 = \sum_{i=1}^{n} r_i x_i \tag{4.37}$$

subject to:

$$\sum_{i=1}^{n} x_i = D \tag{4.38}$$

$$\sum_{i=1}^{n} p_i x_i \le B \tag{4.39}$$

$$x_i \le C_i \tag{4.40}$$

$$x_i \ge 0 \tag{4.41}$$

Eq. (4.19) minimizes the net cost for ordering product to satisfy demand. Eq. (4.20) maximizes the service level of suppliers. Eq. (4.21) minimizes the purchasing risk when the firm allocates a certain amount of product to purchase to a certain supplier. Eq. (4.22) puts restriction that order quantity assigned to suppliers must satisfy the total demand. Eq. (4.23) ensures that the total cost of purchasing does not exceed the amount of budget allocated by the firm. Eq. (4.24) guarantees that the order quantity assigned to each supplier will not exceed supplier capacity limit. Eq. (4.25) is non-negativity constraint.

4.3. The proposed Integrated Method

This section presents all methods involved in the proposed fuzzy MOLP model. First, Taguchi loss function is described to quantify the risk associated with purchasing decision, followed by AHP to calculate a relative importance of sub-criteria used to measure risk as well as the relative importance between objectives and constraints in the final formulation. Next, fuzzy MOLP supplier selection model and an enhanced two-phase approach are presented.

4.3.1. Taguchi loss function

In a traditional system, the product is accepted if the quality measurement falls within the specification limit. Otherwise, the product is rejected. The quality losses occur only when the product deviates beyond the specification limits, therefore becoming unacceptable [106]. Taguchi suggests a narrower view of quality acceptability by indicating that any deviation from the quality target value results in a loss. If the quality measurement is the same as the target value, the loss is zero. Otherwise, the loss can be measured using a quadratic function [107].

There are three types of Taguchi loss functions: "target is best" (two-sided *equal* specification or two-sided *unequal* specification), "smaller is better" and "larger is better". If $L(y)$ is the loss associated with a particular value of quality y, m is the target value of the specification, and k is the loss coefficient whose value is constant depending on the cost at the specification limits and the width of the specification, then for "target is best – two sided equal specification" type, "target is best – two sided unequal specification" type, "smaller is better" type, and "larger is better" type, the formulation of $L(y)$ are given is Eq.(4.1)-(4.4), respectively.

$$L(y) = k(y - m)^2 \tag{4.1}$$

$$L(y) = k_1(y - m)^2 \ \ or \ L(y) = k_2(y - m)^2 \tag{4.2}$$

$$L(y) = k(y)^2 \tag{4.3}$$

$$L(y) = k/y^2 \tag{4.4}$$

4.3.2. Analytical hierarchy process

The analytic hierarchy process (AHP) was developed to provide a simple but theoretically multiple-criteria methodology for evaluating alternatives [108]. The major reasons for applying AHP are because it can handle both qualitative and quantitative criteria and because it can be easily understood and applied by the DMs. AHP involves decomposition, pair-wise comparisons, and priority vector generation and synthesis. The procedures of AHP to solve a complex problem involve six essential steps [109]:

1. Define the unstructured problem and state clearly the objectives and outcomes;
2. Decompose the problem into a hierarchical structure with decision elements (e.g., criteria and alternatives);
3. Employ pair-wise comparisons among decision elements and form comparison matrices;
4. Use the eigen value method to estimate the relative weights of the decision elements;
5. Check the consistency property of matrices to ensure that the judgments of decision makers are consistent; and

6. Aggregate the relative weights of decision elements to obtain an overall rating for the alternatives.

4.3.3. Fuzzy multi-objective linear programming

A linear multi-objective problem can be stated as: find vector x in the transformed form $X^T = |x_1, x_2, \dots, X_n|$ which minimize objective function Z_k and maximize objective function Z_l with

$$Z_k = \sum_{i=1}^{n} c_{ki} x_i \ , \quad k = 1,2,\dots, p \tag{4.5}$$

$$Z_l = \sum_{i=1}^{n} c_{li} x_i \ , \ l = p+1, p+2,\dots, q \tag{4.6}$$

subject to:

$$x \in X_d \ , X_d = \{ x | g(x) \le b_r , \quad r = 1, 2, \dots, m \} \tag{4.7}$$

where X_d is the set of feasible solution that satisfy the set of system constraints.

Zimmermann [110] first adopted the fuzzy programming model proposed by Bellman and Zadeh [111] into conventional LP problems. The fuzzy formulation for (4.5)-(4.7) can be stated as

$$Z_k = \sum_{i=1}^{n} c_{ki} x_i \le\sim Z_k^0 \ , \ k = 1,2,\dots, p \tag{4.8}$$

$$Z_l = \sum_{i=1}^{n} c_{li} x_i \ge\sim Z_l^0 \ , \ l = p+1, p+2,\dots, q \tag{4.9}$$

subject to:

$$\tilde{g}_r(x) = \sum_{i=1}^{n} a_{ri} x_i \le\sim b_r , \ \ r = 1,2,\dots, h \tag{4.10}$$

$$g_p(x) = \sum_{i=1}^{n} a_{pi} x_i \le b_p, \quad p = h+1, \ldots, m \tag{4.11}$$

$$x_i \ge 0, \quad i = 1, 2, \ldots, n \tag{4.12}$$

The above fuzzy MOLP is characterized by a linear membership function whose value changes between 0 and 1. The membership function for fuzzy objectives are given as

$$\mu_{Z_k}(x) = \begin{cases} 1 & \text{if} \quad Z_k(x) \le Z_k^{min} \\ \dfrac{Z_k^{max} - Z_k(x)}{Z_k^{max} - Z_k^{min}} & \text{if} \quad Z_k^{min} \le Z_k(x) \le Z_k^{max} \\ 0 & \text{if} \quad Z_k(x) \ge Z_k^{max} \end{cases} \tag{4.13}$$

$$\mu_{Z_l}(x) = \begin{cases} 0 & \text{if} \quad Z_l(x) \le Z_l^{min} \\ \dfrac{Z_l(x) - Z_l^{min}}{Z_l^{max} - Z_l^{min}} & \text{if} \quad Z_l^{min} \le Z_l(x) \le Z_l^{max} \\ 1 & \text{if} \quad Z_l(x) \ge Z_l^{max} \end{cases} \tag{4.14}$$

and the linear membership function for fuzzy constraints is given as

$$\mu_{gr}(x) = \begin{cases} 0 & \text{if} \quad g_r(x) \ge b_r + d_r \\ \dfrac{1 - (g_r(x) - b_r)}{d_r} & \text{if} \quad b_r \le g_r(x) \le b \quad , r = 1, 2, \ldots, h \\ 1 & \text{if} \quad g_r(x) \le b_r \end{cases} \tag{4.15}$$

where d_r is subjectively chosen tolerance interval expressing the limit of the violation of the r-th inequalities constraints. In the above formulation, Z_k^{max}, Z_l^{max}, Z_k^{min} and Z_l^{min} means the maximum value (worst solution) and the minimum value (best solution) of Z_k and Z_l, respectively. They are obtained by solving a single objective optimization problem respectively under each objective function [112].

Zimmermann [110] proposed a max-min operator approach to solve the above fuzzy MOLP. The Eq. (4.5)-(4.7) can be transformed into the following crisp formulation by introducing additional variable λ which represent an overall achievement level for both fuzzy objectives and constraints.

$$\text{Max} \ \ \lambda \tag{4.16}$$

Subject to:

$$\lambda \leq \mu_{zj}(x),\ j = 1,2,...,q \qquad \text{for fuzzy objectives} \tag{4.17}$$

$$\lambda \leq \mu_{gr}(x),\ \ r = 1,2,...,h \qquad \text{for fuzzy constraints} \tag{4.18}$$

$$g_p(x) \leq b_p,\ p = h+1,...,m \quad \text{for } crisp \text{ constraints} \tag{4.19}$$

$$x_i \geq 0,\ \ i = 1,2,..,n \quad \text{and} \quad \mu_{zj}, \mu_{gr}, \lambda \in [0,1] \tag{4.20}$$

4.3.4. An enhanced two-phase fuzzy programming

Li et al. [103] proposed a two-phase approach to compute efficient solutions of fuzzy MOLP as the improvement of compromise approach of Wu et al. [104]. The steps of two-phase approach are as follow:

Step 1: Solve the max-min operator problem and output the optimal value, say x^0.

Step 2: Set the lower bound $\lambda_j^l = \mu_{Zj}(x^0)$ for objective function and $\gamma_r^l = \mu_{gr}(x^0)$ for fuzzy constraints and solve the following model to get a final solution *x*.

$$\text{Max} \sum_{j=1}^{q} \omega_j \lambda_j + \sum_{r=1}^{h} \beta_r \gamma_r \tag{4.21}$$

subject to:

$$\lambda_j^l \le \lambda_j \le \mu_{zj}(x),\ \ j=1,2,...,q \tag{4.22}$$

$$\gamma_r^l \le \gamma_r \le \mu_{gr}(x),\ \ \ r=1,2,...,h \tag{4.23}$$

$$g_p(x) \le b_p,\ p=h+1,...,m \tag{4.24}$$

$$x_i \ge 0,\ \ i=1,2,..,n \tag{4.25}$$

$$\lambda_j, \gamma_r \in [0,1] \tag{4.26}$$

$$\sum_{j=1}^{q}\omega_j + \sum_{r=1}^{h}\beta_r = 1,\ \ \ \omega_j, \beta_r \ge 0 \tag{4.27}$$

It should be noted that the value of minimum acceptable achievement level is a compromised preference value of decision maker. However, this method may not necessarily yield a feasible solution when the minimum acceptable achievement level is closer or equal to the most optimistic value. Moreover, due to the problem structure of supplier selection under consideration, formulating linear programming model requires a careful parameter setting because selection criteria are quantified using wide range of numerical input. Inappropriate parameter setting may also result in infeasible solution. To release the above-mentioned shortcomings and to help obtain a more reasonable compromise solution, therefore, this research proposes an enhanced two-phase approach of fuzzy MOLP. Therefore, we propose to solve the following model to get the final solution *x*:

$$Max\ \ (1-p)\left(\sum_{j=1}^{q}\omega_j\lambda_j + \sum_{r=1}^{h}\beta_r\gamma_r\right) - p\left(\sum_{j=1}^{q}\varepsilon_j + \sum_{r=1}^{h}\delta_r\right) \tag{4.28}$$

Subject to:

$$\lambda_j^l - \varepsilon_j \le \lambda_j \le \mu_{zj}(x),\ j = 1,2,...,q \tag{4.29}$$

$$\gamma_r^l - \delta_r \le \gamma_r \le \mu_{gr}(x),\ \ r = 1,2,...,h \tag{4.30}$$

$$g_p(x) \le b_p,\ p = h+1,\dots,m \tag{4.31}$$

$$x_i \ge 0,\ \ i = 1,2,..,n \quad and \quad \lambda_j, \gamma_r \in [0,1] \tag{4.32}$$

$$\sum_{j=1}^{q} \omega_j + \sum_{r=1}^{h} \beta_r = 1;\ \omega_j, \beta_r \ge 0 \tag{4.33}$$

$$0 \le \varepsilon_j \le \lambda_j^l;\ \ 0 \le \delta_r \le \gamma_r^l \tag{4.34}$$

where ε_j and δ_r are augmented variables to relax the overall achievement level resulted from the foregoing max-min operator problem , respectively, and p is a weighting factor which control the original objective function value and the relaxation value. Apparently, it is desirable such relaxation is as small as possible as long as the feasibility is hold.

4.3.5. Solution procedures

The proposed fuzzy MOLP supplier selection problem is constructed through the following steps:

Step 1: Define the criteria for supplier selection problem

Step 2: Construct the MOLP supplier selection problem according to defined criteria (minimize purchasing cost, maximize service level, and minimize purchasing risk) and constraint of the buyer and suppliers. The purchasing risk is quantified as followed:

a. Define sub-criteria
b. Measure the relative important of each sub-criteria using AHP
c. For each sub-criterion, define a target value, calculate loss coefficient and Taguchi loss

d. Find the weighted Taguchi loss by employing the output of AHP. This value is used in MOLP model as the coefficient of objective of minimizing purchasing risk

Step 3: Find membership function for each selection criteria and constraint.

a. Determine a lower bound of each objective by solving MOLP as a single objective supplier selection problem using each time only one objective.
b. As in a), determine an upper bound of each objective by solving MOLP as a single objective supplier selection problem using each time only one objective.

Step 4: Calculate the relative importance of criteria and constraints using AHP.

Step 5: Reformulate the MOLP supplier selection into equivalent crisp model using the enhanced two-phase fuzzy MOLP and find the set of feasible solution.

4.4. Numerical Experiment and Analysis

Suppose that one firm should manage three suppliers for one product. Management wants to improve the efficiency of the purchasing process by evaluating their suppliers. The management considers three objective functions i.e. minimizing net cost, maximizing service level and minimizing purchasing risk, subject to constraints regarding the demand of product, supplier capacity limitation, firm's budget allocation, etc. The estimated value of suppliers' net price, service level and suppliers' capacity are given in Table 4.1. An allocated budget of the firm to purchase the product is $20,000. The demand is a fuzzy number and is predicted to be about 1400 unit with refrac-

Table 4.1. Suppliers' quantitative information

	Net Cost/unit ($)	Service Level (% fill rate)	Capacity (unit)
Supplier 1	10	75	500
Supplier 2	12	90	600
Supplier 3	9	85	550

Table 4.2. The specification limit and range of five leading criteria

Criteria	Target Value	Range	Specification Limit
Quality (% defect rate)	0%	0-3%	3%
Order fulfillment	100%	80%-100%	80%
On-time delivery (days)	0	-10 to 0 and 0 to 5	10 days earlier, 5 days delay
Distance/Proximity (miles)	The closest	0-40%	40%

Table 4.3. Actual value of the four sub-criteria

Supplier	Quality (% defect)	Order Ful-fillment (% unit)	On-time delivery (days)	Distance/ Proximity (miles)
1	1.0%	90%	2	6
2	1.2%	95%	4	7
3	1.5%	97%	-1	9

tion of -100 and 150 units.

Purchasing risk is measured from four sub-criteria: quality, order fulfillment, on-time delivery, and distance/proximity. Concerning product quality, DM set the target value of defect parts at zero and the upper specification limit at 3% to indicate the allowable deviation from the target value. Zero loss will occur for 0% defective parts and 100% loss will occur at the specification limit of 3% defective parts. For order fulfillment rate, the loss will be zero for the supplier who fulfills all order quantity (100%) and the total loss will occur if supplier can only satisfy 80% of total order. For on-time delivery, the specification limit of delivery is 10 days and 5 days for early and delay shipment, respectively. The DM will tolerate the shipment for a maximum of 5 days delay and 10 days early. In this case, the manufacturer will incur 100% loss if shipment is delayed for 5 days or earlier for 10 days from scheduled shipment, and on contrary, no loss incurred if the shipment is on time. For distance/proximity, a zero-loss will occur at the closest supplier and the specification limit is up to 40% of the closest supplier. It means that the manufacturer will incur 100% loss if there are other suppliers in consideration whose distance reaches the specification limit. The specification limit and range value of each selection criterion are presented in Table 4.2.

Calculating the value of k from Eq. (4.1)-(4.4) gives 1111.11, 0.64, and 6.25 for quality, order fulfillment, distance/proximity, respectively. For on-time delivery, $k_1 = 4$ and $k_2 = 1$ (since an unequal two side specification is considered for on-time delivery, there exists two loses coefficients, k_1 and k_2). The actual values in Table 4.3, together with the value of loss coefficient k previously calculated for these four sub-criteria, are used to calculate the individual Taguchi Loss for each supplier for each criterion using Eq. (4.1)-(4.4). For example, the actual quality value of supplier A is 1.0% defective rate, which means 1.0% deviation from the target value. Individual Taguchi loss is then calculated by entering this value into eq. (3.1)-(3.4). The result is shown in Table 4.4.

Suppose the pair-wise comparison matrix and local weight for

Table 4.4. Taguchi loss $(L(y))$

Supplier	**Quality**	**Order Fulfillment**	**On-time delivery**	**Distance/ Proximity**	**Weighted Taguchi Loss**	**Normalized Taguchi Loss**
1	11.11	79.01	16.00	0.00	34.078	0.284
2	16.00	70.91	64.00	18.06	43.627	0.363
3	25.00	68.06	1.00	156.25	42.411	0.353
				Total	120.116	1.000

Table 4.5. Pair-wise comparison matrix

a) Sub-criteria	Quality	Order Ful-fillment	On-time delivery	Distance / Proximity	Local Weight
Quality	1	2	2	5	0.417
Order Fulfillment	1/2	1	3	5	0.334
On-time delivery	1/2	1/3	1	5	0.191
Distance/Proximity	1/5	1/5	1/5	1	0.058
b) Criteria	**Net price**	**Service Level**	**Purchasing Risk**	**Demand**	**Local Weight**
Net Cost	1	2	3	3	0.447
Service Level	1/2	1	2	3	0.282
Purchasing risk	1/3	1/2	1	2	0.164
Demand	1/3	1/3	1/2	1	0.106

each of these four sub-criteria using AHP is that shown in Table 4.5a. The consistency Ratio (CR) of table 5 is 0.0971 (less than 0.1). The weighted Taguchi loss is then calculated using Taguchi losses and the local weight of criteria (Table 4.5a). Table 4.4 shows the weighted Taguchi loss and the normalized Taguchi loss for each supplier. The normalized Taguchi loss, which represents the loss score, is then used as a coefficient of purchasing risk in fuzzy MOLP. Based on suppliers' data in Table 4.1 and the normalized Taguchi Loss in Table 4.4, the fuzzy MOLP supplier selection of the presented problem is constructed according to Eq. (4.8)-(4.12) as follow:

$$\text{Min } Z_1 = 10x_1 + 12x_2 + 9x_3 \lesssim Z_1^0$$

$$\text{Max } Z_2 = 0.75x_1 + 0.9x_2 + 0.85x_3 \gtrsim Z_2^0$$

$$\text{Min } Z_3 = 0.284x_1 + 0.363x_2 + 0.353x_3 \lesssim Z_3^0$$

Subject to:

$$x_1 + x_2 + x_3 \cong 1400$$

$$10x_1 + 12x_2 + 9x_3 \leq 20000$$

$$x_1 \leq 500$$

$x_2 \le 600$

$x_3 \le 550$

$x_i \ge 0$

The criteria and constraint can be considered equally important and added together for comparison. However, such a comparison is generally unfair due to certain criteria that that may be more important than others. In this model, the weight of cost, service level, purchasing risk and demand are derived from AHP. Table 4.5b shows the pair-wise comparison matrix and local weights for criteria and constraint. The consistency Ratio (CR) is 0.026 (less than 0.1).

Calculating the membership function using max-min operator (Eq. (4.16)) gives 0.566, 0.566 and 0.566 for $\mu_{z1}(x^0)$, $\mu_{z2}(x^0)$, $\mu_{z3}(x^0)$, respectively. The crisp formulation of the above fuzzy MOLP using the enhanced two-phase approach according to Eq. (4.28)-(4.34) is given as

$$\text{Max } \begin{Bmatrix} (1-p)(0.447\lambda_1 + 0.282\lambda_2 + 0.164\lambda_3 + 0.106\gamma_1) \\ -p(\varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \delta_1) \end{Bmatrix}$$

subject to:

$$0.566 - \varepsilon_1 \le \lambda_1 \le \frac{14900 - (10x_1 + 12x_2 + 9x_3)}{750}$$

$$0.566 - \varepsilon_2 \le \lambda_2 \le \frac{14900 - (10x_1 + 12x_2 + 9x_3)}{750}$$

$$0.566 - \varepsilon_3 \le \lambda_3 \le \frac{(0.75x_1 + 0.90x_2 + 0.85x_3) - 1158}{37}$$

$$0.847 - \delta_1 \le \gamma_1 \le \frac{1550 - (x_1 + x_2 + x_3)}{150}$$

$$12x_1 + 16x_2 + 12x_3 \leq 20000$$

$$x_1 \leq 500$$

$$x_2 \leq 600$$

$$x_3 \leq 550$$

$$\omega_1 + \omega_2 + \omega_3 + \beta_1 = 1$$

$$\varepsilon_1 \leq 0.566,\ \varepsilon_2 \leq 0.566,\ \varepsilon_3 \leq 0.566,\ \delta_1 \leq 0.847$$

$$\lambda_1, \lambda_2, \lambda_3, \gamma_1 \in [0,1]$$

$$x_1, x_2, x_3, \omega_1, \omega_2, \omega_3, \beta_1 \geq 0$$

In this problem, the original two-phase approach fails to yield a feasible solution. The constraint associated with λ_1 cannot be satisfied because the value of λ_1 equal to 0.526 which is lower than the designated value of its lower bound (λ_1^l=0.566).

Table 4.6 provides a set of the feasible solutions resulted by utilizing the proposed method which includes the overall achievement level, individual achievement level, ordering plan and the objective value of the equivalent crisp model along with the upper and lower bounds of fuzzy objectives and constraint. As shown in the Table 4.6, the overall achievement level of the proposed approach is known to be better than that of Max-min operator (λ = 0.566) when value of p is lower than 0.5. When p is equal or greater than 0.5, the overall achievement level decreases. A lower p value indicates the model attempts to find a solution by relaxing more the critical objective related to the corresponding constraint to achieve a better achievement level of the other objective.

In this model, the service level (Z_2) and the purchasing risk (Z_3) are a critical objectives as the corresponding constraints are relaxed for almost any p value (critical constraint). This implies that the

Table 4.6. Comparison of Max-min operator and the proposed approach

	Max-min	The Proposed Method						
	Operator	$p = 0.10$	$p = 0.30$	$p = 0.54$	$p = 0.60$	$p = 0.70$	$p = 0.90$	$p = 1.00$
Objective Function		0.608	0.529	0.456	0.439	0.413	0.360	0.334
First Term of obj. function *(Overall achievement level)*	$\lambda = 0.566$	0.665	0.545	0.467	0.444	0.419	0.368	0.342
Second Term of obj. function *(Overall relaxation degree)*		0.570	0.022	0.021	0.009	0.008	0.008	0.008
μ_{z1}	0.566	0.991	0.630	0.616	0.570	0.570	0.570	0.570
μ_{z2}	0.566	0.000	0.548	0.570	0.570	0.566	0.566	0.566
μ_{z3}	0.566	0.980	0.570	0.549	0.561	0.566	0.566	0.566
ε_1	-	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ε_2	-	0.570	0.022	0.000	0.000	0.004	0.004	0.004
ε_3	-	0.000	0.000	0.021	0.900	0.004	0.004	0.004
x_1	500	500	499	499	499	500	500	500
x_2	390	351	374	379	389	389	389	389
x_3	533	550	550	550	550	535	534	534
Z_1	14475.42	14156.67	14,427.15	14,437.87	14,472.50	14,472.50	14,472.50	14,472.50
Z_2	1178.95	1158.00	1178.29	1179.09	1179.09	1178.94	1178.94	1178.94
Z_3	471.60	463.40	471.60	472.02	471.78	471.69	471.69	471.69

Membership Function	$\mu = 0$	$\mu = 1$	$\mu = 0$
Net Cost (Z_1)	-	14150	14900
Service Level (Z_2)	1158	1195	-
Purchasing Risk (Z_3)	-	463	483
Demand	1300	1400	1550

model tends to sacrifice the performance of these objectives because it is at less of cost decreasing the performance of these objectives rather than decreasing other. The greatest relaxation is occurred when p is 0.10. The achievement level of Z_2 is totally relaxed (μ_{z2}= 0) to achieve a better achievement level for Z_1 followed by Z_3. The achievement level of Z_2reaches the best possible value for the entire value of p when Z_3 is relaxed for p is equal to 0.54 and 0.6. Moreover, $Z_1$is free from relaxation as it is the most important objective, whose assigned weight is the highest, according to the DM's preference ($\omega_1 \gg \omega_2 > \omega_3$).

In this fuzzy formulation, all suppliers are selected to supply the product to the firm. Moreover, upon more careful observation, it is revealed that ordering to Supplier 1 and Supplier 3 is more preferable. It is inferred form the order quantity assigned to these suppliers as they receive the biggest amount of order quantity which is equal/closer to their full capacity. In this case, it is not profitable to order more quantity to Supplier 2 because it offers the most expensive price and the highest purchasing risk among others. As mentioned above, the price (net cost) is put as the main concern of the DM (the highest weight). Thus, placing a smaller order quantity to supplier 2 is the best decision.

Without loss of generality, suppose that the DM wants to select p equals 0.10. In this solution, μ_{z1} and μ_{z3} improve to 0.991 and 0.980, respectively, which results in the best value of Z_1 and Z_3. However, the DMs should carefully notice that the achievement level of service level, the second most important criteria, declines toward the worst performance (μ_{z2} = 0). Eventually, final decision should be made by the DM to choose the most favorable decision among the feasible alternative solutions according to his/her preference.

4.5. Conclusion

Supplier selection is an essential task within the purchasing function that needs careful screening under some qualitative and quantitative criteria. Moreover, most information required to assess supplier is usually not known precisely and typically fuzzy in nature over the planning horizon. Concerning such characteristics, this research proposes integrated methodology for FMOLP model for supplier selection.

In formulated problem, the most common fuzzy objectives and parameter in practical ordering decision have been presented. AHP is used to facilitate the subjective judgment on qualitative/quantitative criteria and TLF is employed to quantify the purchasing risk. For the purpose of solving the FMOLP problem, the enhanced two-phase fuzzy programming model has been developed. Through numerical experiment, we demonstrate the promising advantage of our proposed approach over the max-min operator (Zimmermann's approach). Finally, this integrated approach provides a set of potential feasible solutions which guide DMs to select the best solution according to their preference. This also refers to a multi-objective optimization problem that should be concerned in future studies.

Chapter 5

POSSIBILISTIC PROGRAMMING MODEL FOR FUZZY MULTI-OBJECTIVE PERIODIC REVIEW INVENTORY IN TWO-STAGE SUPPLY CHAIN

5.1. Introduction

In today's global market, innovative technologies have shortened the product life cycle and increased the demand variability along the supply chain system. This ultimately forces enterprises to increasingly focus on the role of inventory. The excess inventory in the supply chain blocks the cash flow and indeed gives a tremendous impact on the enterprise while insufficient inventory results in poor responsiveness to the customer demand. In the context of supply chain (SC) system, determining inventory control policy is quite challenging due to the interaction among the different levels with different goals. Even such a policy can be identified, it usually has a very complex structure and is not suitable for implementation. Therefore, it is reasonable to consider simple, cost-effective heuristic policies, which can be readily applicable in practice [113]. In this regard, the periodic review inventory system plays an important role because of its simplicity and easiness in implementation, and therefore, it is mostly employed at different levels of the supply chain network [114].

The issue of considering uncertainty in inventory control has received a great deal of concern in the field of production/inventory management. In the context of periodic review inventory system, many research have focused on the use of stochastic approach under different concerns. While the usefulness of stochastic approach has been documented, it is not always applicable in coding the information regarding the imprecision of data and vagueness of goals. To avoid this drawback, the fuzzy approach is employed for modeling uncertain parameters and goals in inventory problem. The fuzzy approach copes with the uncertainty related to imprecision due to unavailability and incompleteness of data as well as vagueness of goals in which the use of conventional probability distribution is impossible in this case. Moreover, it is frequently emphasized in the literature that fuzzy approach has had a great impact in preference modeling and multi-objective problem and has helped bring optimization techniques closer to the users' needs [115]. Recently, the fuzzy approach has also been employed extensively for the modeling of parameters in periodic review inventory system. Petrovic et al. [116] considered fuzzy demand in a single product inventory control of distribution supply chain of single-warehouse, multiple-retailer in which inventory of each member is replenished by adopting periodic review system. They proposed interactive method to determine the optimal review period and order-up-to level inventory that give the lowest total cost in the fuzzy sense characterized by linear membership function. Vijayan and Kumaran [117] examined the impact and sensitiveness of the impreciseness of fuzzy cost components to the ordering quantity in periodic review and continuous review inventory models in which a fraction of demand is backordered, and the remaining fraction is lost during the stockout period. Lin [118] provided a solution procedure to find the optimal review period and optimal lead time in periodic review inventory model considering the fuzziness of expected demand shortage and backorder rate and used the signed distance method to defuzzify the total expected annual cost. Dey and Chakraborty [114] developed the periodic review inventory model with a constant lead-time in a mixed fuzzy and stochastic environment by incorporating the customer demand as a fuzzy random variable. The aim is to determine the optimal inventory level and the optimal period of review such that the total fuzzy expected annual cost which is defuzzified by its possibilistic mean is minimized. Chang et al. [119] studies a mixtures model of periodic review inventory for single-retailer single-supplier involving variable lead time with backorders and lost sales by further considering the fuzziness of lead-time demand and annual average demand. Using centroid method for defuzzification, they found the optimal solution for order quantity and lead time in the fuzzy sense such that the total cost has a minimum value.

Earlier research of fuzzy periodic review system in the SC were limited in implementation in that the inventory problem is solved for a simple SC structure to satisfy a single objective problem. In current globalization, however, the SC network has become dynamic and complex in a structure which imposes a high degree of uncertainty and this significantly influences the overall performance of the SC network [120]. Moreover, it is mostly the case that each SC member considers more than one factor in their goals to sustain or improve their competitive position. The nature of operations makes one goal often conflicts with each other and complexity in SC structure makes it is difficult to align all of these goals.

This research proposes a periodic review inventory model in a typical SC system where multiple manufacturers, multiple retailers is considered. The aim of this paper is to develop a multi-objective periodic review inventory model in an uncertain environment by simultaneously incorporating the imprecise nature of some critical parameters such as demand, lead time and cost parameters. N this model, each retailer places orders periodically to multiple manufacturers and each manufacturer is replenished periodically from an external supplier. The problem is to determine the ordering policy for raw material and the safety stock level of each manufacturer, and the order allocation and the target stock level of each retailer that can yield satisfactory minimum total cost while maintaining low loss rates. Several alternative solutions are obtained by solving a proposed multi-objective possibilistic mixed integer programming (MOPMIP) inventory model.

This research contributes to the existing literature in the following ways. First, it presents a comprehensive and practical, but tractable, MOPMIP inventory model for two-stage supply chain system considering the imprecision of some critical data. And second, it introduces an integrated solution procedure which provides a systematic framework to facilitate the fuzzy decision-making process, enabling the DM to adjust the decision and to obtain a more preferred satisfactory solution in both *decentralized* and *centralized* SC system.

5.2. Model Formulation

5.2.1. System description

The model has the following assumptions.

1. Only a single product is considered in the model. Without loss of the generality, the manufacturer uses one unit of raw material to produce one unit of product.
2. For both manufacturer and retailer, only one order is allowed to place at any period.
3. The production rate of the manufacturer is assumed fixed and higher than the average demands.
4. Unfulfilled demand at the manufacturer is considered as backorder while unfulfilled demand at the retailer is considered as shortages.
5. Due to incompleteness and/or unavailability of required data over the specified planning horizon, uncertainty in demand, lead time and cost parameter are assumed to be imprecise (fuzzy) in nature with a triangular pattern.

The supply chain in this study operates under the make-to-stock environment, in which imprecise parameters such as demand,

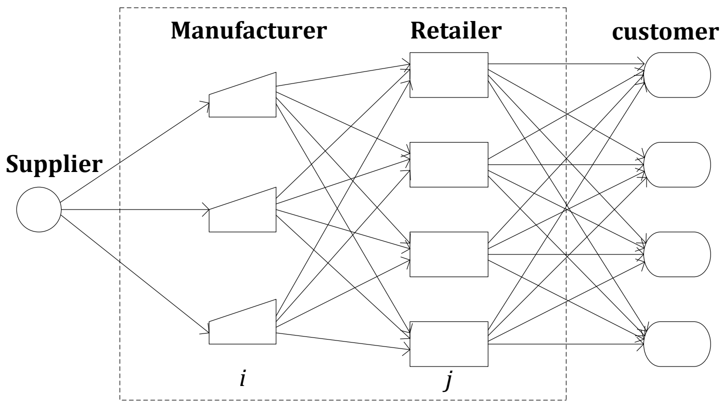


Figure 5.1. Supply chain Network

lead-time and cost parameters are considered. The supply chain consists of supplier, manufacturer, retailer and the end customers of which each of these members is a representative different supply chain echelons. However, this research focuses on a relationship between manufacturer and retailer (suppliers and end customers are considered as external members in the chain) as shown in Figure 5.1.

- *Manufacturer*

The manufacturer uses the periodic review system to control the inventory and orders raw material based on the discrete lot sizing policy. In addition, the manufacturer also holds some safety stock to cover the effect of uncertainty in demand and delivery lead-time. This safety stock will only be used when a normal inventory level cannot satisfy the retailers' demand and it must be filled back as soon as possible after having used.

- *Retailer*

The retailer uses the periodic review with order up to the target stock level (*T, R*) policy. The retailer makes a single order in every cycle to the manufacturer to raise up its inventory to the target stock level. In addition, since the retailer may receive replenishment from more than one manufacturer, the retailer must determine the appropriate strategy to allocate the order quantity to each manufacturer. Any unfulfilled demand is considered as lost sales due to the fact that in practice the customers have a plenty of choices to acquire the products and buy the same product from other shops when the stock out occurs at the first shop, especially when the retailer is viewed as department stores, supermarkets or conventional stores.

5.2.2. *Formulation of the model*

In this section, we develop a multi-objective mix-integer programming inventory model stated in the previous section. The model is described based on the following notation listed for major parameters.

Index

T = Number of planning horizon

t = Period (t = 1,2,…,T).

i = Number of manufacturer

j = Number of retailer

tp = Number of days in each period

Parameters of Manufacturer

$\widetilde{D}_{i,t}$ Forecast demand of manufacturer i at period t.

$Q_{i,t}$ Order quantity of manufacturer at period t.

$Qp_{i,t}$ Production quantity of manufacturer i during supplier's late delivery at period t.

$Sr_{i,t}$ Amount of raw material left at manufacturer i after production during supplier's late delivery at period t.

PR_i Production rate of Manufacturer i.

$\widetilde{ls}_{i,t}$ lead time of supplier to manufacturer i at period t.

$Qpr_{i,t}$ Production quantity of manufacturer i at period t.

$Es_{i,t}$ Ending stock of raw materials of manufacturer i at period t.

$Ess_{i,t}$ Ending safety stock of manufacturer i at period t.

$Qm_{i,t}$ Ordering quantity of manufacturer i at period t.

$Qb_{ij,t}$ Backorder quantity of manufacturer i for retailer j at period t.

$Qsl_{ij,t}$ Sales volume of manufacturer i at period t.

$Qa_{i,t}$ Available quantity of product at manufacturer i at period t.

$EI_{i,t}$ Ending inventory of manufacturer i at period t.

Parameters of Retailer

$\tilde{d}_{i,t}$ Total end customer demand at period t.

$db_{j,t}$ End customer demand at retailer j at period t before receiving replenishment.

$dr_{j,t}$ End customer demand at retailer j at period t after receiving replenishment.

$\widetilde{lm}_{i,t}$ Lead time of manufacturer i to retailer j at period t.

Ir_{t} Ending inventory of product of retailer j at period t.

$Qsr_{j,t}$ Shortage quantity of retailer j at period t after receiving replenishment.

$Qor_{ji,t}$ Order quantity of retailer j to manufacturer i at period t.

LR_j Loss rate of retailer j.

Cost Parameters

$\tilde{o}_{i,t}$ Order cost of manufacturer i at period t ($).

$\tilde{r}_{i,t}$ Unit purchasing cost of manufacturer i ($).

$\widetilde{m}_{i,t}$ Unit production cost of manufacturer i ($).

$\tilde{h}_{i,t}$ Unit holding cost of raw material of manufacturer i ($).

$\tilde{f}_{i,t}$ Unit holding cost of product of manufacturer i ($).

$\tilde{b}_{i,t}$ Unit backorder cost of manufacturer i ($).

$\tilde{t}_{i,t}$ Unit transportation cost of manufacturer i ($).

$\tilde{p}_{i,t}$ Unit purchasing cost of retailer j ($).

$\tilde{c}_{i,t}$ Unit holding cost of finished product of retailer j ($).

$\tilde{s}_{i,t}$ Unit shortage cost of finished product of retailer j ($).

TCM_i Total Cost of manufacturers ($).

TCR_j Total Cost of retailers ($).

Decision Variables

LS_i Lot sizing policy of manufacturer i, $LS_i = 1$ if manufacturer i

place the order, and $LS_i = 0$ if not place the order but combine it to foregoing order placement.

SS_i Safety stock level of manufacturer *i* (unit).

R_j Target stock level of retailer *j* (unit).

OA_{ji} Order allocation of retailer *j* to manufacturer *i.*

It should be noted that the notations with wave signed on it indicate parameters tainted with uncertainty (imprecise parameters).

5.2.3. The objective Functions

In today's dynamic globalization, competition among organizations exhibits a dynamic nature and it is based on various factors such as cost, time, service level, quality, etc. In such environment, the organization may formulate one or more factors in their goals to sustain or improve their competitive position. In this sense, it is assumed for the case problem we deal with that the manufacturers consider cost while the retailers consider cost and loss rate as the core factors of their competitiveness.

Following are the objective functions for the proposed inventory model.

$$\text{Min} \quad TCM_i = \left\{ \begin{array}{l} \sum_{t=1}^{T} \tilde{r}_i \times Q_{i,t} + \sum_{t=1}^{T} \tilde{m}_i \times Qpr_{i,t} + \sum_{t=1}^{T} \tilde{h}_i \times Es_{i,t} + \\ \sum_{t=1}^{T} \tilde{f}_i \times (Ess_{i,t} + EI_{i,t}) + \sum_{t=1}^{T} \sum_{j=1}^{J} \tilde{b}_i \times Qb_{ij,t} + \sum_{t=1}^{T} \sum_{j=1}^{J} \tilde{t}_i \times Qsl_{ij,t} \end{array} \right\} \tag{5.1}$$

$$\text{Min} \quad TCR_j = \sum_{t=1}^{T} \sum_{i=1}^{I} \tilde{p}_j \times Qsl_{ij,t} + \sum_{t=1}^{T} \tilde{c}_j \times Ir_{j,t} + \sum_{t=1}^{T} \tilde{s}_j \times Qsr_{j,t} \tag{5.2}$$

$$\text{Min} \quad LR_j = \sum_{t=1}^{T} \left(\frac{Qsr_{j,t}}{\tilde{d}_j} \right) \tag{5.3}$$

where

$$Q_{i,t} = \max\left\{0\ ,\ \tilde{D}_{i,t} + f_{i,t-1} + Qb_{i,t} - BI_{i,t} - Bs_{i,t}\right\} \tag{5.4}$$

$$Qpr_{i,t} = \begin{cases} Qp_{i,t} + \left((tp - \tilde{ls}_{i,t}) \times PR_i\right) & \text{if } (Sr_{i,t} + Q_{i,t}) > (tp - \tilde{ls}_{i,t}) \times PR_i \\ Qp_{i,t} + Sr_{i,t} + Q_{i,t} & \text{otherwise} \end{cases} \tag{5.5}$$

$$Es_{i,t} = \begin{cases} (Sr_{i,t} + Q_{i,t}) - \quad \left((tp - \tilde{ls}_{i,t}) \times PR_i\right) & \text{if } (Sr_{i,t} + Q_{i,t}) > \quad (tp - \tilde{ls}_{i,t}) \times PR_i \\ 0 & \text{otherwise} \end{cases} \tag{5.6}$$

$$ESS_{i,t} = \begin{cases} 0 & \text{if } \sum_j Qor_{ji,t} \geq Qa_{i,t} \\ Qa_{i,t} - \sum_j Qor_{ji,t} & \text{if } \sum_j Qor_{ji,t} > Qpr_{i,t-1} + BI_{i,t} \text{ and } \sum_j Qor_{ji,t} < Qa_{i,t} \\ BSS_{i,t} & \text{if } BSS_{i,t} = SS_i \text{ and } \sum_j Qor_{ji,t} \leq Qpr_{i,t-1} + BI_{i,t} \\ SS_i & \text{if } BSS_{i,t} < SS_i \text{ and } \sum_j Qor_{ji,t} \leq Qpr_{i,t-1} + BI_{i,t} \\ & \quad \text{and } Qpr_{i,t-1} + BI_{i,t} - \sum_j Qor_{ji,t} \geq SS_i - BSS_{i,t} \\ BSS_{i,t} + Qpr_{i,t-1} + BI_{i,t} - \sum_j Qor_{ji,t} & \text{otherwise} \end{cases} \tag{5.7}$$

$$EI_{i,t} = \begin{cases} Qpr_{i,t-1} + BI_{i,t} - (\sum_j Qor_{ji,t} + \sum_j Qb_{ij,t}) & \text{if } BSS_{i,t} = SS_i \text{ and } \\ & \quad Qpr_{i,t-1} + BI_{i,t} > \sum_j Qor_{ji,t} + \sum_j Qb_{ij,t} \\ Qpr_{i,t-1} + BI_{i,t} - & \text{if } BSS_{i,t} < SS_i \text{ and } \\ \quad -(\sum_j Qor_{ji,t} + \sum_j Qb_{ij,t}) & \quad Qpr_{i,t-1} + BI_{i,t} > \sum_j Qor_{ji,t} + \sum_j Qb_{ij,t} \text{ and } \\ \quad -(SS_i - BSS_{i,t}) & \quad Qpr_{i,t-1} + BI_{i,t} - (\sum_j Qor_{ji,t} + \sum_j Qb_{ij,t}) > \\ & \quad (SS_i - BSS_{i,t}) \\ 0 & \text{otherwise} \end{cases} \tag{5.8}$$

$$Qsl_{ij,t} = \begin{cases} Qor_{ji,t} + Qb_{ij,t} & \text{if} \quad Qa_{i,t} \geq Qor_{ji,t} + Qb_{ij,t} \\ Qa_{i,t} + Qb_{ij,t} & \text{otherwise} \end{cases} \tag{5.9}$$

$$db_{j,t} = l\tilde{m}_{i,t} \times (\tilde{d}_{j,t} / tp) \tag{5.10}$$

$$dr_{j,t} = \tilde{d}_{j,t} - db_{j,t} \tag{5.11}$$

The ordering quantity of manufacturer ($Q_{i,t}$) is directly influenced by lot sizing policy (LS_i) which is adopted for ordering raw material. For example, if there are 6 planning horizon, there are 2^{T-1} or 32 possible ordering policies for manufacturer to choose. In this case, the first policy may follow lot for lot or place order at every period. The second possible policy may combine order of period 1, 2 and 3 and then use lot for lot the rest four periods. After the best pattern of LS_i is selected, the manufacturer will check the amount of inventory on hand at the beginning of the period (Eq. 5.4). If the amount on hand is less than the sum of the demand and the amount to fill back the safety stock, then the manufacturer will place the order to supplier. Otherwise no order will be issued.

The uncertainty of the delivery lead-time from the supplier has an influence on the production quantity of manufacturer. Normally, production time at period t is equal to the review period deducted by actual delivery lead time of the supplier. However, when late delivery happens, the manufacturer can still start producing the product ($Qp_{i,t}$) if raw material is available on hand. Otherwise, the manufacturer has to wait for new replenishment. Consequently, we can determine total production quantity and ending raw material on hand with Eq. (5.5) and Eq. (5.6), respectively.

As shown in Eq. (5.7) and (5.8), the ending safety stock ($ESS_{i,t}$)

and the ending inventory of finished product ($EI_{i,t}$) have different meanings. $Ess_{i,t}$ is the amount of safety stock left at the end of each period while $EI_{i,t}$ is the number of finished products that is produced beyond the retailer's demand and is left from fulfilling the safety stock. The sales volume ($Qsl_{i,t}$) of the manufacturer is determined based on total order quantity of retailer (Eq. (5.9)). When total order quantity of retailer exceeds the available quantity on hand, the shortage quantity will be backordered next period ($Qb_{i,t}$).

The retailer makes a regular order to the manufacturer periodically to raise up the inventory to the target stock level. The order quantity ($Qor_{j,t}$) is determined by comparing the ending inventory ($Ir_{j,t-1}$) with the desired target stock level (R_j), which is equal to (R_j-$Ir_{j,t-1}$). As stated in Eqs. (5.10) and (5.11), the end customer demand ($\tilde{d}_{j,t}$) at retailer is divided into two types: the demand before receiving replenishment ($db_{j,t}$) and the demand after receiving replenishment ($dr_{j,t}$). The shortage occurred when end customer demand exceeds the inventory and the shortage quantity ($Qsr_{j,t}$) is considered as a full lost.

5.3. Solution methodology

Generally, fuzzy programming can be classified into *flexible programming* and *possibilistic programming* [121]. *Flexible programming* deals with flexibility in the given target value of the objective function and the elasticity of constraints while the *possibilistic programming* handle the uncertainty related to ill-known parameter due to the lack of historical data. The possibilistic programming uses possibility distribution to measure the occurrence of possible value for each of uncertain parameter. This value is mostly determined based on available data as well as experts' knowledge. Based on the above definition and since we are dealing with imprecise parameters, possibilistic programming is used to handle imprecise parameters such as demand, lead time and cost parameters in the proposed inventory model. Thus, our proposed inventory model is a multi-objective possibilistic mixed integer programming (MOPMIP) inventory model.

Subsequently, a solution procedure is proposed to solve MOPMIP inventory model. First, MOPMIP inventory model is transformed into the auxiliary crisp MOPMIP model. This step adopts modified S-curve membership functions to represent all objective functions. The Torabi and Hassini's aggregation function is then proposed to solve the auxiliary crisp MOMIP model.

5.3.1. The equivalent auxiliary crisp MOPMIP model

Solving optimization problem requires a condition in which all variables and parameters involved must be defined in *crisp* form. Therefore, in the case where fuzziness is embedded to optimization problem, such fuzziness should be cleared up by transforming the problem into equivalent *crisp* formulation before moving to the solution stage. In this research, this transformation is carried out using possibilistic programming. For this purpose, one method of possibilistic programming named Jimenez method is applied due to its computational efficiency [122]. The Jimenez method is based on the definition of the "expected value" and the "expected interval" of a fuzzy number.

Assume that $\tilde{c}$ is a triangular fuzzy number. The following equation can be defined as the possibility distribution of $\tilde{c}$.

$$\mu_{\tilde{c}}(x)=\begin{cases} f_c(x)=\dfrac{x-c^{pes}}{c^{mos}-c^{pes}} & \text{if} \quad c^{pes}\le x\le c^{mos} \\ 1 & \text{if} \quad x=c^{mos} \\ g_c(x)=\dfrac{c^{opt}-x}{c^{opt}-c^{mos}} & \text{if} \quad c^{mos}\le x\le c^{opt} \\ 0 & \text{if} \quad x\le c^{pes} \;\; or \;\; x\ge c^{opt} \end{cases} \tag{5.12}$$

where c^{pes}, c^{mos} and c^{opt} are the three prominent points (the most likely, the most pessimistic and the most optimistic value), respectively. Eq. (5.13) and (5.14) define the expected interval (EI) and the expected value (EV) of triangular fuzzy number $\tilde{c}$.

$$\begin{aligned} EI(\tilde{c}) &= \left[E_1^c, E_2^c\right]=\left[\int_0^1 f_c^{-1}(x)dx,\ \int_0^1 g_c^{-1}(x)dx\right] \\ &=\left[\frac{1}{2}(c^{pes}+c^{mos}),\ \frac{1}{2}(c^{mos}+c^{opt})\right] \end{aligned} \tag{5.13}$$

$$EV(\tilde{c})=\frac{E_1^c+E_2^c}{2}=\frac{c^{pes}+2c^{mos}+c^{opt}}{4} \tag{4.14}$$

Assuming all imprecise parameters in this model follow the triangular pattern, according to Eq. (5.13) and (5.14) the auxiliary crisp formulation of the proposed inventory model (except for Eq. (5.7), (5.8) and (5.9)) can be reformulated as follows.

Min $TCM_i =$

$$\left\{\begin{aligned} &\sum_{t=1}^{T}\left(\frac{r_i^{pes}+2r_i^{mos}+r_i^{opt}}{4}\right)Q_{i,t}+\sum_{t=1}^{T}\left(\frac{m_i^{pes}+2m_i^{mos}+m_i^{opt}}{4}\right)Qpr_{i,t}+ \\ &\sum_{t=1}^{T}\left(\frac{h_i^{pes}+2h_i^{mos}+h_i^{opt}}{4}\right)Es_{i,t}+\sum_{t=1}^{T}\left(\frac{f_i^{pes}+2f_i^{mos}+f_i^{opt}}{4}\right)\left(Ess_{i,t}+EI_{i,t}\right) \\ &+\sum_{t=1}^{T}\sum_{j=1}^{J}\left(\frac{b_i^{pes}+2b_i^{mos}+b_i^{opt}}{4}\right)Qb_{ij,t}+\sum_{t=1}^{T}\sum_{j=1}^{J}\left(\frac{t_i^{pes}+2t_i^{mos}+t_i^{opt}}{4}\right)Qsl_{ij,t} \end{aligned}\right\} \tag{5.15}$$

$$\text{Min}\quad TCR_j =$$

$$\left\{\begin{aligned}&\sum_{t=1}^{T}\sum_{i=1}^{I}\left(\frac{p_i^{pes}+2p_i^{mos}+p_i^{opt}}{4}\right)Qsl_{j,t}+\sum_{t=1}^{T}\left(\frac{c_i^{pes}+2c_i^{mos}+c_i^{opt}}{4}\right)Ir_{j,t}+\\&\sum_{t=1}^{T}\left(\frac{s_i^{pes}+2s_i^{mos}+s_i^{opt}}{4}\right)Qsr_{j,t}\end{aligned}\right\} \tag{5.16}$$

$$\text{Min}\quad LR_j = \sum_{t=1}^{T}\left(\frac{4Qsr_{j,t}}{d_{j,t}^{pes}+2d_{j,t}^{mos}+d_{j,t}^{opt}}\right) \tag{5.17}$$

$$Q_{i,t} = \max\left\{0, \left(\frac{D_{i,t}^{pes}+2D_{i,t}^{mos}+D_{i,t}^{opt}}{4}\right)+f_{i,t-1}+Qs_{i,t-1}-BI_{i,t}-Bs_{i,t}\right\} \tag{5.18}$$

$$Qpr_{i,t} =$$

$$\begin{cases} Qp_{i,t}+\left(\left(tp-\frac{ls_{i,t}^{pes}+2ls_{i,t}^{mos}+ls_{i,t}^{opt}}{4}\right)\times PR_i\right) & \text{if } (Sr_{i,t}+Q_{i,t}) > \left(\left(tp-\frac{ls_{i,t}^{pes}+2ls_{i,t}^{mos}+ls_{i,t}^{opt}}{4}\right)\times PR_i\right)\\ Qp_{i,t}+Sr_{i,t}+Q_{i,t} & \text{otherwise}\end{cases} \tag{5.19}$$

$$Es_{i,t} =$$

$$\begin{cases} (Sr_{i,t}+Q_{i,t})-\left(\left(tp-\frac{ls_{i,t}^{pes}+2ls_{i,t}^{mos}+ls_{i,t}^{opt}}{4}\right)\times PR_i\right) & \text{if } (Sr_{i,t}+Q_{i,t}) > \left(\left(tp-\frac{ls_{i,t}^{pes}+2ls_{i,t}^{mos}+ls_{i,t}^{opt}}{4}\right)\times PR_i\right)\\ 0 & \text{otherwise}\end{cases} \tag{5.20}$$

$$db_{j,t} = \left(\frac{lm_{ij,t}^{pes}+2lm_{ij,t}^{mos}+lm_{ij,t}^{opt}}{4}\right)\times\left(\frac{d_{j,t}^{pes}+2d_{j,t}^{mos}+d_{j,t}^{opt}}{4tp}\right) \tag{5.21}$$

5.3.2. The modified S-curve membership function

Membership function is a function which represent of satisfaction degree (possibility degree) of a certain variables. There are many types of membership function such as linear, exponential, etc.

In this research, the modified s-curve membership function (Figure 5.2) is employed because it is considered much more easily in handling compared to other membership functions [123]. The modified s-curve membership function is a particular case of the logistic function with specified parameters and its formulation is defined as follow:

$$\mu(x) = \begin{cases} 1 & x < x^a \\ 0.999 & x = x^a \\ \dfrac{B}{1 + Ce^{\delta x}} & x^a < x < x^b \\ 0.001 & x = x^b \\ 0 & x >^b \end{cases} \tag{5.22}$$

where μ is the degree of satisfaction. The term δ determines the shape of membership function $\mu(x)$, where $\delta > 0$. The larger the value of parameter δ, the greater the vagueness is. As can be seen in Figure 5.2, the degree of satisfaction is redefined as $0.001 \leq \mu(x) \leq 0.999$. This range is chosen because we assume that the availability of supply of resources (raw material and product) are not necessarily be always 100% of the requirement which, at the same time, implies that the total cost and the unsatisfied demand will not be 0% at both manufacturers and retailers. In this research this type of member-

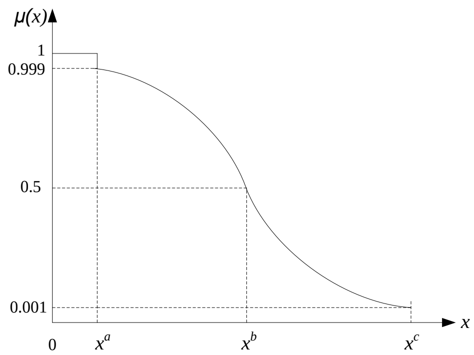


Figure 5.2. Modified S-Curve Membership Function

ship is applied to represent the fuzzy goals: minimizing total cost of manufacturer, minimizing the total cost of retailer, and minimizing the loss rate of retailers.

5.3.3. Torabi and Hassini aggregation function

Torabi and Hassini [124] proposed a new aggregation function of fuzzy approach (TH method). This method has been proven to yield an efficient solution [127]. According to Torabi and Hassini, a fuzzy multi-objective model could be transformed in a single objective model as follows:

$$\begin{aligned}
&\text{Max} \quad \gamma\lambda_0 + (1-\gamma)\sum_k w_k \mu_{Z_k} \\
&\text{subject to:} \;\; \lambda_0 \le \mu_{Z_k} \\
&\qquad\qquad\quad \lambda_0, \mu_{Z_k}, \gamma \in [0,1]
\end{aligned} \tag{5.23}$$

where μ_{zk} and $\lambda_0 = \min\{\mu_{zk}\}$ denote the satisfaction degree of k-th objective (individual satisfaction degree of each objective) and the minimum satisfaction degree of the objectives, respectively. Moreover, w_k and γ indicate the relative importance of the k-th objective function and the coefficient of compensation, respectively. The w_k parameters are determined by the decision maker based on her/his preferences so that $\sum w_k = 1$, $w_k > 0$. This aggregation function results in a compromise value between the max-min operator and weighted-sum operator based on the value of γ.

5.3.4. The integrated solution procedures

As mention earlier, our proposed inventory model is a fuzzy multi-objective model which belongs to a possibilistic mixed-integer programming (MOPMIP) problem. To solve the problem, we propose integrated solution procedures which provide a systematic framework that facilitates the fuzzy decision-making process as shown in Figure 5.3.

Since the proposed MOPMIP inventory model is typically difficult to solve optimally in most real-life cases, performing the above procedure to search satisfactory solutions in the proposed MOPMIP model requires a tough computational experience. Hence, in order to alleviate such computational complexity, the model is solved with a Differential Evolution (DE). The DE is a kind of evolutional search methods and known as a practical and effective method to solve such

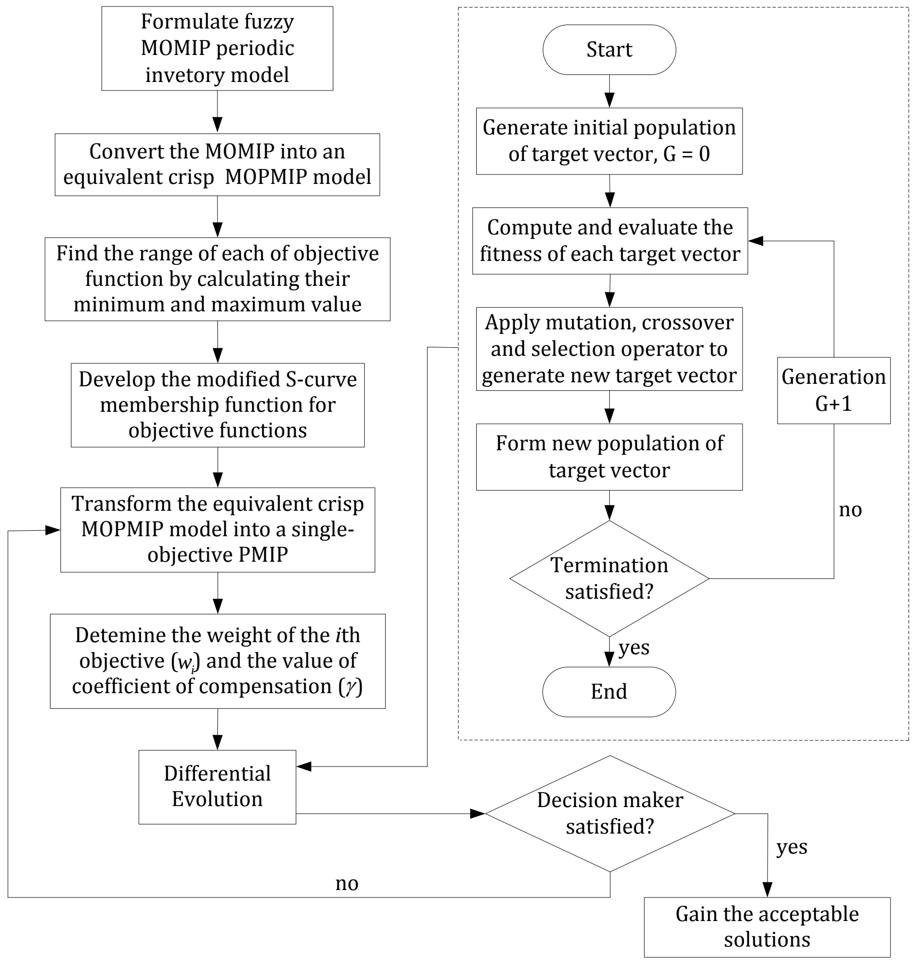


Figure 5.3. Flowchart of Solution Procedures

problems [79, 80].

The steps of the proposed solution procedures are summarized as follows:

Step 1: Formulate the fuzzy multi objectives mixed-integer programming (MOMIP) periodic review inventory model (Eqs. (5.1) – (5.11)).

Step 2: Convert the MOMIP inventory model into an equivalent crisp MOPMIP model. To this end, all the imprecise cost parameters in the objective functions as well as the demand and lead time parameters are converted into the crisp ones using Jimenez method (see section 5.3.1).

Step 3: Determine the rage of each objective function by calculating the upper bound (UB) and lower bound (LB) of each objective function. To do so, equivalent crisp MOPMIP model should be solved each time only one objective.

$$Z_1^{UB} = \min \sum_{i=1}^{I} TCM_i , \quad Z_1^{LB} = \max \sum_{i=1}^{I} TCM_i$$
$$Z_2^{UB} = \min \sum_{j=1}^{J} TCR_j , \quad Z_2^{LB} = \max \sum_{j=1}^{J} TCR_j$$
$$Z_3^{UB} = \min \sum_{j=1}^{J} LR_j , \quad Z_3^{LB} = \max \sum_{j=1}^{J} LR_j$$

Step 4: Develop the modified S-curve membership function for the objective functions using Eq. (5.22).

$$\mu_{Z_1} = \begin{cases} 1 & Z_1 < Z_1^l \\ 0.999 & Z_1 = Z_1^l \\ \dfrac{B}{1 + Ce^{\delta\left(Z_1 - Z_1^l / Z_1^u - Z_1^l\right)}} & Z_1^l < Z_1 < Z_1^u \\ 0.001 & Z_1 = Z_1^u \\ 0 & Z_1 > Z_1^l \end{cases} \qquad \mu_{Z_2} = \begin{cases} 1 & Z_2 < Z_2^l \\ 0.999 & Z_2 = Z_2^l \\ \dfrac{B}{1 + Ce^{\delta\left(Z_2 - Z_2^l / Z_2^u - Z_2^l\right)}} & Z_2^l < Z_2 < Z_2^u \\ 0.001 & Z_2 = Z_2^u \\ 0 & Z_2 > Z_2^l \end{cases}$$

$$\mu_{Z_3} = \begin{cases} 1 & Z_3 < Z_3^l \\ 0.999 & Z_3 = Z_2^l \\ \dfrac{B}{1 + Ce^{\delta\left(Z_3 - Z_3^l / Z_3^u - Z_3^l\right)}} & Z_3^l < Z_3 < Z_3^u \\ 0.001 & Z_3 = Z_3^u \\ 0 & Z_3 > Z_3^l \end{cases}$$

Step 5: Transform the equivalent crisp MOPMIP model into a single-objective model based on the TH method. Employing the TH method in Eq. (5.23), the single objective formulation of the inventory model can be formulated as follow.

$$\begin{aligned} &\text{Max} \quad \gamma\lambda_0 + (1-\gamma)\sum_{k}\left(w_1\mu_{Z1} + w_2\mu_{Z2} + w_3\mu_{Z3}\right) \\ &\text{subject to}: \quad \lambda_0 \le \mu_{Z1},\ \lambda_0 \le \mu_{Z2},\ \lambda_0 \le \mu_{Z3} \\ &\qquad\qquad\quad \lambda_0, \mu_{Z_k}, \gamma \in [0,1] \\ &\qquad\qquad\quad \text{Eqs.(4.19)-(4.23)} \end{aligned}$$

Step 6: Determine the weight of the k-th objective (w_k) and the value of coefficient of compensation (γ), and solve the corresponding single-objective model using the Differential Evolution algorithm (See Chapter 3 Section 2.4).

Step 7: Present the set of compromise solution to the DM. If the decision maker(s) is satisfied with the current solution, stop. Otherwise, search another solution by repeating step 6.

5.4. Computational Experiment and Analysis

In this research, a hypothetically constructed SC system consisting of multi-manufacturer and multi-retailer is developed for

Table 5.1. Input Parameters

<table>
<tr><th rowspan="2">Input Parameters</th><th colspan="3">Value</th></tr>
<tr><th colspan="2">M1</th><th>M2</th></tr>
<tr><td>$\widetilde{D}$ (unit)</td><td colspan="2">{3661, 3950, 4476}[a],
{3011, 3500, 4036},
{3611, 4450, 4808},
{3276, 3900, 4404},
{3105, 3700, 4202},
{3252, 4050, 4550}</td><td>{3214, 3500, 4050},
{3246, 3900, 4544},
{3654, 4450, 4985},
{3545, 4100, 4665},
{3589, 4200, 4721},
{3108, 3700, 4280}</td></tr>
<tr><td>$\widetilde{ls}$ (day)</td><td colspan="2">{3, 4, 6},{3, 4, 6},{1, 3, 7},
{3, 4, 6},{1, 4, 8},{3, 4, 6}</td><td>{1, 3, 6},{2, 4, 8},{1, 3, 5},
{2, 4, 7},{1, 3, 6},{1, 3, 6}</td></tr>
<tr><td>$\widetilde{lm}$ (day)</td><td colspan="2">to R1: {1, 3, 5},{3, 6, 8},{4, 6, 9},
{2, 4, 6},{2, 4, 7},{1, 3, 5},
to R2: {4, 6, 9},{1, 3, 5},{2, 4, 6},
{4, 6, 9},{3, 5, 8},{1, 3, 5}
to R3: {2, 4, 6},{1, 3, 5},{2, 4, 7},
{1, 3, 5},{4, 6, 9},{4, 7, 9}</td><td>to R1: {3, 5, 7},{1, 3, 5},{1, 3, 5},
{4, 6, 8},{5, 7, 9},{1, 3, 5},
to R2: {1, 3, 5},{5, 7, 9},{3, 5, 7},
{1, 3, 5},{2, 4, 6},{5, 7, 9}
to R3: {5, 7, 9},{4, 6, 8},{1, 3, 5},
{3, 6, 8},{2, 4, 6},{1, 3, 5}</td></tr>
<tr><th></th><th>R1</th><th>R2</th><th>R3</th></tr>
<tr><td>$\tilde{d}$ (unit)</td><td>{1576, 2500, 2976}
{1836, 2300, 2836}
{1908, 2700, 3208}
{1504, 2200, 2804}
{1702, 2500, 3020}
{1850, 2800, 2650}</td><td>{2081, 2800, 3462}
{2254, 3000, 3399}
{1952, 2500, 2921}
{2184, 2800, 3442}
{1602, 2400, 2931}
{2650, 3200, 3684}</td><td>{2050, 2500, 2922}
{1996, 2700, 3252}
{2291, 3000, 3511}
{1854, 2600, 3220}
{1540, 2200, 2931}
{2050, 2700, 3280}</td></tr>
</table>

Table 5.2. Cost Parameters

<table>
<tr><th rowspan="2">Cost Parameters</th><th colspan="3">Value</th></tr>
<tr><th colspan="2">M1</th><th>M2</th></tr>
<tr><td>$\tilde{o}$ ($)</td><td colspan="2">{80, 100, 130}</td><td>{70, 110, 140}</td></tr>
<tr><td>$\tilde{r}$ ($)</td><td colspan="2">{3, 5, 7}</td><td>{3, 5, 7}</td></tr>
<tr><td>$\widetilde{m}$ ($)</td><td colspan="2">{3, 5, 8}</td><td>{3, 6, 9}</td></tr>
<tr><td>$\tilde{h}$ ($)</td><td colspan="2">{0.11, 0.15, 0.17}</td><td>{0.11, 0.15, 0.17}</td></tr>
<tr><td>$\tilde{f}$ ($)</td><td colspan="2">{0.3, 0.4, 0.5}</td><td>{0.3, 0.4, 0.5}</td></tr>
<tr><td>$\tilde{b}$ ($)</td><td colspan="2">{8, 10, 14}</td><td>{8, 10, 14}</td></tr>
<tr><td>$\tilde{t}$ ($)</td><td colspan="2">to R1: {3, 5, 7}
to R2: {3, 6, 8}
to R3: {4, 6, 8}</td><td>to R1: {3, 5, 7}
to R2: {3, 6, 8}
to R3: {4, 6, 8}</td></tr>
<tr><th></th><th>R1</th><th>R2</th><th>R3</th></tr>
<tr><td>$\tilde{p}$ ($)</td><td>to M1: {15, 20, 25}
to M2: {15, 20, 25}</td><td>to M1: {15, 20, 25}
to M2: {15, 20, 25}</td><td>to M1: {15, 20, 25}
to M2: {15, 20, 25}</td></tr>
<tr><td>$\tilde{c}$ ($)</td><td>{0.1, 0.3, 0.5}</td><td>{0.1, 0.3, 0.5}</td><td>{0.1, 0.3, 0.5}</td></tr>
<tr><td>$\tilde{s}$ ($)</td><td>{17, 20, 23}</td><td>{17, 20, 23}</td><td>{17, 20, 23}</td></tr>
</table>

computational experiment. To illustrate the usefulness of the fuzzy MOPMIP inventory model using the proposed solution procedure, the model is implemented to solve the SC system consisting of two manufacturers and three retailers and the result is reported in this section utilizing parameters shown in Table 5.1 and 5.2. It is assumed that all members belong to one central major enterprise. It is also assumed that the DM of each member determines the estimation of the possibility distribution of the imprecise parameters by deciding three prominent values (i.e., the most likely, the most pessimistic and the most optimistic values) based on their available data and knowledge.

In this SC configuration, each manufacturer has a similar characteristic except that they are distinguished by their production capabilities. As a result, production rate of manufacture 1 (450 units) is slightly higher than that of manufacturer 2 (400 units). Planning horizon for 6 periods are provided in which each period consists of 10 days (tp). Without loss of generality, the SCs control is measured based on the aggregate performance i.e., the measures is aggregated for all manufacturers and for all retailers. To provide the DMs with the broad decision spectrum, several results with different value of variable of compensation is (γ-level) are provided in performance testing, and for each γ value a solution set is generated by the aid of the TH method (Table 5.3).

As seen, the proposed fuzzy inventory model is referred to the mixed-integer programming problem which is very difficult to solve in real-life cases. Hence, some alternative fuzzy solution methods such as LH method [125], SO method [126], etc., are developed in literatures. Among them, the SO method is employed in this study by means that the effectiveness of the proposed model using TH method is compared with that of using the SO method (see Appendix).

The modified S-curve membership function for all fuzzy objectives has adopted the same values for B, C and δ parameters. These values are B = 1; C = 0.001001 and δ = 13.813 [123]. Supposed the relative importance of objectives is provided from linguistic statement that all are equivalent i.e., $\omega_1 = \omega_2 = \omega_3$. Based on this relationship the weight vector is set as: ω = (0.33, 0.33, 0.33) which means that all the objectives are equally important as each other. Due to the nature of problem dependence, key parameters (M, CR and F) in DE should be chosen wisely and appropriately to get fast convergence and avoid the problem of premature convergence. According to our preliminary experiments, an appropriate value of M, CR, F and G are set as follows: M = 100, F = 0.8 and CR = 0.5 and G = 5000.

- *Consideration from the major interest*

According to Table 5.3, the TH method has a superiority over the SO method in terms of the value of minimum satisfaction degree of objectives because the solutions derived from the TH method are more balanced compared to those of SO method. Particularly, the solutions provided by the SO method are unbalanced in low γ-levels (i.e., 0.0-0.4), that is to say that the comprehensive satisfaction degree of objectives is small and the method pays more attention to some specific objectives rather than to comprehensive satisfaction degree.

In this model, the satisfaction degree (μ_{z1}) of the first objective (Z_1) is always the lowest compared to (μ_{z2}) and (μ_{z3}) in all γ-levels. This indicates that the first objective is a critical objective as it bounds the minimum satisfaction degree of objectives involved. Consequently, the method attempts to maximize the satisfaction degree of the second and the third objective while giving less attention to the performance of the first objective. As a result, for the lower γ-levels the SO method provides totally unsatisfactory solution for the first objective whose value likely move toward its worst possible

Table 5.3. Summary of test result

Item	TH method						SO method					
	$\gamma = 0.0$	$\gamma = 0.2$	$\gamma = 0.4$	$\gamma = 0.6$	$\gamma = 0.8$	$\gamma = 1.0$	$\gamma = 0.0$	$\gamma = 0.2$	$\gamma = 0.4$	$\gamma = 0.6$	$\gamma = 0.8$	$\gamma = 1.0$
Satisfaction degree:												
λ_0	0.827	0.885	0.889	0.908	0.915	0.916	0.001	0.001	0.368	0.881	0.890	0.890
μ_{z1}	0.827	0.885	0.899	0.908	0.915	0.916	0.001	0.001	0.368	0.881	0.890	0.890
μ_{z2}	0.986	0.910	0.890	0.978	0.918	0.925	0.996	0.998	0.995	0.923	0.908	0.968
μ_{z3}	0.991	0.996	0.992	0.917	0.940	0.997	0.997	0.998	0.998	0.995	0.996	0.902
Objectives value:												
Z_1	846745	792133	774292	763315	752954	751037	1826787	1818736	1090546	796285	785860	786198
Z_2	461850	735474	767052	525444	721752	706706	276616	183676	305930	711040	738348	582036
Z_3	20.55%	15.70%	19.71%	35.96%	0.3366	12.82%	13.29%	11.47%	9.36%	16.99%	15.91%	37.17%
Decision variables:												
LS_1	100011	111111	110111	100010	100010	101011	100000	100000	100001	111011	101011	101110
LS_2	110011	101000	111001	110100	101000	111000	100000	100000	101010	111101	111000	110011
ss_1	356	0	376	249	201	0	1177	1177	1145	380	0	740
ss_2	497	0	278	0	79	1192	1192	281	1192	1192	67	821
S_1	3500	3546	3500	3500	3500	3647	4550	4550	4550	3795	3500	3500
S_2	3892	4162	3892	751	991	3892	5059	4988	4767	3929	3950	3892
S_3	3654	4634	3654	3654	3654	4750	4750	4750	4750	3721	4750	666
OA_{11}	100%	100%	100%	100%	100%	100%	0	37%	100%	100%	100%	100%
OA_{12}	0	0	0	0	0	0	100%	63%	0	0	0	0
OA_{21}	0	100%	100%	2%	1%	100%	52%	27%	72%	100%	100%	84%
OA_{22}	100%	0	0	98%	99%	0	48%	73%	28%	0	0	16%
OA_{31}	0	39%	0	81%	93%	17%	23%	70%	63%	61%	3%	52%
OA_{12}	100%	61%	100%	19%	7%	83%	77%	30%	37%	39%	97%	48%
Range value of objective:												
$[Z_1^{min}, Z_1^{max}]$ = [$228619, $1836880]					$[Z_2^{min}, Z_2^{max}]$ = [$86724, $2037710]				$[Z_3^{min}, Z_3^{max}]$ = [5.92%, 98.00%]			

value. However, in the high γ-levels, the performance of the two methods is quite similar and both of them find the solutions with insignificant differences while the TH method provides more evenly acceptable results.

According to information provided in Table 5.3, changing the γ-level does not give significant influences on decision adjustment in the TH method. However, regarding the SO method, ordering raw material in a big batch, holding higher volume of safety stock and setting a higher volume of target stock level were found to cause the poor performance of the first objective in low γ-levels due to the increase in of inventory holding cost. As can be seen in Figure 5.4, the aggregate holding cost of manufacturers in SO method reported significantly higher in the low γ-levels. On the contrary, the TH method provides more equitable result by proposing to order raw material in big batches and small lots, holding more moderate amount of safety stock and setting lower level of target stock.

From the above illustrative case, decision making support can be provided to improve the performance of Z_1 as a critical objective. From strategic level, this can be done by giving the main concern to prioritize more Z_1 than to other objectives. In this case, the DM in

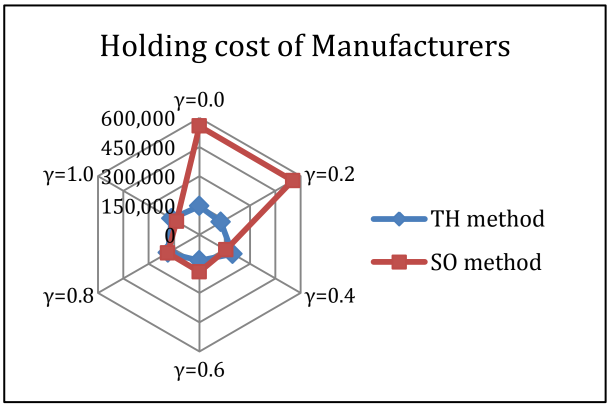


Figure 5.4. Holding cost of Manufacturers

major enterprise plays an important role to formulate the relative importance of each objective. On the other hand, from the tactical level, the improvement can also be achieved by adjusting the decision toward reducing the inventory level by ordering raw material in a smaller lot and lowering the amount of safety stock.

- *Consideration from the extended interest*

The minimum satisfaction degree of objective represents the comprehensive satisfaction degree by which all objectives involved are guaranteed to have the same value of satisfaction degree. This value is controlled by γ to ensure yielding both balanced and unbalanced compromise solution. Higher γ-levels mean more concern is given to achieve a higher minimum satisfaction degree of objectives (λ_0) and hence more balanced solution is derived. On the contrary, low γ-levels indicate that the method pays more attention to maximize the satisfaction degree of some specific objectives than to comprehensive satisfaction degree and accordingly more unbalanced solution. In this case, we can distinguish the unbalanced solutions from the least unbalanced solution (γ = 0.9) to the most unbalanced solution (γ = 0.0).

With the viewpoint of decision making, the γ-level controls the power of the DM to the solution. While the balanced solutions indicate no contribution of the DM to the solutions, the most unbalanced solution (the lowest γ-level, i.e., γ = 0.0) allows a complete authorization of the DM to make a decision according to his preferences. Consequently, we think that all unbalanced solutions and the balanced solution may represent a typical *decentralized* and *centralized* SC system, respectively. In the *decentralized* system, various operational decisions are made at different companies or a certain group of com-

Table 5.4. Result obtained for some weight combinations

Item	Problem instances					
	1	2	3	4	5	6
ω_1	0.5	0.3	0.3	0.4	0.4	0.2
ω_2	0.3	0.5	0.2	0.2	0.4	0.4
ω_3	0.2	0.2	0.5	0.4	0.2	0.4
μ_{z1}	0.992	0.933	0.921	0.946	0.950	0.807
μ_{z2}	0.965	0.995	0.892	0.878	0.990	0.996
μ_{z3}	0.955	0.966	0.998	0.995	0.958	0.990
Z_1	473248	723853	743132	695743	687176	862316
Z_2	593354	302512	764512	782876	416440	283816
Z_3	31.60%	30.73%	11.50%	17.16%	30.28%	21.25%

pany in the same stage which tries to optimize their own objectives. More specifically, the company such as regional distributor of automotive products performs collaborative operational decision with other regional distributors in order to improve their responsiveness to the customer demand. To this end, this study assumes that the members in the same SC stage collaborate as the independent group of enterprise in which all operational decision are made on their own authority while the major enterprise focuses more in a strategic planning. In most situations, however, the major enterprise may be urged to decide which member(s) should be prioritized in order to improve their performance(s).

Generally speaking, in the *centralized* SC, the major enterprise attempts to make a *centralized* decision for synchronizing production and distribution flows across the SC. For this purpose, the DM of major enterprise determines the relative importance of objectives and this will result in different weight combinations as presented in Table 4. From Table 5.4 we know that the loss rate of retailers (Z_3) is almost insensitive to the weight structures. While changing the weights influences the loss rate of retailers slightly, it causes considerable changes in the total cost of manufacturers (Z_1) and the total cost of retailers (Z_2) especially in low weight level. This can be seen from Table 5.4 that while changing the weight from 0.2 to 0.5 causes μ_{z3} to slightly change from 0.955 to 0.998, it generates significant change of μ_{z1} from 0.807 to 0.992 and μ_{z3} from 0.878 to 0.995. Therefore, the major enterprise as a central DM should carefully consider these behaviors when choosing the weight combination to make the right decisions.

5.5. Conclusion

This study has proposed MOPMIP model of periodic review inventory problem in multi-manufacturer multi-retailer SC system. A solution procedure is developed to solve the model and to provide a systematic framework that facilitates the fuzzy decision-making process, enabling the DM to adjust the decision and to obtain a more preferred satisfactory solution. The computational experiment indicates that the proposed solution procedures obtain a promising result which produces more balanced solutions set based on the DM's preferences. It also provides decision support to identify critical objective and provides a realistic recommendation for improvement from the perspective of strategic and operational aspect by offering the flexibility to adjust the decision considering the DM's preference. Moreover, noticing that the proposed solution method has a specific feature to control the authority of the DM, it is also becomes feasible to apply the result in both *decentralized* and *centralized* SC system.

This research is an anticipating works in the design of periodic review inventory control under uncertainty in the context of SC system using possibilistic programming approach. Therefore many possible researches can be developed in this scope. For example, addressing collaborative planning in SC system such as supplier selection-inventory control and inventory control-transportation planning will becomes an attractive research avenue with significance practical relevance.

Appendix 5.1

Selim and Ozkarahan Method:

$$\text{Max} \quad \gamma\lambda_0 + (1-\gamma)\sum_k w_k \lambda_k$$

$$\text{subject to}: \ \lambda_0 + \lambda_k \le \mu_{Z_k}$$

$$\lambda_0, \mu_{Z_k}, \gamma \in [0,1]$$

In this model, λ_k denotes the difference between the satisfaction degree of k-th objective (individual satisfaction degree of each objective) with the minimum satisfaction degree of the objectives $(\lambda_k = \mu_{Z_k} - \lambda_0)$.

Chapter 6

CONCLUSION

6.1. Concluding remark

Most companies are now facing dynamic challenges that require not only well-planning capacity, but also robust SC networks that allow the members involved to address and respond any changes in a short notice. In particular, when inventory is stuck in the various stages of the supply chain, the company may be forced to operate at critical cash flow levels. On the other hand, of the various activities involved in SC network, purchasing is one of the most strategic functions because it provides opportunities to reduce costs across the entire supply chain. An essential task within the purchasing function is supplier selection, given that the cost of raw materials and component parts represents the largest percentage of the total product cost in most industries.

From this point of view, this thesis addresses some issues in inventory and supplier selection problem. To be more practically relevant, we study both issues under uncertain environment and approach such problem using either stochastic approach or fuzzy approach.

Chapter 3 investigated a multi-objective problem of periodic review inventory in two-echelon supply chain system under uncertainty in demand and lead time. In this study, we propose different strategies to solve the stock-out problem - beside the traditional mechanism - in serial replenishment system which require a higher level of coordination. While stochastic approach is utilized to tackle the uncertainty, the multi-objective Differential Evolution (DE) is applied after giving its modified algorithm to work with the problem. It was found that the coordination strategy is become more effective as the uncertainty increases in the system. By cooperating, manufacturers can avoid frequent backorder and reduce excess inventory as a whole. Though retailers are required to keep a bit high inventory level to maintain the good responsiveness to the customer demand, this stock level is more effective to reduce the loss rate of supply chain.

Chapter 4 studied multi-objective supplier selection problem by considering both qualitative and quantitative criteria under uncertainty. Unlike Chapter 1 which applied stochastic approach, this research incorporated fuzzy approach is proposed due to the fact that most information required to assess supplier is not always available and/or usually not known precisely over the planning horizon. Concerning such characteristics, this research proposes integrated methodology for fuzzy multi-objective linear programming model for supplier selection. To improve in the methodological process of deriving optimal solution, the enhanced two-phase fuzzy programming model has been developed in this study. Through numerical experiment, we show some promising advantage of our proposed approach over the existing methods in providing a set of potential feasible solutions which guide DMs to select the best solution according to their preference.

Chapter 5 presented a multi-objective possiblistic mixed integer programming (MOPMIP) model of periodic review inventory problem in multi-manufacturer multi-retailer Supply Chain system. Possibilistic programming is one method under Fuzzy Set Theory (FST) which is designed to handle the uncertainty related to ill-known parameters due to the lack of precise data. Specifically, we attempt to develop a multi-objective periodic review inventory model in a mixed imprecise and/or uncertain environment by incorporating the fuzziness of demand, lead time and cost parameters. A solution procedure is developed using the Torabi and Hassini (TH) method to solve the model and to provide a systematic framework that facilitates the fuzzy decision-making process, enabling the DM to adjust the decision and to obtain a more preferred satisfactory solution. Then the solutions are derived by the aid of Differential solution. The proposed solution procedures obtain a promising result which produces more balanced solutions and provide decision support to identify critical objective. It is also becomes feasible to apply the result in both decentralized and centralized SC system.

6.2. Future research

Several possible research can be developed to extend the current research. Since the proposed research problem is carried out in small scale problem, it is more appealing to devote the future research plan to more general and large scale configurations of the supply chain system. Moreover, combining two or more idea of the current researches into collaborative planning in SC will becomes an attractive research avenue with significance practical relevance.

References

[1] C. A. Weber, J.R. Current, W.C Benton, Vendor Selection Criteria and Methods, European Journal of Operational Research, 50(1)(1991), pp. 2-18.

[2] W. Ho, X. Xu, P.K. Dey, Multi-criteria Decision Making Approaches for Supplier Evaluation and Selection: A Literature Review, European Journal of Operational Research, 202(1)(2010), pp. 16-24.

[3] S. J. New, The scope of supply chain management research, Supply Chain Management, 2 (1) (1997), pp. 15-22.

[4] A. Lockamy III, W. I Smith, Target costing for supply chain management: criteria and selection, Industrial Management & Data Systems, 100 (5) (2000), pp. 210-218.

[5] D. Simchi-Lev, P. Kaminsky, E. Simchi-Lev, E, Designing and Managing the Supply Chain, Irwin McGraw-Hill, Boston, MA (2000).

[6] C. Scott, R. Westbrook, New strategic tools for supply chain management, International Journal of Physical Distribution and Logistics, 21 (1) (1991), pp. 23-33.

[7] S. J. New, P. Payne, Research frameworks in logistics: three models, seven dinners and a survey, Int'l Journal of Physical Distribution and Logistics Management, 25 (10) (1995), pp. 60-77.

[8] B. M. Beamon, Supply chain design and analysis: Models and methods, International Journal of Production Economics, 55 (1998), pp. 281-294.

[9] C. Harland, Supply chain operational performance roles, Integrated Manufacturing Systems, 8 (2) (1997), pp. 70-78.

[10] S. Geary, P. Childerhouse, and D. Towill, Uncertainty and the seamless supply chain, Supply chain management review, July/ august 2002.

[11] K. Mitra , R. D. Gudi , S. C. Patwardhan , G. Sardar, Towards resilient supply chains: Uncertainty analysis using fuzzy mathematical programming, Computer Aided Chemical Engineering, 25 (2008), pp. 701–706.

[12] N.V. Sahinidis, Optimization under uncertianty: state-of-the-art and opportunities, Computer and Chemical Engineering, 28 (2004), pp. 971-983.

[13] S.A. MirHassani, C. Lucas, G. Mitra, E. Messina, C.A. Poojari, Computational solution of capacity planning models under uncertainty, Parallel Computing, 26 (5) (2000), pp. 511–538.

[14] M. C. Georgiadis, P. Tsiakis, P. Longinidis, M. K. Sofioglou, Optimal design of supply chain networks under uncertain transient demand variations, Omega 39 (3) (2011), pp. 254–272.

[15] A. Alonso-Ayuso, L.F. Escudero, A. Garín, M.T. Ortuño, G. Pérez, An approach for strategic supply chain planning under uncertainty based on stochastic 0–1 programming, Journal of Global Optimization (2002).

[16] H.J. Zimmermann, Fuzzy programming and linear programming with several objective functions, Fuzzy Set and System, 1 (1978), pp. 45–55.

[17] H.J. Zimmermann, Fuzzy Set Theory and Its Application, Kluwer Academic Publishers, Boston (1991).

[18] M.L. Liu, N.V. Sahinidis, Process planning in a fuzzy environment, European Journal of Operation Research, 100 (1997), pp. 142–169.

[19] H. Selim, C. Araz, I. Ozkarahan, Collaborative production-distribution planning in supply chain: a fuzzy goal programming approach, Transportation Research E, 44 (2008), pp. 396–419.

[20] C.L. Chen, T.W. Yuan, W.C. Lee, Multi-criteria fuzzy optimization for locating warehouses and distribution centers in a supply chain network, Journal Chinese Institutes of Chemical Engineers, 38 (2007), pp. 393–407.

[21] T.F. Liang, Distribution planning decisions using interactive fuzzy multi-objective linear programming, Fuzzy Set and System, 157 (2006), pp. 1303–1316.

[22] D. Newhart, L. Stott, F.J. Vasko, Consolidating product sizes to minimize inventory levels for a multi-stage production and distribution systems, Journal of the Operational Research Society, 44 (7) (1993), pp. 637-644.

[23] D. F. Pyke, M. A. Cohen, Performance characteristics of stochastic integrated production-distribution system, European Journal of Operational Research, 68 (1) (1993), pp. 23-48.

[24] D. F. Pyke, M. A. Cohen, Multi-product integrated production distribution systems, European Journal of Operational Research, 74 (1994), pp. 18-49.

[25] T. Altiok, R. Ranjan, Multi-stage, pull type production/inventory systems, IIE Transactions, 27 (1995) pp. 190-200.

[26] K. Ishii, K. Takahashi, R. Muramatsu, Integrated production, inventory and distribution systems, International Journal of Production Research, 26 (3) (1998), pp. 473-482.

[27] M. Khouja, A. Mehrez, Multi-Production constrained newsboy problem with progressive multiple discounts, Computer and Industrial Engineering, 36 (1) (1996), pp. 95-101.

[28] R. Ganeshan, Managing supply chain inventories: A multiple retailer, one warehouse, multiple supplier model, International Journal of Production Economics, 59(1999), pp. 341-354.

[29] J. Gjerdrum, N. Shan, L. G, Papageorgiou, A combined optimization and agent-based approach to supply chain modeling and performance assessment, Production Planning and Control, 12 (1) (2001), pp. 81-88.

[30] P. A. Miranda, R. A. Garrido, Incorporating inventory control decisions into a strategic distribution network design model with stochastic demand, Transportation Research Part E, 40 (2004), pp. 183-207.

[31] P. Seferlis, N. F. Giannelos, A two-layered optimization-based control strategy for multi-echelon supply chain networks, Computer and Chemical Engineering, 28(2004), pp. 799-809.

[32] F. Hedderich, R. Giesecke, D. Ohmsen, Identifying and evaluating Chinese suppliers: China sourcing practices of german manufacturing companies, Practix, 9 (2006), pp. 1–8.

[33] J. L. Lunsford, P. Glader, Boeing's nuts-and-bolts problem; Shortage of fasteners tests ability to finish dreamliners, Wall Street Journal (June 19, 2007), p. A8.

[34] J. Spencer, N. Casey, Toy recall shows challenge China poses to partners, Wall Street Journal (August 3, 2007), p. A1.

[35] D. Welch, Made in China: Faulty tires; How a Chinese supplier's bad decision turned into one importer's worst nightmare, and may mean the end of his business, July 12, 2007.
http://www.businessweek.com/bwdaily/dnflash/content/jul2007/db20070711_487422.htm.

[36] R. Myers, Food fights, CFO Magazine, June, 2007.

[37] C. Jensen, Recalls of chinese auto parts are a mounting concern, NewYork Times Wheels Blog.
http://wheels.blogs.nytimes.com/2008/12/19/recalls-of-chinese-auto-parts-are-a-mounting-concern/2008.

[38] G. W. Dickson, An analysis of vendor selection: system and decisions, Journal of Purchasing, 1 (1966), p. 5-17.

[39] C. A. Weber, J.R. Current, W. C. Benton, Vendor selection criteria and methods, European Journal of Operational Research, 50 (1991) 2-18.

[40] W. Ho, X. Xu, P. K. Dey, Multi-criteria decision making approaches for supplier evaluation and selection: A literature review, European Journal of Operational Research, 202 (2010), p. 16–24.

[41] A. M. Braglia, A. Petroni, A quality assurance-oriented methodology for handling trade-offs in supplier selection International Journal of Physical Distribution and Logistics Management, 30 (2) (2000), pp. 96–111.

[42] R. Narasimhan, S. Talluri, D. Mendez, Supplier evaluation and rationalization via data envelopment analysis: An empirical examination, Journal of Supply Chain Management, 37 (3) (2001), pp. 28–37.

[43] A. Ross, F.P. Buffa, C. Dröge, D. Carrington, Supplier evaluation in a dyadic relationship: An action research approach, Journal of Business Logistics, 27 (2) (2006), pp. 75–102.

[44] T. Wu, D. Shunk, J. Blackhurst, R. Appalla, AIDEA: A methodology for supplier evaluation and selection in a supplier-based manufacturing environment, Int'l Journal of Manufacturing Technology and Management, 11 (2) (2007), pp. 174–192.

[45] G.H. Hong, S.C. Park, D.S. Jang, H.M. Rho, An effective supplier selection method for constructing a competitive supply-relationship, Expert Systems with Applications, 28 (4) (2005), pp. 629–639.

[46] S.H. Ghodsypour, C. O'Brien, The total cost of logistics in supplier selection, under conditions of multiple sourcing, multiple criteria and capacity constraint, Int'l Journal of Production Economics, 73 (1) (2001), pp. 15–27.

[47] B. Karpak, E. Kumcu, R.R. Kasuganti, Purchasing materials in the supply chain: Managing a multi-objective task, European Journal of Purchasing and Supply Management, 7 (3) (2001), pp. 209–216.

[48] R. Narasimhan, S. Talluri, S.K. Mahapatra, Multiproduct, multicriteria model for supplier selection with product life-cycle considerations, Decision Sciences, 37 (4) (2006), pp. 577–603.

[49] K.L. Choy, W.B. Lee, A generic tool for the selection and management of supplier relationships in an outsourced manufacturing environment: The application of case based reasoning, Logistics Information Management, 15 (4) (2002), pp. 235–253.

[50] K.L. Choy, W.B. Lee, V. Lo, A knowledge-based supplier intelligence retrieval system for outsource manufacturing, Knowledge-Based Systems, 18 (1) (2005), pp. 1–17.

[51] K.L. Choy, W.B. Lee, A generic tool for the selection and management of supplier relationships in an outsourced manufacturing environment: The application of case based reasoning, Logistics Information Management, 15 (4) (2002), pp. 235–253.

[52] C. Muralidharan, N. Anantharaman, S.G. Deshmukh, A multi-criteria group decision-making model for supplier rating, Journal of Supply Chain Management, 38 (4) (2002), pp. 22–33.

[53] M.M. Akarte, N.V. Surendra, B. Ravi, N. Rangaraj, Web based casting supplier evaluation using analytical hierarchy process, Journal of the Operational Research Society, 52 (5) (2001), pp. 511–522.

[54] F.T.S. Chan, Interactive selection model for supplier selection process: An analytical hierarchy process approach, International Journal Production Research, 41 (15) (2003), pp. 3549–3579.

[55] C.T. Chen, C.T. Lin, S.F. Huang, A fuzzy approach for supplier evaluation and selection in supply chain management, Int'l Journal of Production Economics, 102 (2) (2006), pp. 289–301.

[56] A. Sarkar, P.K.J. Mohapatra, Evaluation of supplier capability and performance: A method for supply base reduction, Journal of Purchasing and Supply Management, 12 (3) (2006), pp. 148–163.

[57] R. Florez-Lopez, Strategic supplier selection in the added-value perspective: A CI approach, Information Sciences, 177 (5) (2007), pp. 1169–1179.

[58] M. Sevkli, S.C.L. Koh, S. Zaim, M. Demirbag, E. Tatoglu, An application of data envelopment analytic hierarchy process for supplier selection: A case study of BEKO in Turkey, Int'l Journal of Production Research, 45 (9) (2007), pp. 1973–2003.

[59] T.J. Kull, S. Talluri, A supply-risk reduction model using integrated multi-criteria decision making, IEEE Transactions on Engineering Management, 55 (3) (2008), pp. 409–419.

[60] W. Xia, Z. Wu, Supplier selection with multiple criteria in volume discount environments, OMEGA – Int'l Journal of Management Science, 35 (5) (2007), pp. 494–504.

[61] F.T.S. Chan, N. Kumar, Global supplier development considering risk factors using fuzzy extended AHP-based approach, OMEGA – Int'l Journal of Management Science, 35 (4) (2007), pp. 417–431.

[62] A. Amid, S.H. Ghodsypour, C. O'Brien, Fuzzy multiobjective linear model for supplier selection in a supply chain, Int'l Journal of Production Economics, 104 (2) (2006), pp. 394–407.

[63] Y. Shimizu, Z. Zhang, R. Batres, Frontiers in Computing Technologies for Manufacturing Applications, Springer, 2007.

[64] K. Deb, Multi-objective Optimization Using Evolutionary Algorithm, Wiley, 2002.

[65] J. Horn, Multicriteria decision making - Handbook of Evolutionary Computation, Institute of Physics Publishing, Bristol (UK), 1997.

[66] R. E. Steuer, Multiple Criteria Optimization: Theory, Computation, and Application, Wiley, New York, 1986.

[67] C-L. Hwang, A. S. M. Masud, Multiple Objectives Decision Making Methods and Applications, Springer, Berlin, 1979.

[68] J. L. Cohon, Multicriteria programming: brief review and application, Design Optimization (1985), Academic Press. Orlando, Florida.

[69] A. E. Silver, D. F. Pyke, R. Peterson, Inventory Management and Production Planning and Scheduling, Wiley, New York, 1998.

[70] D. Simchi-Levi, P. Kaminsky, E. Simchi-Lev, Designing and Managing the Supply Chain, Irwin McGraw-Hill, Boston, MA, 2000

[71] S. Axsäter, A heuristic for triggering emergency orders in an inventory system, European Journal of Operational Research, 176(2)(2007), pp.880-891.

[72] K. Prasertwattana, Y. Shimizu, Optimization of Periodic Review Inventory Model with Emergency order in Two-Echelon Supply Chain using Differential Evolution, International Journal of Computational Science,1 (2007), pp. 69-89.

[73] A. Durán, G. Gutiérrez, R.I. Zequeira, A continuous review inventory model with order expediting, International Journal of Production Economics, 87(2)(2004), pp.157-169.

[74] S. Sinha, S. P. Sarmah, Supply-chain coordination model with insufficient production capacity and option for outsourcing, Eurpean journal of Mathematical and Computer Modelling, 46(11-12)(2007), pp. 1442-1452.

[75] Y. Ouyang, The effect of information sharing on supply chain stability and the bullwhip effect, European Journal of Operational Research, 182(3)(2007), pp. 1107-112.

[76] H. Zhou, W. C. Benton. Jr., Supply chain practice and information sharing, Journal of Operations Management, 25(6)(2007), pp.1348-1365.

[77] S.P. Sarmah, D. Acharya, S. K. Goyal, S.K., Buyer vendor coordination models in supply chain management, European Journal of Operational Research, 175(1)(2006), pp. 1-15.

[78] D. Gupta, W. Weerawat, Supplier–manufacturer coordination in capacitated two-stage supply chains, European Journal of Operational Research, 175(1)(2006), pp. 67-89.

[79] R. Storn, K. Price, Differential evolution - a simple and efficient adaptive scheme for global optimization over continuous spaces, Technical Report TR-95-12, International Computer Science, 1995, Berkeley, California.

[80] R. Storn, K. Price, Differential Evolution - A Fast and Efficient Heuristic for Global Optimization over Continuous Spaces, Journal of Global Optimization, 11(1997), pp.341–359.

[81] H. S. Abbas, R. Shaker, The Pareto Differential Algorithm, Int. J. Artificial Intelligence Tools, 11(4)(2002), pp. 531-552.

[82] F. Xue, A. C. Sanderson, R. J. Graves, Pareto-based Multi-objective Differential Evolution, Congress on Evolutionary Computation (CEE 2003), 3(2003), pp. 862-869.

[83] K. E. Parsopoulos, D. K. Tasoulis, N. G. Pavlidis, V. P. Plagianakos, M. N. Vrahatis, Vector Evaluated Differential Evolution for Multiobjective Optimization, Proc., IEEE 2004 Congress on Evolutionary Computation, pp. 201-211, Portland, Ore.

[84] T. Robic, B. Filipic, DEMO: Differential Evolution for Multi-objective Optimization". Proc., 3rd int. Conf. on Evolutionary Multi-criterion Optimization, 2005, pp. 520-533.

[85] M. J. Reddy, D. N. Kumar, Multiobjective Differential Evolution with Application to Reservoir System Optimization, Journal of Computing in Civil engineering, 2007, ASCE.

[86] R. J. Tersine, Principles of inventory and material management, Prentice Hall, Englewood Cliffs, New Jersey, 1996.

[87] R. A. Aliev, B. Fazlollahi, B. G, Guirimov, R. R. Aliev, Fuzzy-genetic approach to aggregate production–distribution planning in supply chain management, The Int. J. Information Science, 177(2007), pp. 4241-4255.

[88] R. Kaslingam, C. Lee, Selection of vendors – a mixed integer programming approach, Computers and Industrial Engineering , 31(1996), pp. 347–350.

[89] S. Chaudhry, F. G. Forst, J. L. Zydiak, Vendor selection with price breaks, European Journal of Operation Research, 70(1993), pp. 52–66.

[90] C.A. Weber, J. R. Current, A. Desai, Non-cooperative negotiation strategies for vendor selection, European Journal of Operation Research, 108 (1998), pp. 228–223.

[91] N. E. Dahel, Vendor selection and order quantity allocation in volume discount environment, Supply Chain Management, 8(4)(2003), pp. 335-342.

[92] W. Xia, Z. Wu, Supplier selection with multiple criteria in volume discount environments, The Int. J. management Science, 35(2005), pp. 494-504.

[93] A. Kokangul, Z. Susuz, Integrated analytical hierarchy process, Applied mathematical Modeling, 33(2009), pp. 1417-1429.

[94] I. Chamodrakaz, D. Batis, D. Martakos, Supplier selection in electronic marketplaces using satisfying fuzzy AHP, Expert Systems with Applications, 37(2009), pp. 490-498.

[95] I. Eroll, W. G. Farell, A methodology for selection problem with multiple, conflicting objectives and both qualitative and quantitative criteria, Int. J. Production Economics, 86(2003), pp. 187-199.

[96] M. Kumar, P. Vrat, R. Shankar, A fuzzy programming approach for vendor selection problem in a supply chain, Int. J. Production Economics, 101(2006), pp. 273–285.

[97] A. Amid, S. H. Ghodsypour, C. O'Brien, Fuzzy multi-objective linear model for supplier selection in a supply chain, Int. J. Production Economics, 104(2006), pp. 394–407.

[98] A. Amid, S. H. Ghodsypour, C. O'Brien, A weighted max–min model for fuzzy multi-objective supplier selection in a supply chain, Int. J. Production Economics, 131(2011), pp. 139-145.

[99] C. H. Kagnicuoglu, A fuzzy multi-objective programming approach for supplier selection in a supply chain, The Bussiness Review, Cambridge, 6(1) (2010), pp. 107-115.

[100] A. Yucel, A. F. Guneri, A weighted additive fuzzy programming approach for multi-criteria supplier selection, Expert Systems with Applications, 38(2011), pp. 6281–6286.

[101] G. H. Tzeng, S. H. Tasur, Application of multiple criteria decision making for network improvement plan model, Journal of Advanced Transportation, 31(1) (1998), pp. 49-74.

[102] G. H. Tzeng, Y. W. Chen, Implementing an effective schedule for reconstructing post-earthquake road-network based on asymmetric traffic assignment – an application of genetic algorithm, Int'l Journal of operation and quantitative management, 4(3)(1998), pp. 229-246.

[103] X-q. Li, B. Zhang, H. Li, Computing efficient solutions to fuzzy multiple objective linear programming problem, Fuzzy sets and systems, 157(2005), pp. 1328-1332.

[104] Y-k. Wu, S-m. Guu, A compromise model for solving fuzzy multiple objective linear programming problems, J. Chinese Inst. Ind. Eng., 18(5) (2001), pp. 87-93.

[105] S. H. Ghodsypour, C. O'Brien, A decision support system for supplier selection using an integrated analytical hierarchy process and linear programming, int'l Journal of Production Economics, 56-57 (1998) pp. 199-212.

[106] W. N. Pi, C. Low, Supplier evaluation and selection via Taguchi loss functions and an AHP, Int J. Advanced Manufacturing Technology, 27(2006), pp. 625–630.

[107] R. B. Kethley, B. D. Waller, T. A. Festervand, Improving customer service in the real estate industry: a property selection model using Taguchi loss functions, Total Quality Management, 13(6)(2002), pp. 739–748.

[108] T. L. Saaty, The Analytic Hierarchy Process. New York: McGraw-Hill, 1980.

[109] A. H. I. Lee, A fuzzy supplier selection model with the consideration of benefits, opportunities, costs and risks, Expert Systems with Applications, 36(2)(2009), pp. 2879-2893.

[110] H. J. Zimmermann, Fuzzy programming and linear programming with several objective functions, Fuzzy sets and systems, 1(1978), pp. 45-46.

[111] R. E. Bellman, L. A. Zadeh, Decision making in a fuzzy environment, Management science, 1(1970), pp. B141-B164.

[112] Y. J. Lai, C. L. Hwang, Fuzzy multiple objective decision making, methods and applications, Springer-verlag, 1994.

[113] A. E. Silver, D. F. Pyke, R. Peterson, Inventory Management and Production Planning and Scheduling, Wiley, New York, NY (1998).

[114] O. Dey, D. Chakraborty, Fuzzy periodic review system with fuzzy random variable demand, European Journal of Operation Research, 198 (2009), pp.113–120.

[115] H. Selim, C. Araz, I. Ozkarahan, Collaborative production-distribution planning in supply chain: A fuzzy goal programming approach, Transportation Research Part E, 44 (2008), pp. 396-419.

[116] D. Petrovic, R. Y. Xie, K. Burnham, R. Petrovic, Coordinated control of distribution supply chains in the presence of fuzzy customer demand, European Journal of Operation Research, 185 (2008), pp. 146-158.

[117] T. Vijayan, M. Kumaran, Inventory models with a mixture of backorders and lost sales under fuzzy cost, European Journal of Operation Research, 189(1) (2008), pp. 105–119.

[118] Y-J. Lin, A periodic review inventory model involving fuzzy expected demand short and fuzzy backorder rate, Computer & Industrial Engineering, 54 (2008), pp. 666–676.

[119] H-C. Chang, J-S. Yao, L-Y. Ouyang, Fuzzy mixture inventory model involving fuzzy random variable lead time demand and fuzzy total demand, European Journal of Operation Research, 169 (2006), pp. 65–80.

[120] W. Klibi, A. Martel, A. Guitouni, The design of robust value-creating supply chain network: a critical review, European Journal of Operation Research, 203 (2010), pp. 283-293.

[121] M. Inuiguchi, J. Ramik, Possibilistic linear programming: a brief review of fuzzy mathematical programming and a com-

parison with stock programming in portfolios selection problem, Fuzzy Sets and Systems, 111 (2000), pp. 3-28.

[122] M. Jimenez, M. Arenas, A. Bilbao, M. V. Rodriguez, Linear programming with fuzzy parameters: An interactive method resolution, European Journal of Operation Research, 177 (2007), pp. 1599–1609.

[123] P. Vasant, R. Nagarajan, S. Yaacob, Solving fuzzy linear programming problem with modified S-curve membership function, Int'l Journal of uncertainty Fuzziness and Knowlegde-Based Systems, 13 (2005), pp. 97-109.

[124] S. A. Torabi, E. Hassini, An interactive possibilistic programming approach for multiple objective supply chain master planning, Fuzzy Sets and Systems, 159(2) (2008), pp. 193-214.

[125] Y. J. lai, C. L. Hwang, Possibilistic linear programming for managing interest rate risk, Fuzzy sets and systems, 54 (1993), pp. 135-146.

[126] H. Selim, I. Ozkarahan, A supply chain distribution network design model: an interactive fuzzy goal programming-based solution approach, Int'l. Journal of Advanced manufacturing Technology (2007), in press.

[127] M.s. Pishvaee, S. A. Torabi, A possibilistic programming approach for closed-loop supply chain network design under uncertainty, Fuzzy Sets and Systems, 161 (2010), pp. 2668-2683.

[128] M. T. Melo, S. Nickel, F.Saldanha-da-Gama, Facility Location and Supply Chain Management - A review, European Journal of Operational Research, 196 (2009), pp. 401-412.

[129] L. C. Yeun, W. R. Ismail, K. Omar, M. Zirour, Vehicle Routing Problem: Models and Solutions, Journal of Quality Measurement and Analysis, 4(1)(2008), pp. 205-218.

[130] H. Hashimoto, T. Ibaraki, S. Imahori, M. Yagiura, The Vehicle Routing Problem with Flexible Time Windows and Traveling Times, Discrete Applied Mathematics, 154(16)(2006), pp. 2271-2290.

[131] D. Mester, O. Braysy, W. Dullaert, A Multi-parametric Evolution Strategies Algorithm for Vehicle Routing Problems, Expert Systems with Applications, 32(2)(2007), pp. 508-517.

[132] I. Gribkovskaia, O. Halskau, G. Laporte, M. Vlcek, General Solutions to the Single Vehicle Routing Problem with Pickups and Deliveries, European Journal of Operational Research, 180(2)(2007), pp. 568-584.

[133] E. Mota, V. Campos, A. Corberan, A New Metaheuristic for the Vehicle Routing Problem with Split Demands, EvoCOP 2007, LNCS 4446, pp. 121-129.

[134] Y. Zhong, M. H. Cole, A Vehicle Routing Problem with Backhauls and Time Windows: A Guided Local Search Solution, Transportation Research, Part E, 41(2)(2005), pp. 131-144.

[135] S. Chen, A. Imai, B. Zhao, A SA-based Heuristic for the Multi-Depot Vehicle Routing Problem, Japan Institute of Navigation, 113(9)(2005), pp. 209-216, in Japanese.

[136] B. Crevier, J-F. Cordeau, G. Laporte, The Multi-depot Vehicle Routing Problem with Inter-depot Routes, European Journal of Operational Research, 176(2)(2007), pp. 756-773.

[137] T-H. Wu, C. Low, J-W. Bai, Heuristic Solutions to Multi-depot Location-routing Problems, Computers & Operations Research, 29(10)(2002), pp. 1393-1415.

[138] T. Bou, M. Arakawa, Proposal of a Hybrid Search Method for the Bi-objective Logistics Problem of Minimizing Total Distance Traveled and Average Completion Time, Journal of Japan Industrial Management Association, 61(4)(2010), pp. 224-233, in Japanese.

[139] T. Murata, R. Itai, Multi-objective Vehicle Routing Problems Using Two-fold EMO Algorithms to Enhance Solution Similarity on Non-dominated Solutions, Evolutionary Multi-Criterion Optimization, LNCS 3410(2005), pp. 885-896.

[140] M. J. Geiger, Fast Approximation Heuristics for Multi-objective Vehicle Routing Problems, EvoApplications, Part II (2010), LNCS 6025: pp.441-450.

[141] N. Jozefowiez, F. Semet, E-G. Talbi, Multiobjective Vehicle Routing Problems, European Journal of Operational Research, 189(2)(2008), pp. 293-309.

[142] K. C. Tan, Y. H. Chew, L. H. Lee, A Hybrid Multi-objective Evolutionary Algorithm for Solving Truck and Trailer Vehicle Routing Problems, European Journal of Operational Research, 172(3)(2006), pp. 855-885.

[143] J. M. Pasia, K. F. Doerner, R. F. Hartl, M. Reimann, A Population-based Local Search for Solving a Bi-objective Vehicle Routing Problem, EvoCOP (2007), LNCS 4446, pp. 166-175.

[144] Q-H. Zhao, S. Chen, S. C-X. Zang, Model and Algorithm for Inventory/routing Decision in a Three-echelon Logistics System. European Journal of Operational Research, 191(3)(2008), pp. 623-635.

[145] D. Tuzun, L. I. Burke, A Two-phase Tabu Search Approach to the Location Routing Problem. European Journal of Operational Research, 116(1)(1999), pp. 87-99.

[146] M. Albareda-Sambola, J. A. Diaz, E. Fernandez, A Compact Model and Tight Bounds for a Combined Location-routing Problem, Computers & Operations Research, 32(3)(2005), pp. 407-428.

[147] C. Prins, C. Prodhon, R. W. Calvo, A Memetic Algorithm with Population Management (MA-PM) for the Capacitated Location-routing Problem, EvoCOP (2006), LNCS 3906, pp. 183-194.

[148] M. Kubiak, P. Wesolek, Accelerating Local Search in a Memetic Algorithm for the Capacitated Vehicle Routing Problem, EvoCOP (2007), LNCS 4446, pp.96-107.

[149] C. Prins, A Simple and Effective Evolutionary Algorithm for the Vehicle Routing Problem, Computers & Operations Research, 31(12)(2004), pp. 1985-2002.

[150] J. Kytojoki, T. Nuortio, O. Braysy, M. Gendreau, An Efficient Variable Neighbor-hood Search Heuristic for Very Large Scale Vehicle Routing Problems, Computers & Operations Research, 34(9)(2007), pp. 2743-2757.

[151] M-C. Lai, H. Sohn, D. L. Bricker, A Hybrid Benders/Genetic Algorithm for Vehicle Routing and Scheduling Problem, International Journal of Industrial Engineering: Theory, Applications and Practice, 19(1)(2012).

[152] T. Wada, Y. Shimizu, A Hybrid Meta-heuristic Approach for Optimal Design of Total Supply Chain Network, Transactions of the Institute of Systems, Control and Information Engineers, 19(2)(2006), pp. 69-77.

[153] Y. Shimizu, T. Wada, Hybrid Tabu Search Approach for Hierarchical Logistics Optimization, Transactions of the Institute of

Systems, Control and Information Engineers, 17(6)(2004), pp. 241-248, in Japanese.

[154] URL “ http://mit.edu/dimitrib/www/home.html”

[155] Y. Shimizu, A Meta-heuristic Approach for Variants of VRP in Terms of Generalized Saving Method. Transactions of the Institute of Systems, Control and Information Engineers, 24(12)(2011), pp. 287-295.

[156] Y. Shimizu, Advanced Saving Method to Evaluate Economic Concern, Transactions of the Institute of Systems, Control and Information Engineers, 24(2)(2011), pp. 39-41.

[157] URL “http://homepage2.nifty.com/mohri/AG2KML_help.htm“

[158] Y. Shimizu, M. Ikeda, A Parallel Hybrid Binary PSO for Capacitated Logistics Network Optimization. Journal of Advanced Mechanical Design, Systems, and Manufacturing, 4(3)(2010), pp. 616-626.

Appendix A

DAILY PLANNING FOR THREE ECHELON LOGISTICS CONSIDERING INVENTORY CONDITIONS

A.1. Introduction

Due to agility, greenness and service innovation, daily logistics optimization is becoming extremely important especially for small businesses like convenience stores or super markets in Japan. Recently, a review of articles published in the last decade within the context of supply chain management has been considerably emerged [128]. Thereat, they reveal a scarcity of models that capture dynamic aspects relevant to real-world applications, and emphasize an increasing need for extensive studies on such topic.

Noticing such circumstance, and to enrich the prospects of this thesis, we present a daily logistics optimization at a tactical and operational level. Specifically, we associate with vehicle routing problem (VRP) considering a substantial inventory issue.

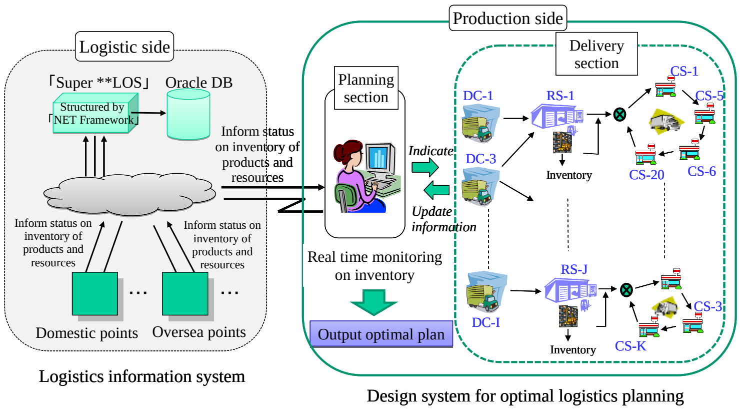


Figure A.1. Global idea of DSS on logistics planning

Moreover, taking into account dynamic demand and inventory of warehouse, we try to give an operational and practical approach amenable to innovative resolution to the daily logistics optimization. The final scope of this study refers to an integrated decision support system with formation system that can dynamically manage appropriate data based on the inventory of resources and the demand of products (See Figure A.1).

A.2. Problem statement

A.2.2. Review of related studies

Regarding the transportation among the depots and customers, each vehicle must take a circular route from its depot as a starting point and a destination at the same time. This generic problem has been studied popularly as VRP [129]. The VRP is a well-known NP-hard combinatorial optimization problem, which minimizes the total distance traveled by a fleet of vehicles under various constraints. Recent studies on VRP application can be roughly classified into the following four kinds.

One of them is an extension from the generic customer demand satisfaction and vehicle payload limit. For examples, practical conditions such as customer availability or time window [130, 131], pick up [132], split and mixed deliveries [133] are concerned not only separately but in a combined manner [134]. The second is known as the multi-depot problem that tries to deliver from multiple depots [135, 136, and 137]. The thirds are concerned in the multi-objective formulation for the single depot and multi-depot problems [138-143]. Though these three classes might belong to an operational level, the last one [144, 146, 147 and 147] corresponds to a tactical concern. That is, the decision on the allocations of depot is involved besides VRP.

Though many of those studies are solved by using a certain meta-heuristic method [148, 149], a certain local search is applied in the literature [150]. To effectively reduce the computational difficulty, a hybrid algorithm of Benders' decomposition with genetic algorithm is also proposed [151]. Due to the difficulty of solution, however, only small problems with no less than a hundred customers are solved to validate the effectiveness except for the literature [150]. Moreover, though actual transportation cost depends not only on the distance but also load (Ton-Kilo basis), those studies consider only distance (Kilo basis) to derive the route. Hence, the tactical concerns mentioned above are unfavorable to make a generic and consistent dealing over the multiple decision levels, i.e., allocation problem and VRP.

A.2.2. Problem formulations

Taking a global logistics network composed of distribution center (DC), depots, and customers, we try to decide the available depots, paths from major DCs to sub-DCs or depots (RS) and circular routes from every depot to its client customers (See Delivery section in Figure A.1).

Index set

I	index for DC
J	index for depot
K	index for customer
V	index for vehicle
P	$= J \cup K$
T	index for planning horizon

Variables

$f_{ij}(t)$	load from DC i to depot j at period t
$g_{pp'v}(t)$	load of vehicle v on the path from $p \in P$ to $p' \in P$ at period t
$r_j(t)$	take over inventory at depot j at period t
$s_j(t)$	consume from inventory at depot j at period t
$x_j(t)$	= 1 if depot j is open; otherwise 0 at period t
$y_v(t)$	= 1 if vehicle v is used; otherwise 0 at period t
$z_{pp'v}(t)$	= 1 if vehicle v travels on the path from $p \in P$ to $p' \in P$; otherwise 0 at period t

Parameters

C_{ij}	transportation cost per unit load per unit distance from DC i to depot j
c_v	transportation cost per unit load per unit distance of vehicle v
$D_k(t)$	demand of customer k at period t
$D_{pp'}$	path distance between $p \in P$ and $p' \in P$
F_v	fixed charge to operating vehicle v

Ha_j handling cost per unit load at depot j

Ho_j holding cost per unit load at depot j

Hp_i shipping cost per unit load from DC i

Hs_j shipping cost per unit load from depot j

M auxiliary constant (Large real number)

P_i^{max} maximum load available at DC i

P_i^{min} minimum load required to ship from DC i

Q_v own weight of vehicle v

Q_j maximum capacity at depot j

S_j maximum inventory at depot j

W_v maximum capacity of vehicle v

The goal of this problem is to minimize total cost for daily logistics over planning horizon T. This problem is formulated as the following mixed-integer programming problem under mild assumptions, e.g., round-trip transport between DC and depot; uni-modal transport; averaged time invariant unit costs and system parameters except for demand and inventory, independency or decision per each planning period, etc.

Minimize for every T

$$\left\{ \begin{aligned} &\sum_{i \in I} \sum_{j \in J} \left(C_{ij} d1_{ij} + Hp_i \right) f_{ij}(t) + \sum_{v \in V} \sum_{p \in P} \sum_{p' \in P} c_v d2_{pp'} \left(g_{pp'y}(t) + q_v \right) z_{pp'v}(t) \\ &+ \sum_{j \in J} \left(Ho_j r_j(t) + Ha_j s_j(t) + Hs_j \left(s_j(t) + \sum_{i \in I} f_{ij}(t) \right) \right) + \sum_{v \in V} F_v y_v(t) \end{aligned} \right\} \tag{A.1}$$

subject to

$$\sum_{p \in P} z_{kpv}(t) \leq 1, \quad \forall k \in K; \forall v \in V, \quad \exists t \in T \tag{A.2}$$

$$\sum_{p'\in P} z_{pp'v}(t) - \sum_{p'\in P} z_{p'pv}(t) = 0, \quad \forall p \in P; \forall v \in V, \quad \exists t \in T \tag{A.3}$$

$$\sum_{j\in J} z_{jj'v}(t) = 0, \quad \forall j \in J, \forall v \in V, \quad \exists t \in T \tag{A.4}$$

$$s_j(t) + \sum_{i\in I} f_{ij}(t) = \sum_{v\in V}\sum_{k\in K} g_{jkv}(t), \quad \forall j \in J, \quad \exists t \in T \tag{A.5}$$

$$r_j(t) + s_j(t) + \sum_{i\in I} f_{ij}(t) \le Q_j x_j(t), \quad \forall j \in J, \quad \exists t \in T \tag{A.6}$$

$$g_{pp'v}(t) \le W_v z_{pp'v}(t), \quad \forall p \in P; \forall p' \in P; \forall v \in V, \quad \exists t \in T \tag{A.7}$$

$$\sum_{p\in P}\sum_{p'\in P} z_{pp'v}(t) \le M y_v(t), \quad \forall v \in V, \quad \exists t \in T \tag{A.8}$$

$$\sum_{k\in K} g_{kjv}(t) = 0, \quad \forall j \in J; \forall v \in V, \quad \exists t \in T \tag{A.9}$$

$$\sum_{v\in V}\sum_{p\in P} g_{pkv}(t) - \sum_{v\in V}\sum_{p\in P} g_{kpv}(t) = D_k(t), \quad \forall k \in K, \quad \forall t \in T \tag{A.10}$$

$$\sum_{p\in P}\left(g_{pkv}(t) - D_k(t) z_{pkv}(t)\right) = \sum_{p\in P} g_{kpv}(t), \forall k \in K, \forall v \in V, \forall t \in T \tag{A.11}$$

$$\sum_{j\in J}\sum_{k\in K} z_{jkv}(t) = y_v(t), \quad \forall v \in V, \quad \exists t \in T \tag{A.12}$$

$$\sum_{j\in J}\sum_{k\in K} z_{kjv}(t) = y_v(t), \quad \forall v \in V, \quad \exists t \in T \tag{A.13}$$

$$P_i^{min} \le \sum_{j\in J} f_{ij}(t) \le P_i^{max}, \quad \forall i \in I, \quad \exists t \in T \tag{A.14}$$

$$r_j(t)+s_j(t) \leqq S_j x_j(t), \quad \forall j \in J, \quad \exists t \in T \tag{A.15}$$

$x_j(t) \in \{0,1\}, \forall j \in J, \forall t \in T$; $y_v(t) \in \{0,1\}, \forall v \in V, \forall t \in T$

$s_j(t) \geq 0, \forall j \in J, \forall t \in T$; $r_j(t) \geq 0, \forall j \in J, \forall t \in T$

$z_{pp'v}(t) \in \{0,1\}, \forall p \in P; \forall p' \in P; \forall v \in V, \forall t \in T$

$f_{ij}(t) \geq 0, \forall i \in I; \forall j \in J, \forall t \in T$; $g_{pp'v}(t) \geq 0, \forall p \in P; \forall p' \in P; \forall v \in V, \forall t \in T$

In (A.1), the objective function is composed of round-trip transportation costs between every DC and depot, circular transportation costs for traveling to every customer, shipping costs at DC, holding, handling and shipping costs at depot, and fixed operational charge of vehicles. Several constraints are applied: vehicles cannot visit a customer twice (Eq.(A.2)); vehicles entering a location must leave it (Eq.(A.3)); no travel between distribution centers (DCs) (Eq.(A.4)); material balance (Eq.(A.5)); upper bound of the capacity at depot (Eq.(A.6)); upper bound of the load capacity for vehicle (Eq.(A.7)); each vehicle must travel on a certain path (Eq.(A.8)); vehicles return to the depot empty (Eq.(A.9)); customer demand is satisfied (Eq.(A.10)); sum of inlet good must be greater than that of outlet by its demand (Eq.(A.11)); each vehicle leaves only one depot and returns back there (Eq.(A.12) and (A.13)); and the amounts of good available from DC are bounded (Eq.(A.14)); and the amounts of inventory are upper bounded (Eq.(A.15)). We also assume the following inventory control policy.

$$r_j(t) = \begin{cases} (1-\zeta)r_j(t-1) & \text{if} \quad (1-\zeta)r_j(t-1) \geq R_j \\ S_j - (1-\zeta)r_j(t-1) & \text{if} \quad (1-\zeta)r_j(t-1) < R_j, \quad \forall j \in J, \quad \forall t \in T \end{cases} \quad \text{(A.16)}$$

where ζ (<1) and R_j are a fouling rate of unsold goods and an ordering point at depot *j*, respectively.

We know that it is almost impossible to solve the above problem with practical size using any currently available commercial software. Against this, we have successfully solved various logistics optimization problems under complicated situations resulting from a variety of real-life conditions, by using a method called hybrid Tabu search (HybTS) [152, 153]. This is a two-level solution method in which the upper level sub-problem optimizes the selection of available depots while the lower level sub-problem optimizes the paths from DCs to customers via depots so as to minimize the total cost. Since HybTS is not only a practical and powerful method but flexible and suitable for a variety of extensions, we will deploy the similar idea to solve the problem under consideration.

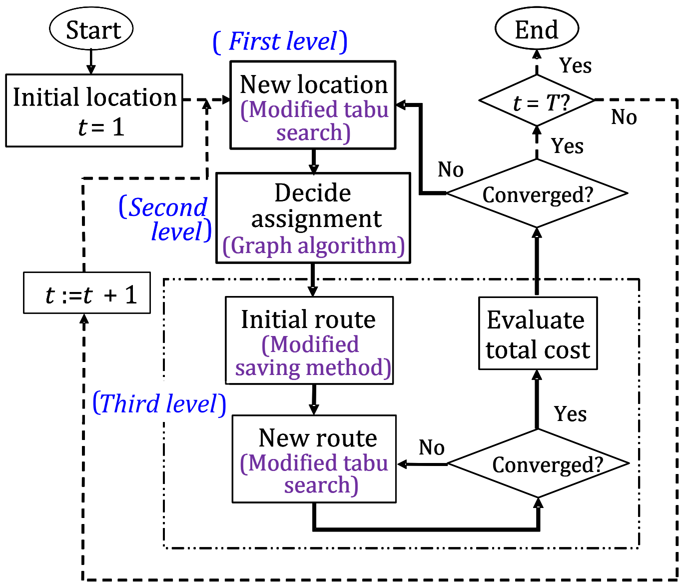


Figure A.2. Flowchart od Solution Procedures

A.3. Daily decision associated with inventory condition

A.3.1. Multi-level approach incorporating vehicle routing problem

A For the daily logistics optimization, it is meaningful to take into account the use of inventory control at every depot. To make the foregoing hierarchical approach available for the present case, we have majorly invented two new ideas and integrated them into the similar framework of our hybrid method. In our best knowledge, such global approach has not been reported anywhere.

In its first level, we choose the available depots using the modified Tabu search. Then, in the second level, we tentatively obtain round trip paths from DCs to customers via depots using a graph algorithm for the minimum cost flow (MCF) problem. Assigning the customers thus allocated as the clients for each depot, we derive eve-

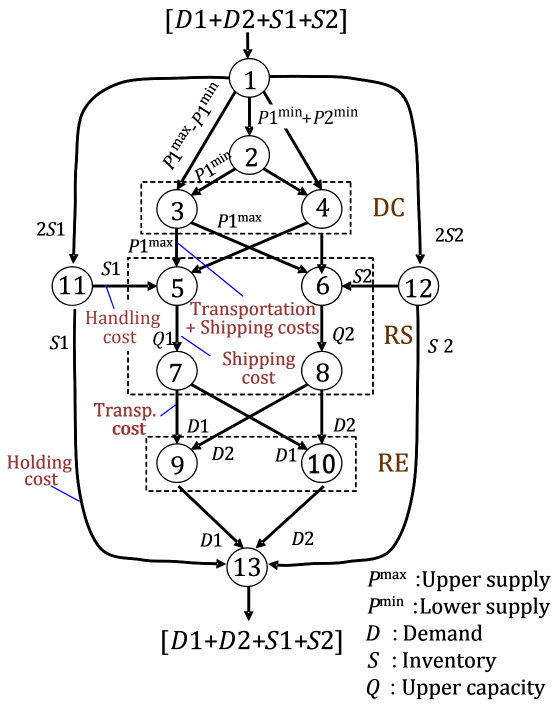


Figure A.3. Example of MCF graph

Table A.1. Labeling on the edge for MCF graph

Edge (from to)	Cost	Capacity	Case in Fig.3
Source - ∑ (Dummy)	$-M$	$\sum_{i\in I} P_i^{min}$	#1 - #2
Source - DC i	0	$P_i^{max} - P_i^{min}$	#1 - #3, #1 - #4
∑ - DC i	0	P_i^{min}	#2 - #3, #2 - #4
DC i - RS j	$C_{ij}d1_{ij} + Hp_i$	P_i^{max}	#3 - #5, #3 - #6, *etc.*
Between double nodes of RS j	Hs_j	Q_j	#5 - #7, #6 - #8
Stock - RS j	Ha_j	S_j	#11 - #5, #12 - #6
Source - Stock j	0	$2S_j$	#1 - #11, #1 - #12
Stock j - Sink	Ho_j	S_j	#11 - #13, #12 - #13
RS j - Customer k	$c_v d2_{jk}$	D_j	#7 - #9, #7 - #10, *etc.*
Customer k - Sink	0	D_k	#9 - #13, #10 - #13

ry vehicle route of depot using the modified saving method and modified Tabu search. The result thus obtained is fed back to the first level to evaluate another set of available depots. This procedure will be repeated until a given convergence condition has been satisfied. The procedure of this algorithm is illustrated in Figure A.2.

In developing the above algorithm, we need to obtain the MCF graph that considers the inventory at each the depot. For example, the case where $|I|=|J|=|K|=2$ is illustrated in Figure A.3. In Table A.1, we summarized information required to put on the edges and nodes in the graph. In terms of the MCF graph thus derived, we can solve the original allocation problem extremely fast through a graph algorithm like RELAX4 [154] together with its sensitivity analysis. The sensitivity analysis is amenable to repeatedly solve the problem with slightly different parameters one after another. After all, we can efficiently allocate each depot to its client customers on the Ton-Kilo basis.

Then, to solve the VRP in terms of Ton-Kilo basis, we applied the hybrid approach composed of the modified saving method and the modified Tabu search in a hybrid manner [155, 156]. Thereat, we noted that the fixed operational cost for the working vehicle should be involved in the economic evaluation. After all, the algorithm of the modified saving method is outlined as follows.

Step 1: Create round trip routes from the depot to all customers. Compute the saving value by $s_{i,j} = (d_{0,j} - d_{0,i} - d_{i,j})D_j + (d_{0,j}+d_{i,0} - d_{i,j})w$, where D_j, q and d_{ij} denotes the demand at location j, weight of vehicle itself and distance between locations i and j, respectively.

Step2: Order these pairs in descending order of savings.

Step3: Merge the path following the order as long as the feasibility is satisfied and the saving is greater than $-C_{tf}/c_v$, where C_{tf} denotes the fixed operational cost of the vehicle.

However, since the modified saving method derives only an approximated solution, we move on the modified Tabu search to update such initial solution. The modified Tabu search is a variant that probabilistically accepts the degraded candidate like simulated annealing in its local search.

Here, we can emphasize such an advantage that transportation costs are able to be accounted on the same Ton-kilo basis at the upper (first and second) and lower (third) level procedures in Figure A.2.

A.3.2. Analysis of inventory level on demand variation

It is commonly known holding too much inventory slips the economical efficiency while the stock-out or opportunity loss will happen in the opposite case. For the daily logistics, therefore, it is of special importance to correctly estimate the demand and properly manage the inventory. Generally speaking, however, correctly estimate the demand is almost impossible in many cases while it is possible to roughly estimate the extent of deviation from experience.

Under such circumstance, it is relevant and practical to try to reveal the relation between the extent of demand deviation and the inventory level through parametric approach. Through such analyses, we can setup a reliable inventory level to maintain the economically efficient logistics while preventing from the state of stock-out. Though such consideration is able to present many prospects for the robust and reliable logistic systems, it has not been almost concerned in the network optimization of logistics so far due to computational difficulties.

A.4. Numerical experiment

A.4.1. Setup of test problem

To examine some performance of the proposed method, we provided several benchmark problems with different problem sizes, i.e., $\{|I|, |J|, |K|\}$. Every system parameter are set randomly within the respective prescribed interval as summarized in Table A.2. Location of every member is also generated randomly, and distances between

Table A.2. Notes on parameter setup

Member	Item	Range	Remarks
DC	Hp	$100\times[0.2, 0.8]$	<3>
	P^{max}	$1000\times[0, 1]+P^{min}$	<5>, Total P^{max} >Total capacity of RS
	P^{min}	$1000\times[0.2, 0.8]$	<5>, Total P^{min} > Total demand
RS	Hs	$100\times[0.2, 0.8]$	<3>
	Ha	$50\times[0.2, 0.8]$	<3>
	Ho	$100\times[0.2, 0.8]$	<5>
	Q	$p\times[0.2, 0.8]$	<5>, $p=100\times\|K\|/\|J\|$
	S	$x\times[0.5, 0.7]$	<3>, Varying at each time
RE	D	$100\times[0.2, 0.8]$	<3>, Total demand < Total capacity of RS*

C_{ij} = 3, c_v = 1, W_v = 500, F_v = 50000, q_v = 10; <n> multiple of n

them are calculated as the Euclidian distance.

A.4.2. Result for leading condition

Regarding each demand, we randomly changed the amount daily within 100(1±α)% from the foregoing day. On the other hand, the unsold goods at each depot are remained as the inventory and it is possible to use them in the following days. However, it is supposed to be spoiled randomly within ζ and the goods are supplied to the upper limit when the inventory level becomes below the prescribed safety level (Rj=βSj).

First, we solved the smaller size problems like |I|=3, |J|=10 and |K|=100 over 30 days and |I|=5, |J|=20 and |K|=200 over 10 days. Parameters α, β and ζ are set at 0.3, 0.5 and 0.1, respectively. Figures A.4 and A.5 illustrate the changes of demands and inventory during the planning horizon. Under these conditions, we derive the optimal cost that broadly changes with the demand fluctuation as shown in

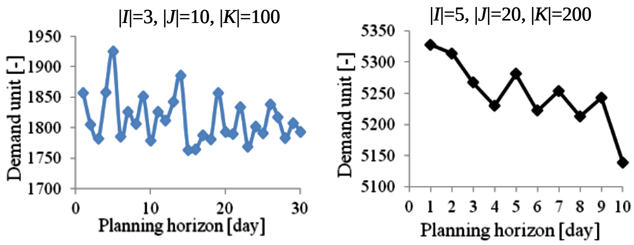


Figure A.4. Variations of demand

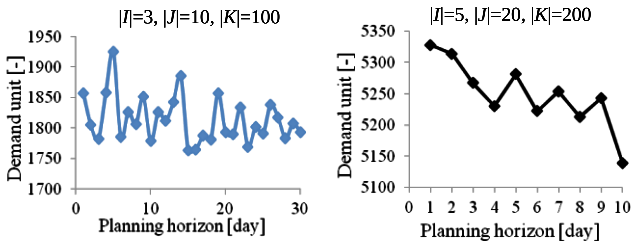


Figure A.5. Variations of inventory

Figure A.6. In Figure A.7, we can see that the change of working numbers of depot is moderated and kept nearly constant (around 60%). However, working rate of each depot differs greatly as shown in Figure A.8. This observation is available for considering the re-structuring of logistics at the next stage. That is, the depots of low working rate may be integrated into the other higher ones.

Moreover, we solved the larger problems to examine the necessary computation time. Fixing the planning horizon at 1, $|I|$=10, and $|J|$=30, we solved the problems like $|K|$={250, 500, 1000, 1500, 2000, 2500}. As expected a priori, the required CPU time increases exponentially with the problem size as shown in Figure A.9. Even for these larger size problems, however, we can obtain the result within a reasonable time or around several hours.

Figure A.10 shows the convergence profile for the largest problem. We can confirm the sufficient convergence. From all of these

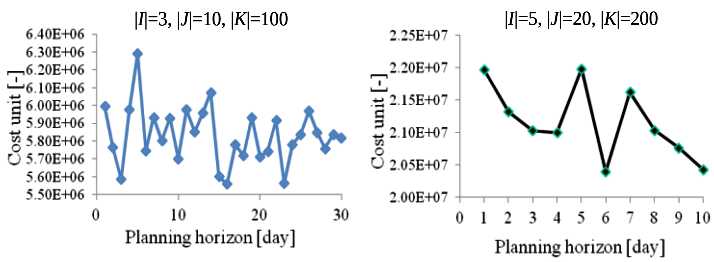


Figure A.6. Trend of optimal cost

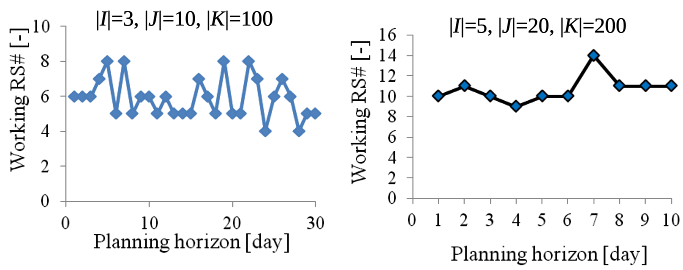


Figure A.7. Variations of number of working depot

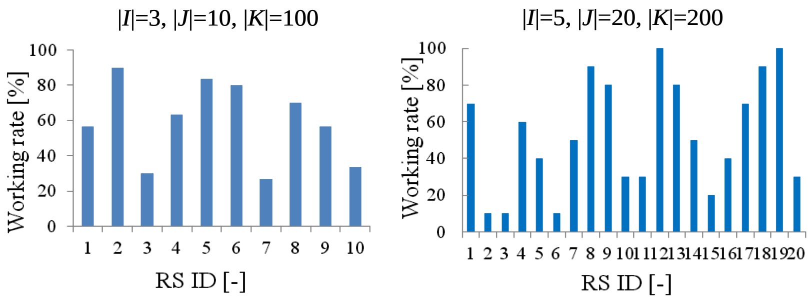


Figure A.8. Working rate of each RS

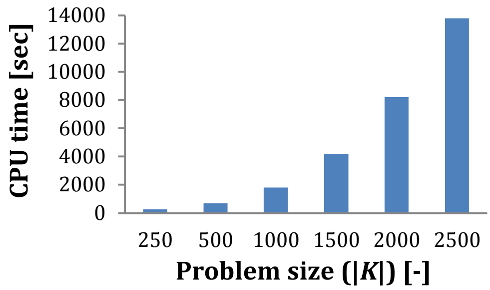


Figure A.9. CPU time vs. Problem size

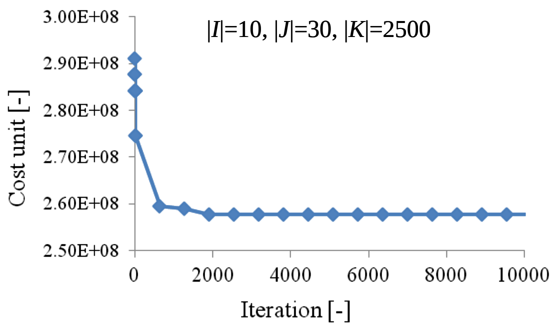


Figure A.10. Solution convergence

results, we can claim the significance of the approach and computational effectiveness of the proposed method.

A.4.3. Results over wide range of deviations

To analyze the effect of inventory condition against demand deviations, we carried out a parametric study regarding ordering points using a small model like $|I|$=2, $|J|$=5, $|K|$=100 over 30 days. Actually, we solved every pair of problem with five different ordering points (β={0.1, 0.2, 0.3, 0.4, 0.5}) and four different ranges of demand variation (α={0.2, 0.3, 0.4, 0.5}). This comes to that 600 optimization problems were totally solved. Now, we show the results in Figure A.11 and A.12 by applying the same value setting as before.

Figure A.11 shows feature of total cost regarding the range of demand deviation and the level of ordering point. Due to the non-deterministic parameter setting, complicatedly winding profile is observed. But its trend is plausible since the region where the minimum cost locates will move on the higher ordering point according

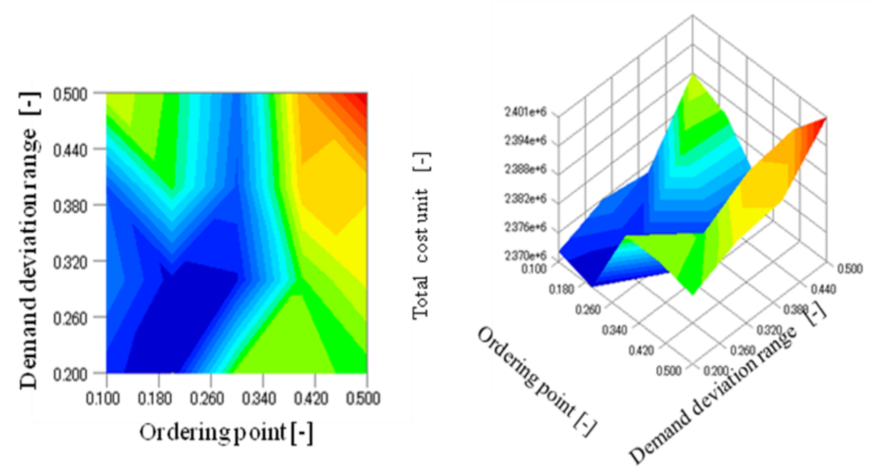


Figure A.11. Total cost with demand deviation range and ordering point

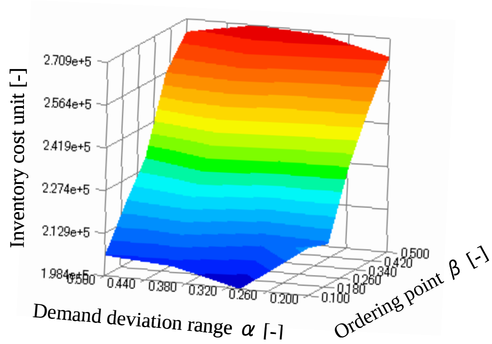


Figure A.12. Inventory cost with demand deviation range & ordering point to the increase in the deviation ranges as a whole. This fact suggests that it is important to control the ordering point or inventory level according to the demand deviation in the cost management. When we cut off only the inventory cost from the total cost, its changes are rather simple as shown in Figure A.12. Since higher stock level needs more holding cost, the cost increases proportionally with the ordering point regardless of the deviation ranges of demand.

Finally, from these parametric studies, we claim the adequateness of the applied model behind the mathematical formulation. Plausibility of the results can support the significance of the approach if the realistic parameters were used in real world optimization.

A.4.4. Prospect as a working tool

To realize the planning system illustrated in Figure A.1 as a goal, it is essential to provide a user friendly interface to manage the system. At the planning section in production side, this goal is closely related to data handling and visualization of the circumstance at hard. Regarding this matter, we can effectively utilize some software developed by Google Maps API. By now, we have deployed the following step-wise procedure by making Java scripts and appropriate free software.

Step 1: Collect the address of members in an Excel spread sheet or text sheet.

Step 2: Add the information of longitude and latitude of every one into the sheet. We are available a free software named AGtoKML [157]) for this purpose.

Step 3: Calculate the distance between every pair of members using a procedure of Google Map API known as Gio-coding.

Step 4: Solve the optimization problem by the developed method.

Step 5: Display the routes obtained from Step 4 in Google map.

In the result of the illustrative problem with $|I|$=1, $|J|$=3 and $|K|$=17, every depot has a single route. In Figure A.13, for simplicity, only the routing paths from depot 1 are shown in terms of the popup marks (A(=L) – B –…– K – L(=A)). We can see this kind of visual information is upmost for some tasks at operational level. However, there still remain many possibilities to add more amenable service information using GIS applications and Google Map API.

A.5. Conclusion

We have proposed a hierarchical approach to optimize a daily logistics problem including inventory control at depots and vehicle routing for customer delivery. For this purpose, we have extended

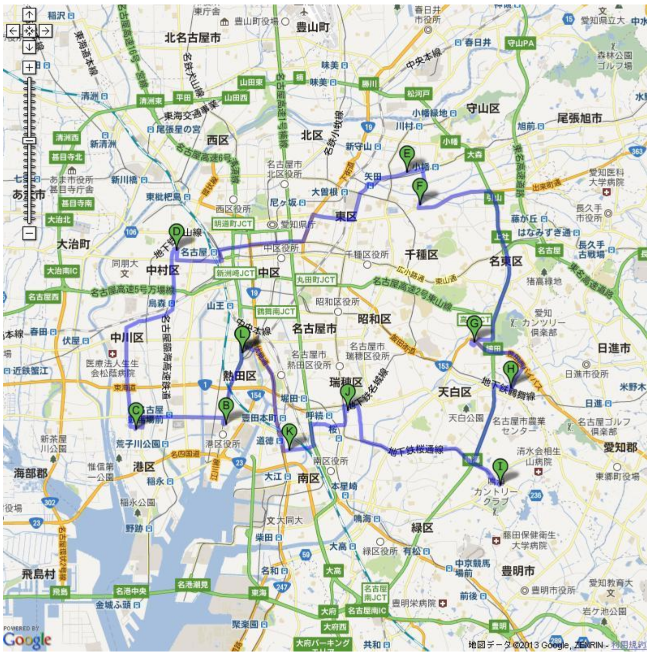


Figure A.13. A part of display of result (Route from Depot 1 (Popup mark L)) our two-level method by virtue of the modified saving method and the modified hybrid tabu search together with the graph algorithm to solve the MCF problem in a hybrid manner. In the numerical experiments, we have shown the proposed method can solve the complicated and manifold problem that has never been solved previously within a reasonable computation time. To enhance the solution speed for larger problems in advance, we can apply the parallel computing technique deployed previously [158]. We also mentioned about the Web application referred to Google Maps API targeting at a practical usability. Eventually, this claims the effectiveness of the proposed idea and the prospect of the present challenge.

Future studies should be devoted to relax the conditions assumed here. The step-wise procedures for visualization are favored to be integrated into the series of Java script. Eventually, we aim at establishing a total decision support system as illustrated in Fig.1 for daily optimization associated with low carbon logistics.

List of Publication

1. Peer-reviewed Journals

1.1. D. Fatrias, Y. Shimizu, Multi-objective Analysis of Periodic Review Inventory Problem with Coordinated Replenishment in Two-echelon Supply Chain System through Differential Evolution, Journal of Advanced Mechanical Design, Systems, and Manufacturing, 4(3)(2010), pp. 637-650.

1.2. D. Fatrias, Y. Shimizu, An Enhanced Two-Phase Fuzzy Programming Model for Multi-Objective Supplier Selection Problem, Journal of Industrial Engineering & Management Systems, 11(1)(2012), pp. 1-10.

1.3. D. Fatrias, Y. Shimizu, Possibilistic Programming Model for Fuzzy Multi-Objective Periodic Review Inventory in Two-Stage Supply Chain, International Journal of Applied Decision Sciences, 2013 (Accepted).

1.4. Y. Shimizu, D. Fatrias, Daily Planning for Three Echelon Logistics Considering Inventory Conditions, Journal of Advanced Mechanical Design, Systems, and Manufacturing, 7(3), 2013, pp. 485-497.

2. Conference Papers

2.1. D. Fatrias, Y. Shimizu, An Enhanced Two-phase Approach for Fuzzy Multi-objective Linear Programming in Supplier Selection Problem, Proc. of the Asia Pacific Industrial Engineering & Management Systems Conference 2011 (APIEMS 2011), Beijing, China, October 14-16, 2011.

2.2. D. Fatrias, Y. Shimizu, Possibilistic Programming Approach For Multi-Objective Inventory Problem in Two-Echelon Supply Chain System, International Symposium on Scheduling 2013 (ISS2013), Tokyo, Japan, July 18-20, 2013.