MODELLING AND OPTIMIZATION OF MATERIAL PURCHASING PROCESS IN APPAREL SUPPLY CHAIN

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Modelling and Optimization of Material Purchasing Process in Apparel Supply Chain

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______________________________ (Signed)

Li Zhi (Name of student)

TO MY PARENTS AND MY WIFE

For their constant love, support and encouragement

Abstract

Facing the increasingly fierce competition and the fast-changing customer demand, apparel companies have striven to lower purchasing costs and shorten purchasing lead time using systematic and effective methods of material purchasing decision-making. The purpose of this research is to develop intelligent algorithm-based methodologies for material purchasing decision-making of the apparel supply chain.

An effective supplier selection and order allocation (SSOA) model for material purchasing decision-making in the apparel supply chain is developed through integrating three types of apparel material purchasing problem, namely 1) supplier evaluation and ranking problems at the purchasing pre-selection stage, 2) supplier selection and order allocation for single-item purchasing problems, and 3) supplier selection and order allocation for multi-item purchasing problems at the final purchasing selection stage. On the basis of fuzzy extent analytic hierarchy processes (FEAHP), dynamic programming (DP) and improved differential evolution (DE), these three types of problem are formulated mathematically and solved by effective methodologies.

Supplier pre-evaluation and ranking at the purchasing preparation stage is a multiple criteria decision problem involving qualitative and quantitative factors. In this stage, the decision maker needs to identify critical decision criteria and then evaluate, rank and preselect potential suppliers with respect to those criteria. With consideration for the fuzziness of data involved in deciding the preferences of multiple decision variables, the fuzzy-extended

analytic hierarchy process (FEAHP) -based methodology is developed to determine the multiple decision criteria.

In the final stage of material purchasing, this research investigates common material (e.g. white fabric) purchasing (i.e. single-item multiple-period purchasing). An integrated approach, including FEAHP, multi-objective programming (MOP) and dynamic programming (DP), is developed to identify ultimate suppliers and determine optimum order quantities among selected suppliers to minimize material purchasing risks and total material purchasing costs, with consideration for various types of customer demand, supplier capacity and material prices given by suppliers.

In dealing with fashion accessories purchasing in the final stage of material purchasing, multi-item purchasing, one-time purchasing, price discount and on-time delivery are considered. An improved differential evolution (DE) algorithm and a probability theory-based optimization model are developed to solve a stochastic discrete multi-objective problem. In this model, uncertain delivery delay and uncertain product discount are determined using the probability theory. The ultimate number of selected suppliers and the optimal order allocation strategy are given by an improved DE algorithm, namely the composite discrete differential evolution (CoDDE) algorithm.

Extensive experiments based on industrial data are conducted to validate the proposed models and evaluate the performance of the proposed methodologies. The experiment results demonstrate the effectiveness of the proposed model and methodologies for material purchasing decision-making of the apparel supply chain.

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d_k, the discount offered by supplier k

i , $i = \{1, \ldots, o\} \in Z^+$ the type of products to be manufactured

j , $j = \{1, \ldots, m\} \in Z^+$ the type of materials to be purchased

k , $k = \{1, \ldots, n\} \in Z^+$ the number of candidate suppliers

l_k, the lower bound of the discount offered by supplier k

$rate_k$, the discount rate offered by supplier k, based on manufacturer's order size

P_{jk} , the price of material j charged by supplier k

$PD_i(E(\max(Y_i\xi_i))$, the discount expectation function of product i based on different delays of product i

PD_i^1, the value of the expected price discount rate of product i if the delay of product i lasts longer than 14 days

PD_i^2, the value of the price expectation discount rate of product i if the delay of product i spans 7- 14 days

PN_i, the number of each product

PP_i, the price of product i

$F(X_{jk}, Y_k)$, the expectation function of profits of all products

X_{jk}, the quantity of material j purchased from supplier k

Y_k , 1, if choosing supplier k, otherwise 0

$Z(X_{jk}, Y_k)$, the cost function

ξ_k, the random variables mean of supplier k's delivery delay

Chapter 1 Introduction

1.1 Background

Nowadays textile and apparel industries play a significant role in many economies in both developing and developed worlds (Gereffi & Sturgeon, 2004; Kunz & Garner, 2007; Bruce & Daly, 2011). In today's highly competitive market, the apparel industry is characterized by narrow profit margins, short product life cycles, and volatile and unpredictable customer demands (Sen, 2008). In order to deal with the fierce competition, apparel companies must take every opportunity to optimize their business processes. To achieve this target, academics and practitioners have come to the same conclusion that a company has to work with its supply chain partners to improve the supply chain's overall performance and stays competitive (Aissaoui et al., 2007).

Defined as integrated management of a network of entities, supply chain management (SCM) starts with suppliers' suppliers and ends with customers' customers, which means production and delivery of goods and services to final consumers (Lee & Ng, 1997). The key supply chain processes identified by members of The Global Supply Chain Forum are procurement, demand management, order fulfillment, manufacturing flow management, product development and commercialization, customer relationship management, customer service management, and returns (Lambert & Cooper, 2000). Based on the research by De Boer et al (2001), raw material purchasing can account for 60% of total sales, while shares purchasing normally accounts for 50 to 90% of total turnover in an industrial company. Since material purchasing is crucial to the upstream chain and affects all aspects of the supply chain, its optimization becomes increasingly important.

Generally, material purchasing involves a preparation stage and a final choice stage. In the preparation stage, the decision maker firstly considers the number of suppliers for partnership. There are academic differences over the optimal number of selected suppliers. Single-sourcing can promote cooperation between manufacturers and suppliers but also increase the risk of interruption (Burke et al., 2007), monopolization and forward integration (Nellore et al., 2001). Multi-sourcing can provide greater upside volume flexibility (Ramasesh et al., 1991) and reduce risks of business disruption in the supply chain, but can also increase management costs. Recent research works (Krause, 1999; Nellore et al., 2001; Prahinski & Benton, 2004; Talluri & Narasimhan, 2004) suggest that manufacturers are willing to work with fewer but better suppliers who can provide high-quality and low-cost components in the long term on a mutually beneficial basis. Therefore, eliminating inefficient candidates and reducing the number of suppliers are the most important decisions in the preparation stage of purchasing (Lambert & Cooper, 2000; Talluri & Narasimhan, 2004).

In the final implementation stage, in order to contain the supplier's power over the manufacturer and reduce purchasing costs, the purchasing decision maker needs to determine an optimal order allocation strategy for selecting the best combination of suppliers from pre-selected suppliers. However, different optimal suppliers can be selected and different order allocation strategies can be made according to different purchasing situations. Two differences can be found in modern material purchasing compared with traditional apparel manufacturing.

The first difference is the frequency of purchase. Since fast-fashion companies emphasize quick replenishment and rapid stock turnover, their material purchasing cycles occur more frequently than the traditional purchasing mode, which was based on long-term forecasts from historical sales, occurring one year before each season, with orders placed six months prior to a product launch (Birtwistle et al., 2003). The fast-fashion company can reduce both excess inventory in the supply chain and risks associated with forecasting. However, the frequent buying strategy can incur higher costs, especially for common materials (Bruce & Daly, 2011). In order to avoid excess inventory, the fast-fashion purchasing decision maker tends to split the total demand into multiple purchasing periods rather than make a conclusive purchase once and for all. Hence, optimization of common material purchasing in multi-periods (i.e. single-item multi-period) is another important decision in the final stage of implementation.

Another distinct feature of fast fashion is that the purchasing manager has to order more time-sensitive multiple fashionable items (Güder & Zydiak, 2000; Bruce & Daly, 2011) in small quantities on an ad hoc basis. Since fast-fashion companies are devoted to increasing the number of sale “seasons” and launching more new designs to the market (e.g. Zara launches around 10,000 new designs each year) to meet fashion-conscious customers’ demands (Ghemawat et al., 2003; Sheridan et al., 2006). As a bigger discount can be offered by suppliers achieving economies of scale, the material purchasing manager should evaluate multiple factors on each occasion to maximize profitability.

In reality, it is still common for purchasing managers to do business with certain selected suppliers on the basis of partial requirement (Monczka et al., 2008). As such an inefficient practice helps neither suppliers nor manufacturers to maximize their profits, it is imperative to find an optimal model for supplier selection and order allocation in order to increase profitability and efficiency.

The main purpose of this research is to build an effective model for optimizing material purchasing in the apparel industry. The model should be capable of providing optimal purchasing solutions for the decision maker to select a reasonable number of material suppliers and determine the order quantity of each material in an efficient manner.

1.2 Problem statement

This research proposes a supplier selection and order allocation (SSOA) model to the material purchasing decision maker to solve the following three problems.

(1) Supplier evaluation and ranking problem: in the pre-selection stage of material purchasing, each supplier candidate is evaluated and several appropriate suppliers are chosen, with consideration for the fuzziness in human decision-making and the relevant decision criteria like cost, quality, risk, service performance and supplier profiles.

(2) Single-item multi-period purchasing problem: in the final selection stage of material purchasing, it is intended to achieve an optimal allocation of orders among identified ultimate suppliers with consideration for purchasing prices, supplier capacity, and customer demands in different periods.

(3) Multi-item purchasing problem: in the final selection stage of material purchasing, the actual apparel industry is examined with consideration for multiple objectives to minimize purchasing costs and delivery delay subject to constraints of manufacturer demand, supplier capacity, and material discounts provided by different suppliers.

1.3 Research objectives

To address the three problems stated in section 1.2, this study proposes an effective supplier selection and order allocation (SSOA) model to formulate and optimize the material purchasing of the apparel supply chain with consideration for real-life features and multiple purchasing objectives. Material purchasing involves supplier selection and order allocation. The proposed SSOA model is composed of the following three sub-models: a supplier pre-evaluation and ranking (SPER) sub-model, a single-item purchasing optimization (SIPO) sub-model and a multi-item purchasing optimization (MIPO) sub-model.

Specifically, the objectives of this research are:

(1) To develop a supplier pre-evaluation and ranking (SPER) sub-model for optimizing supplier evaluation and pre-selection of an apparel manufacturer in the apparel supply chain.

(2) To develop a single-item purchasing optimization (SIPO) sub-model for optimizing supplier selection and order allocation of single-item purchasing optimization of multiple purchasing periods.

(3) To develop a multi-item purchasing optimization (MIPO) sub-model for optimizing supplier selection and order allocation of multiple-item purchasing stochastic delivery delay.

1.4 Methodology

To model and optimize material purchasing in the apparel supply chain, a supplier selection and order allocation (SSOA) model will be developed in this research. This model will help the purchasing manager select reliable suppliers and assign optimal orders to selected suppliers so as to minimize cost in material purchasing. The details of the research methodology for the SSOA model are described below:

Supplier pre-evaluation and ranking (SPER) sub-model

To prioritize multiple decision criteria and address fuzzy information involved in supplier pre-selection and ranking, the fuzzy-extended analytic hierarchy process (FEAHP), developed by Chan and Kumar (2007), is modified to rank criteria and candidate suppliers.

Single-item purchasing optimization (SIPO) sub-model

The single-item purchasing optimization (SIPO) model will be developed for the purchasing manager to assign optimal orders to appropriate suppliers in raw fabric (e.g. white fabric) purchasing. Based on the results of the SPER sub-model, supplier rankings and criterion weights are fed into the SIPO model with the aim of minimizing the risk of material purchasing and the total material purchasing costs, subject to constraints of fluctuated manufacturer demands and supplier capacity. A bi-objective model will be proposed using a dynamic programming approach.

Multi-item purchasing optimization (MIPO) sub-model

To examine more practical features in material purchasing, the multi-item purchasing optimization (MIPO) sub-model will be developed to handle multiple items with consideration for uncertain delivery delay, supplier capacity and different discounts according to order size. An improved composite differential evolution (CoDE) algorithm, which employs the real-value CoDE algorithm to handle discrete-value vectors by introducing subtraction and addition operators, is developed to solve this problem.

1.5 Significance of this Research

In using intelligent algorithms to optimize material purchasing decisions for apparel manufacturers, this research is significant in the following aspects:

(1) This research will enrich our understanding of apparel purchasing decision-making from both academic and industrial perspectives.

(2) The supplier pre-selection stage and the final choice stage are often separately discussed without considering the interrelationship between the two issues and many other practical factors, which fails to help decision makers achieve optimal material purchasing

strategies. This research will deal with apparel material purchasing to fill this gap in both academia and industry.

(3) This research will enrich the methodologies of material purchasing decision-making for the apparel industry. The proposed methodologies can also be used in dealing with optimization of material purchasing in other similar manufacturing industries.

(4) This research will improve the capacity for purchasing decision-making in the apparel industry. The proposed methodologies can generate systematic, consistent and optimal solutions to material purchasing for procurement management.

1.6 Structure of this Thesis

The aim of this research is to establish a supplier selection and order allocation (SSOA) model to optimize material purchasing in the apparel industry. The subsequent chapters are summarized as follows:

Chapter 2 gives a comprehensive literature review of existing research in material purchasing decision-making in manufacturing industries.

Chapter 3 identifies major research challenges in making material purchasing decisions for general and apparel procurement. On the basis of these challenges, a solution mechanism is proposed and an SSOA model is set up to deal with material purchasing for apparel procurement.

Chapters 4 to 6 investigate three respective material purchasing optimization problems, namely supplier selection at purchasing preparation, single-item multiple-period order allocation and multi-item single-period order allocation at purchasing execution. The mathematical models and the DE-based methodologies for these problems are presented. By using industrial data from apparel factories, a number of experiments are conducted to validate the effectiveness of the proposed methodologies.

The last chapter summarizes the contributions and limitations of this research. Further research directions are also suggested.

Chapter 2 Literature review

As a necessary part of supply chain management, material purchasing decision-making has drawn much attention in both academia and industry. This chapter reviews the existing approaches to material purchasing in the general manufacturing industry and the apparel industry.

2.1 Definition of supply chain management

The supply chain has been defined in various ways. The APIC dictionary (Cox et al., 1995) defines it as a process from initial sourcing of raw materials to ultimate consumption of finished products across supplier-user companies, and also as functions within or outside of a company that enable a value chain to provide products and services for customers.

The Supply Chain Council (1997) defines the supply chain as four basic processes (i.e. plan, source, make, deliver) transitioning from supply-and-demand management, sourcing, manufacturing, assembly, warehousing, inventory tracking, order entry, distribution to delivery.

Lee and Ng (1997) described the supply chain as “the integrated management of a network of entities, starting with suppliers’ suppliers and ending with customers’ customers for production and delivery of goods and services to final consumers, the activities of which include sourcing, procurement, production scheduling, order processing, inventory management, transportation, warehousing and customer services, and also embodies necessary information systems to monitor all the above activities.”

Summing up the above definitions, we describe the supply chain as all the activities from raw material procurement through final product delivery and all the necessary information systems to monitor these activities.

2.2 Supplier evaluation and selection in supplier pre-selection stage

This section introduces previous studies of supplier pre-selection and techniques for supplier evaluation and selection.

2.2.1 Previous studies in supplier pre-selection stage

One of the major aspects in supplier preparation is criteria for supplier evaluation. Criteria for pre-selection and ranking supplier candidates have been the focus of attention for many scientists and purchasing practitioners since the 1960's. Traditionally, supplier pre-evaluation and ranking were based on picking the least invoice-cost supplier (Degraeve & Roodhooft, 1999). However, companies have come to realize that selecting suppliers merely based on this single criterion could obscure the fact that suppliers may have their respective negative aspects, such as late delivery and poor quality. To overcome such limitations, many researchers proposed multi-criteria-based supplier pre-selection methods for better decision-making (Dickson, 1966; Cardozo & Cagley, 1971; Sheth, 1973; Weber et al., 1991; Kahraman et al., 2003; Zhang et al., 2003; Lee, 2009; Li et al., 2013).

In order to identify and analyze criteria which can impact on supplier pre-selection decision-making, Dickson (1966) performed an extensive study and sent a questionnaire to each of the 273 purchasing agents and managers selected from the membership list of the

National Association of Purchasing Managers (NAPM). The respondents were asked to evaluate the importance of each criterion on a five-point scale ranging from ‘extreme’, ‘considerable’, ‘average’, ‘slight’ to ‘of no importance’. Based on the respondents' replies, 23 criteria were identified in supplier pre-selection. Among these criteria, "quality" was the most important, followed by "delivery" and "performance history". In a similar fashion, Weber et al. 1991 reviewed articles on supplier pre-selection published from 1966 to 1991, and concluded that price, delivery, quality, production capacity and location were the criteria most evaluated in the literature. Based on the 23 criteria of the Dickson (1966) study, the research by Weber’s et al. (1991) and related articles from 1991 to 2003, Zhang et al. (2003) observed that net price, quality and delivery were the most valuable criteria for supplier pre-selection.

With a slew of new business needs emerging, other researchers have expanded Dickson’s 23 criteria and developed new ones. Zhao and Bross (2005) concluded that the most important criteria for supplier selection were cost, quality, service, relationship and organization. Bonney and Jaber (2011) argued that environmental considerations had become an increasingly significant factor in supplier selection.

Although a number of studies of supplier selection criteria have been conducted over the years, pre-selection criteria specifically for the apparel industry have not been proposed.

2.2.2 Techniques for supplier pre-selection and ranking

After determining selection criteria, the process of supplier selection and ranking is conducted. There are two factors in decision-making. One is the two basic types of criterion in supplier pre-selection, namely objective and subjective ones. The former can be measured by quantitative dimensions like cost, while the latter cannot. The other one is that some criteria may conflict with each other. Wind and Robinson (1968) identified possible conflicts, for example, in which the supplier offers the lowest price but not the best quality or offers the best quality but does not deliver on time.

In order to eliminate inefficient supplier candidates, extensive multi-criteria decision-making approaches have been developed to help the purchasing manager make a trade-off between tangible and intangible factors. These approaches include data envelopment analysis (DEA) (Weber et al., 1991; Liu et al., 2000; Wu et al., 2007; Pitchipoo et al., 2012), analytic hierarchy processes (AHP) (Saaty & Bennett, 1977; Akarte et al., 2001; Chan & Chan, 2004; Liu & Hai, 2005; Chan et al., 2007; Ishizaka et al., 2012), analytic network process (ANP) (Sarkis & Talluri, 2002; Bayazit, 2006; Gencer & Gürpinar, 2007), fuzzy set theory (Chen et al., 2006; Florez-Lopez, 2007; Ferreira & Borenstein, 2012), and their hybrids (Cebi，F. & Bayraktar, 2003; Jain et al., 2004; Chan & Kumar, 2007; Mendoza et al., 2008; Lin, 2012).

DEA originates in ‘efficiency’ of a decision alternative evaluated on the basis of benefit criteria (output) and cost criteria (input). The efficiency of an alternative (i.e. a supplier candidate) is defined as the ratio of the weighted sum of its output (i.e. the supplier candidate’s performance) to the weighted sum of its input (i.e. the supplier candidate’s cost). For each supplier candidate, DEA is used to find the most favourable set of weights (i.e. the one that maximizes the supplier candidate's efficiency rating without making his or other supplier candidates' rating higher than one) and therefore helps the purchasing decision maker classify supplier candidates into two categories, namely efficient and inefficient. AHP and ANP belong to the linear weighting model with their similarity consisting in the biggest weight indicating the highest importance. Criterion ratings are multiplied by their weights and summed up to obtain a single figure for each supplier, while the supplier with the highest weight is selected. Their difference is that ANP considers internal interdependency among various supplier selection criteria. The fuzzy sets theory (FST) is applied to model uncertainty and imprecision in supplier selection, and models vague information precisely by setting weights of performance scores on criteria. Simply put, FST is able to describe a statement mathematically; for example, 'criterion A should have a weight of around 0.8'. FST is usually combined with other techniques to improve the performance of the selection technique. Among these algorithms, AHP is the most commonly used (Steuer & Na, 2003; Wallenius et al., 2008). With consideration for vague information in supplier evaluation, this research adopts the integrated method, which is fuzzy-extended AHP， to evaluate and select appropriate suppliers. The details will be discussed in Chapters 3 and 4.

2.3 Supplier selection and order allocation in final purchasing selection stage

This section introduces previous studies of final purchasing selection and techniques for supplier selection and order allocation.

2.3.1 Previous studies in final purchasing selection stage

After potential suppliers are selected, the purchasing decision maker needs to determine an optimal order allocation strategy while selecting the best combination of suppliers from the pre-selected ones. This research classifies the related literature on the basis of different types of material purchasing, including common material (single-item) purchasing and customer-order-depended material (multi-item) purchasing.

Different types of single-item purchasing, have been extensively investigated, including single objective (minimizing purchasing cost) (Ghodsypour & O'Brien, 1998; Ghodsypour & O'Brien, 2001), multi-objectives purchasing (minimizing purchasing cost, lead time, quantity of defective product, maximizing profit) (Ustun, 2008; Lin, 2009; Sawik, 2010; Rezaei & Davoodi, 2011; Yeh & Chuang, 2011; Amin & Zhang, 2012), multi-periods purchasing (Alidaee & Kochenberger, 2005; Ustun, 2008; Aktar Demirtas & Ustun, 2009; Li et al., 2009; Sawik, 2011), and fuzzy information (Kumar et al., 2004; Amid et al., 2006; Amid et al., 2009; Amid et al., 2011; Jolai et al., 2011; Kang et al., 2012). However, few studies have investigated material purchasing by integrating supplier pre-selection and final choice stages. Also, single-item purchasing with elements of fast fashion (e.g. imprecise supplier evaluation, multi-period and multi-objective order allocation) have never been researched.

The literature deals with various practices in multi-item purchasing, such as without-discount policy (Kasilingam & Lee, 1996; Jayaraman et al., 1999; Bonser & Wu, 2001; Basnet & Leung, 2005; Sadeghi Moghadam et al., 2008), discount policy (Chaudhry et al., 1993; Dahel, 2003; Ertogral et al., 2007; Ebrahim et al., 2009; Rezaei & Davoodi, 2012)，and various purchasing uncertainties (e.g. uncertain lead time, supplier capacity, customer demands) (Yano & Lee 1995; Tempelmeier 2002; Rezaei & Davoodi 2006; Rezaei & Davoodi 2008; Yang et al. 2011). However, multi-item purchasing with elements of fast fashion (e.g. uncertain delivery delay, uncertain manufacturer's product discount, various discount policies offered by suppliers and the relationship between total profits of manufacturers and delivery delay of suppliers) has not been researched so far.

2.3.2 Techniques for supplier selection and order allocation.

Supplier selection and order allocation is an optimization problem. Various techniques have been suggested as candidates for construction of the problem's optimal decision-making models, including dynamic programming, mathematical programming and artificial intelligence (AI)-based models.

Dynamic programming has been utilized to deal with multi-period order allocation. Wagner and Whitin (1958) employed a dynamic programming algorithm to solve a dynamic lot-sizing problem with the objective of minimizing the total cost under time-varying demands for single items, inventory holding charges and setup costs. Basnet and Leung (2005) extended the model by Wagner and Whitin to multi-item order allocation with multiple suppliers on a multi-period planning horizon. Alidaee and Kochenberger (2005) solved the single-sink, fixed-charge transportation problem using a dynamic programming method which was able to determine optimal order quantities from a set of potential suppliers and minimize the cost based on total material demands. Li et al. (2009) compared periodic purchasing from the spot market featuring a long-term partnership with a single supplier with consideration for fluctuant stochastic demand and price. Sawik (2011) studied multi-period supplier selection and order allocation in the make-to-order environment and proposed a mixed-integer programming approach to incorporation of risk using the conditional value-at-risk via scenario analysis capable of optimizing dynamic supply portfolios by calculating the value-at-risk cost per part and minimizing the expected worst-case cost per part simultaneously.

Mathematical programming (MP) helps the decision-maker formulate decisions in terms of mathematical objective functions that subsequently need maximizing (e.g. maximizing profit) or minimizing (e.g. minimizing costs) by varying variable values in objective functions (e.g. order quantity by supplier X). Hong et al. (2005) presented a mixed-integer linear programming model for supplier selection The model determines the optimal number of suppliers and the optimal order quantity so that revenue can be maximized. Changes in supplier capacity and customer needs over a period of time are also considered. Ghodsypour and O'Brien (2001) formulated a mixed integer non-linear programming model to deal with multi-criteria sourcing. The model determines the optimal allocation of products to suppliers so that the total cost of annual purchasing can be minimized. Three constraints are considered in the model. Karpak et al. (1999) used goal programming to minimize costs and maximize quality and delivery reliability when selecting suppliers and allocating orders between them. Karpak et al. (2001) built a goal programming (GP) model to evaluate and select suppliers. Three goals are considered in the model, including cost, quality, and delivery reliability. The model determines the optimal order quantity subject to the buyer's demand and the supplier's capacity. In the real-world supply chain, the decision maker must consider uncertain factors along the supply chain. To reduce the risk, many scholars (Demirtas & Üstün, 2008; Soylu &

Kapan Ulusoy, 2011; Tang et al., 2011) proposed multi-objective optimization models to identify appealing trade-offs between two or more conflicting objectives involved in order allocation. Wadhwa and Ravindran (2007) modeled supplier selection as a multi-objective programming problem, in which there are three objective functions, including minimization of price, lead time, and reject products. Three approaches, including the weighted objective method, goal programming method, and compromise programming, were used to compare the solutions. Furthermore, to deal with uncertainty, Xu and Nozick (2009) proposed a two-stage mixed integer stochastic programming model which quantified the tradeoff between risk and cost on the basis of ordering, thus determining optimal supplier sourcing decisions for varying levels of risk tolerance.

Since order allocation in multi-item purchasing, which considers the total purchased quantity discount policy, belongs to the class of NP-hard problems (Goossens et al. 2007), it is very difficult for classical MP techniques to make an optimal decision for material purchasing because their computational time is usually much longer than practical applications can afford. In recent years, some intelligent optimization techniques have become popular and been used extensively in material purchasing.

Tabu search (Glover, 1989; Glover, 1990; Feng et al., 2011) is a mathematical optimization method which belongs to the class of local search techniques and enhances the performance of a local search method using memory structures. Simulated annealing (Van Laarhoven & Aarts, 1987; Kanagaraj & Jawahar, 2009; Che, 2012) is a generic probabilistic meta-algorithm for global optimization problems, which simulates annealing in metallurgy involving heating and controlled cooling of a material to increase its crystals' size and reduce their defects. The artificial neural network (Wei et al., 1997; Choy et al., 2003; Yegnanarayana, 2004; Kuo et al., 2010) was composed of an interconnected group of artificial neurons and was an information processing paradigm inspired by the way biological nervous systems do. The artificial immune system (Dasgupta et al., 2003; Agarwal et al., 2007; Prakash & Deshmukh, 2011) is a type of optimization algorithm inspired by the principles and processes of the vertebrate immune system, which typically exploits the immune system's characteristics of learning and memory to solve a problem. The ant colony optimization algorithm (Dorigo & Stützle, 2003) is a probabilistic technique for solving computational problems and can be used to find good paths through graphs. It is inspired by the behaviour of ants in finding paths from colonies to food. Genetic algorithm (Whitley, 1994; Ding et al., 2005; Rezaei & Davoodi, 2006; Liao & Rittscher, 2007; Yeh & Chuang, 2011) is a global search heuristic inspired by evolutionary biology characterized by inheritance, mutation, selection and crossover (i.e. recombination). Differential evolution (DE) (Price et al., 2005; Kim et al., 2007; Xue et al., 2009; Ponsich & Coello, 2011; Zeng et al., 2012) functions almost identically to genetic algorithms (GA), except for the fact that GAs' mutation is caused by small gene changes and DE's is carried out by the arithmetical combination of selected individuals.

Compared with other intelligent optimization techniques or evolutionary algorithms, the DE algorithm 1) is more simple and straightforward; 2) gives better performances; 3) has a small number of control parameters (Cr, F, and NP in classical DE); and 4) has a low level of space complexity. Hence, DE is generally considered a reliable, accurate, robust and fast optimization technique, which has been successfully applied to a wide range of numerical optimization problems (Ponsich & Coello, 2011; Zeng et al., 2012).

However, DE has been rarely utilized in supplier selection and order allocation, especially in the apparel industry. This research proposes an improved DE algorithm, which modifies mutation operators to solve discrete stochastic multi-item purchasing problems.

2.4 Summary

From the above literature review, the following conclusions can be drawn:

(1) Although there have been a number of supplier selection criteria studies, criteria for supplier pre-selection specifically for apparel material purchasing have yet to be established.

(2) Previous studies of material purchasing decision-making, especially for the apparel industry, are few. Effective methodologies are required to cope with real-world material purchasing control.

(3) Some features of apparel purchasing, such as the relationship between delivery delay, wholesale price and frequent purchasing, have not been investigated. Corresponding methodologies are required to generate an optimal decision-making model of material purchasing with consideration for the above factors.

In summary, previous studies of both material purchasing and its decision-making, especially for apparel material purchasing, are very few, thereby leaving much room for research and exploration. This research will investigate the real-world problems of apparel material purchasing control and consider various realistic situations, such as uncertain material delivery delay and uncertain supplier capacity. Effective methodologies will also be developed to solve these problems. Hopefully, this research will enrich our knowledge of material purchasing decision-making.

Chapter 3 Research challenges and methodology

Chapter 2 presents a detailed review of all the up-to-date findings in supplier selection and order allocation. However, the literature on material purchasing decision-making, especially for apparel material purchasing, has been very limited and made little impact on industrial practice, though effective material purchasing decision-making is known to be helpful in improving the performances of apparel supply chain management.

This chapter identifies the research challenges that hinder the development of material purchasing decision-making methodologies and formulates an effective and efficient solution mechanism.

3.1 Research challenges to material purchasing decision-making for apparel purchasing

For several decades, lots of studies have been dedicated to exploring effective methodologies for material purchasing decision-making. However, these studies are only applicable to simplified procurement situations and have little impact on industrial practice because of various research difficulties. In this research, these difficulties are regarded as challenges which can be classified into two categories, namely research challenges in the pre-selection stage and those in the final stage.

3.1.1 Research challenge in pre-selection stage in material purchasing

In the pre-selection stage of material purchasing, the decision maker usually has to tackle the following two problems.

1) Multi-criteria decision problem

Supplier pre-selection is always a difficult task for the purchasing decision maker. Since each supplier has different strengths and weaknesses, the purchasing decision maker evaluates all potential suppliers according to multiple criteria (Kumar et al. 2006). The challenge to the purchasing manager is how to determine the weight of each criterion and then effectively rank and choose appropriate suppliers.

2) Uncertain information in pre-selection stage

Uncertainties usually emerge in the pre-selection stage of material purchasing. During pre-selection, people are reluctant or unable to assign accurate values in evaluation due to the following reasons: 1) people's thoughts are often vague and ambiguous; 2) the expert's knowledge may be limited; and 3) the situation is highly complex. The decision maker prefers to evaluate in linguistic terms. For example, people tend to use "very good", "good", "so-so", "bad" or "very bad" in evaluating a supplier candidate's performance. It is difficult to deal with the vagueness of information.

3.1.2 Research challenge to final stage in material purchasing

In the final stage of material purchasing, the decision maker usually faces the following two problems.

1) Multi-objective problems

Another factor complicating material purchasing decisions is that objectives may conflict with each other. For example, the supplier offers the lowest price but not the best quality or offers the best quality but fails to deliver on time. Therefore, the purchasing decision maker should know how to make a reasonable trade-off between those conflicting factors and thus find the best suppliers.

2) Uncertain and unpredictable phenomena in final stage of material purchasing

Uncertain and unpredictable phenomena usually occur in real-world purchasing, such as uncertain customer orders, uncertain delivery delay and unpredictable supplier failure. In order to achieve effective material purchasing decision-making, it is important to deal with real-world phenomena of a more complex nature.

3) Complexity of order allocation in purchasing decision making

Since order allocation, which considers the total purchased quantity discount policy in material purchasing, belongs to the class of NP-hard problems (Goossens et al. 2007), it is difficult to get an optimal purchasing decision solution.

3.2. Methodology

The apparel industry has endeavored to overcome challenges and complexities in apparel material purchasing. This section presents an effective solution mechanism to deal with these challenges.

3.2.1 Intelligent supplier selection and order allocation optimization model for material purchasing

In apparel manufacturing, material purchasing is decided with consideration for the following three problems.

(1) Supplier pre-evaluation and ranking (SPER) problems happen in the preparation stage of material purchasing. In order to sort out inefficient supplier candidates, the purchasing decision maker should determine different decision criteria based on different purchasing situations and pre-select potential suppliers.

(2) Single-item purchasing optimization (SIPO) problems happen in the final stage of common material (e.g. white fabric) purchasing. After pre-qualified suppliers are chosen, the purchasing decision maker should determine an optimal order allocation strategy while selecting the best combination of suppliers with consideration for multiple periods, material price fluctuation and supplier capacity.

(3) Multi-item purchasing optimization (MIPO) problems happen in the final stage of fashion accessories purchasing. After pre-qualified suppliers are chosen, the purchasing decision maker should determine an optimal order allocation strategy while selecting the best combination of suppliers, with consideration for multiple material price-breaks offered by suppliers based on total purchased quantity and delivery delay.

On the basis of the above description, the purchasing manager needs at least three types of information to make an effective material purchasing decision, including criteria (for choosing suppliers) information, supplier information (e.g. material price, supplier capacity, delivery delay) and manufacturer product information. Based on the data, an integrated intelligent supplier selection and order allocation optimization (SSOA) model for apparel material purchasing is proposed and its architecture is shown in Figure 3-1.

In the proposed model, apparel manufacturers' material purchasing decisions are made according to the following procedure.

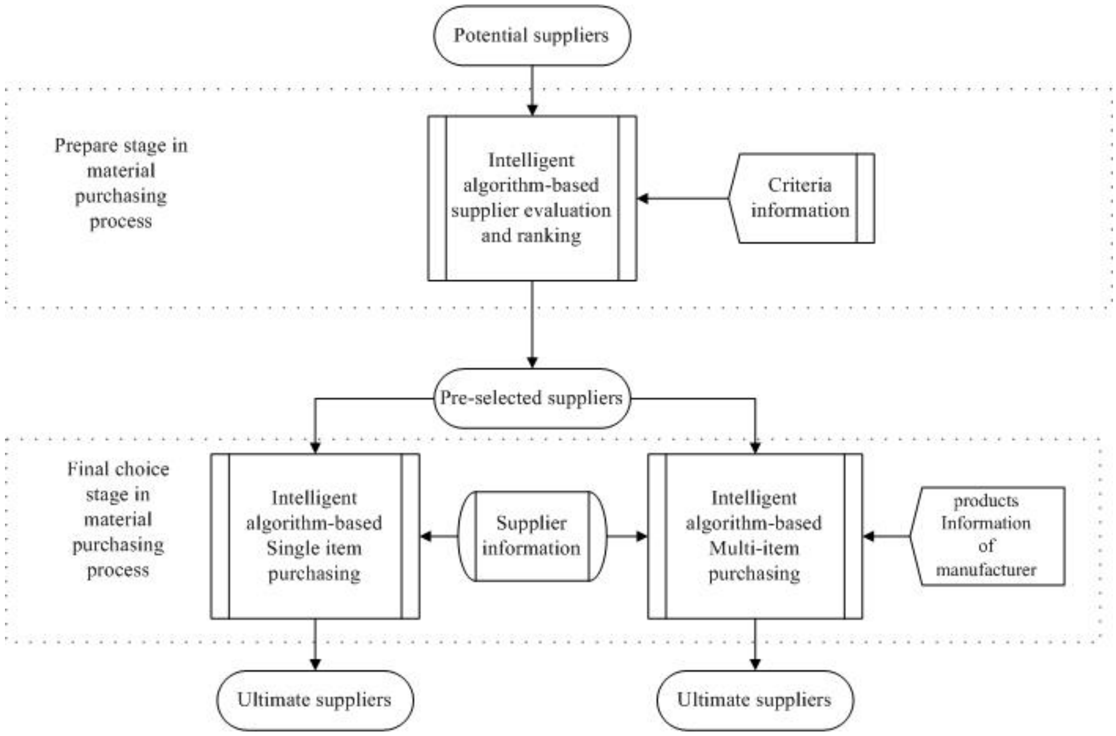

Figure 3-1: Architecture of integrated intelligent material purchasing optimization model for apparel material purchasing

(1) After material demands are confirmed, the supplier pre-evaluation and ranking (SPER) problem arises at the preparation stage of material purchasing. Necessary inputs, including the set of criteria and the comparison information on criteria, attributes or supplier candidates, should be provided by the decision-making group to solve this problem. The investigation into the supplier pre-evaluation and ranking problem generates each criterion's

weight and each supplier candidate's weight. On the basis of each supplier candidate's weights, the decision maker can decide on the choice of pre-qualified suppliers.

(2) The SIPO problem arises after the purchasing manager confirms the choice of pre-qualified suppliers in the final choice stage of common material purchasing. The inputs include material demands in each period, material prices charged by each supplier and different capacities of suppliers in each period. The investigation into the SIPO problem generates the optimized order allocation strategy which allocates the best combination of suppliers to each purchasing period.

(3) The MIPO problem arises after the purchasing manager confirms the choice of pre-qualified suppliers in the final stage of fashion accessories purchasing. The inputs concern material demands, material price, capacity and delivery delay about each supplier, and prices of the manufacturer's own products. The investigation into the MIPO problem generates the optimized order allocation strategy and the best combination of suppliers.

The above tasks are to be investigated in detail in Chapters 4, 5 and 6.

3.2.2 Fuzzy-extended analytic hierarchy process (FEAHP) method

The fuzzy-extended analytic hierarchy process (FEAHP) is adopted as the basis of the proposed methodologies in the supplier pre-evaluation and ranking model. A brief introduction of this cluster analysis is presented in this subsection.

The analytic hierarchy process (AHP) has been widely used to deal with multi-criteria decision-making. It only requires a discrete scale from one to nine. However, humans are uncertain to judge criteria preferences. The linguistic assessment of human feelings and judgments are vague and cannot be represented in precise numbers. Hence, triangular fuzzy numbers are used to determine the priority of decision variables. The synthetic extent analysis is also used to determine the final priority weights based on triangular fuzzy numbers.

3.2.2.1 Triangular fuzzy number and representation of preferences

A fuzzy set is characterized by a membership function, which assigns to each object a grade of membership ranging from 0 and 1. The general terms "large", "medium", and "small" are used in the fuzzy set to capture a range of numerical values. If l, m and u respectively denote the smallest possible value, the most promising value and the largest possible value to describe a fuzzy event, the triangular fuzzy number (TFN) can be denoted as a vector (l, m, u) where, $l \leq m \leq u$. When l =m =u, it is a non-fuzzy number by convention. The membership function can be defined as

$$\mu(x|M) = \begin{cases} (x-l)/(m-l) & l \leq x \leq m \\ (u-x)/(u-m) & m \leq x \leq u \\ 0 & \text{otherwise} \end{cases} \tag{3-1}$$

TFNs M_1, M_3, M_5, M_7 and M_9 are used to represent the pair-wise comparison of decision variables from "Equal" to "Absolutely preferred", and TFNs M_2, M_4, M_6 and M_8 represent the middle preference value among them. Figure 3-2 shows the membership functions of the TFNs, $M_i = (l_i, m_i, u_i)$, where i=1, 2, . . . , 9 and l_i, m_i, u_i are the lower, middle and upper values of the fuzzy number M_i respectively.

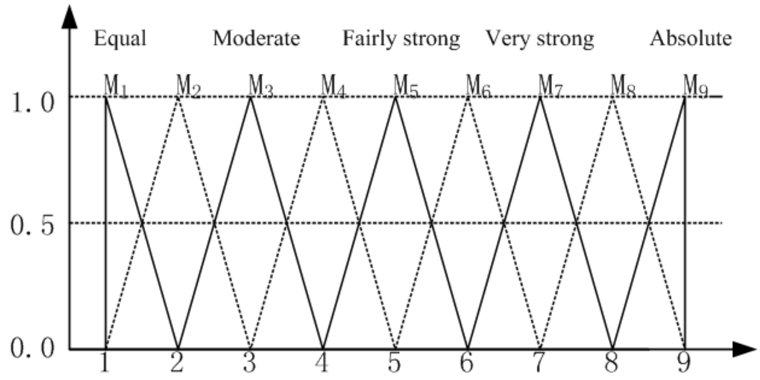

Figure 3-2: Membership functions of triangular fuzzy numbers

3.2.2.2 Fuzzy-extended analytic hierarchy process (FEAHP)

The FEAHP was originally introduced by Chang (1996). Some calculation steps are essential and explained as follows:

Let X=$\{x_1, x_2, x_3, \ldots, x_n\}$ be an object set, and G=$\{g_1, g_2, g_3, \ldots, g_n\}$ be a goal set. According to Chang's method, each object is taken and the extent analysis of each goal is performed. Therefore, *m* extent analysis values for each object can be obtained, with the following signs: $M_{g_i}^1, M_{g_i}^2, \ldots, M_{g_i}^m$, i=1,2, ...,n where $M_{g_i}^j$ (j=1,2, ...,m) are the triangular fuzzy numbers (TFNs).

Step 1. Establishing a hierarchical structure

Constructing a hierarchical structure with decision elements, decision-makers are required to make pair-wise comparisons between decision alternatives and criteria using a nine-point scale (Table 3-1). All matrices are developed and all pair-wise comparisons are obtained from each decision-maker.

Table3-1: Triangular fuzzy numbers

Triangular fuzzy numbers		
linguistic variables	positive triangular fuzzy number	positive reciprocal triangular fuzzy number
extremely strong	(8, 9, 9)	(1/9, 1/9, 1/8)
intermediate	(7, 8, 9)	(1/9, 1/8, 1/7)
very strong	(6, 7, 8)	(1/8, 1/7, 1/6)
intermediate	(5, 6, 7)	(1/7, 1/6, 1/5)
strong	(4, 5, 6)	(1/6, 1/5, 1/4)
intermediate	(3, 4, 5)	(1/5, 1/4, 1/3)
moderately strong	(2, 3, 4)	(1/4, 1/3, 1/2)
intermediate	(1, 2, 3)	(1/3, 1/2, 1)
equally strong	(1, 1, 2)	(1/2, 1, 1)

Step 2. The fuzzy synthetic extent value with respect to the i th object is defined as:

$$S_i = \sum_{j=1}^{m} M_{g_i}^{j} \times \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} \tag{3-2}$$

To obtain $\sum_{j=1}^{m} M_{g_i}^{j}$, the fuzzy addition operation of *m* extent analysis values for a particular matrix is performed as

$$\sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j\right) \tag{3-3}$$

To obtain $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]$, the fuzzy addition operation of $M_{g_i}^{j}$ (j=1,2, ...,m) values is performed as

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{i=1}^{n} l_j, \sum_{i=1}^{n} m, \sum_{i=1}^{n} u_j\right) \tag{3-4}$$

And the inverse of the above vector is computed as

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_j}, \frac{1}{\sum_{i=1}^{n} m}, \frac{1}{\sum_{i=1}^{n} l_j}\right) \tag{3-5}$$

Step 3. As $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ are two triangular fuzzy numbers, the degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as

$$V(M_2 \geq M_1) = \sup_{y \geq x}\left\{\min\left(\mu_{M_1}(x), \mu_{M_2}(y)\right)\right\} \tag{3-6}$$

can be expressed as follows:

$V(M_2 \geq M_1) = hgt(M_2 \cap M_1) = \mu_{M_2}(d)$

$$= \begin{cases} 1 & \text{if } m_2 \geq m_1 \\ \left| \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} \right| & \text{otherwise} \end{cases} \qquad (3\text{-}7)$$

Eq.(3-7) (Figure 3-3) indicates that d is the ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2}. To compare M_1 and M_2, the values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ are needed.

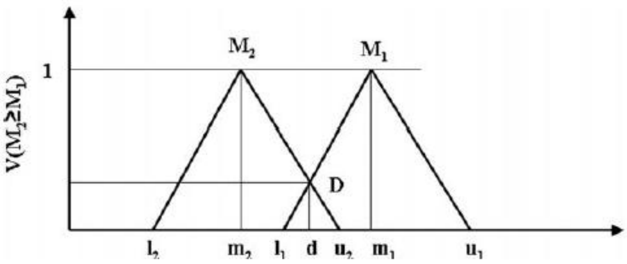

Figure 3-3: The intersection between M1 and M2

Step 4. The degree of possibility that the convex fuzzy number is greater than k convex fuzzy M_i(i=1,2, ...,k) numbers can be defined by

$V(M \geq M_1, M_2, \ldots, M_k)$

$= V[(M \geq M_1) \text{ and } (M \geq M_2) \text{ and } \ldots \text{and } (M \geq M_k)] = \min V(M \geq M_i)$

(i=1, 2, 3, ..., k) (3-8)

Assume that $d(A_i) = \min V(S_i \geq S_k)$ for k=1,2, ...,n ; $k \neq i$. Then the weight vector is given by

$$W' = (d'(A_1), d'(A_2), \ldots, d'(A_n))^{\tau} \qquad (3\text{-}9)$$

where A_i(i=1, 2, 3, ..., n) are n elements.

Step 5. Via normalization, the normalized weight vectors are

$$W = \left(d(A_1), d(A_2), \ldots, d(A_n)\right)^{\tau} \tag{3-10}$$

where W is a non-fuzzy number.

The upward composition of these weights (from the lowest to the highest level) generates the ranking scores (weights) of elements at the lowest level (i.e. suppliers) in fulfilling the top most objective (i.e. suppliers ranking).

3.2.3. Differential evolution (DE) technique

To investigate more real-life features of material purchasing, the multi-item stochastic purchasing optimization (MIPO) sub-model will be developed to handle the purchasing of multiple items. Material purchasing decision-making in this research is extremely intractable owing to its NP-hard nature. Its solution spaces are huge and increase exponentially with the size of the problem. It is difficult for classical optimization techniques to obtain optimal, even acceptable, production decisions.

Differential evolution (DE) is an adaptive random search technique, which can solve problems deemed difficult for classical optimization techniques. And the basic DE is described as follows:

In general, DE is implemented according to the following procedure (Figure 3-1).

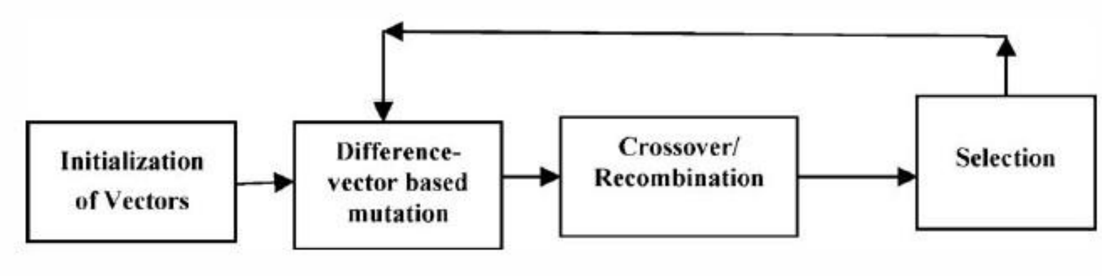

Figure 3-4: Main stages of DE algorithm.

Initialization: Generate an initial population of chromosomes randomly. Each chromosome represents a feasible solution to the problem on the basis of a certain representation.

Fitness Evaluation: Evaluate the fitness of each chromosome in the population by using the fitness function.

Generation of New Population: Create a new population by repeating the following steps until a new population is complete.

Mutation: With a certain scaled number, child chromosomes mutate according to a mutation rule. The control parameter is scalar number F.

Crossover: With a certain crossover probability, child chromosomes crossover according to a mutation rule. The control parameter is crossover rate Cr.

Selection: To keep the population size constant over subsequent generations, whether the target or the trial vector survives to the next generation is determined according to a selection rule.

Acceptance: Place the new chromosomes in a new population.

Test: If the termination criterion is satisfied, stop this procedure and return the best solution; otherwise, go to step 2 to start a new iteration.

In the above procedure, each iteration is called a generation. The new population is supposed to inherit the excellent genes from previous generations so that the average quality of solutions is better than before.

In order to solve an optimization problem, the following processes and operations need to be determined on the basis of the above DE procedure.

Representation: It determines how to create a chromosome. A chromosome is composed of a list of genes. A good representation is crucial because it significantly affects all the subsequent steps of the DE.

Fitness function: It reflects the fitness of each chromosome and is relevant to the objective function to be optimized. Given a particular chromosome, the value of fitness function represents its survival. A fitter chromosome has a better chance of survival.

Control operation: It determines how to perform mutation and crossover. Both operations are random processes with a pre-specified probability. The typical probabilities of crossover rates and mutation operations are between 0 and 1.0 and between 0.4 and 1 respectively.

The advantages of DE are described as follows:

1) DE is more simple and straightforward as compared to most evolutionary algorithms. The main body of the algorithm takes four to five lines to encode any programming language. Simple encoding is important for practitioners since they may not be good at programming and are looking for an algorithm that can be easily implemented and tuned so as to solve their domain-specific problems (Vesterstrom & Thomsen, 2004; Rahnamayan et al., 2008; Das et al., 2009).

2) DE gives better performances than several evolutionary algorithms. In terms of accuracy, convergence speed and robustness, DE is a good choice for application to various real-world optimization problems, while finding an approximate solution in a reasonable amount of computational time is much weighted (Das & Suganthan, 2011).

3) The number of control parameters in DE is very few (i.e. Cr, F, and NP in classical DE). The effects of these parameters on the algorithm are well studied. As will be discussed in the next section, simple adaptation rules for F and Cr have been devised to improve the performance of the algorithm to a large extent without imposing any serious computational burden (Brest et al., 2006; Qin et al., 2009; Zhang & Sanderson, 2009).

4) Compared to most evolutionary algorithms, DE has a low level of space complexity. This feature can extend the use of DE to large-scale and expansive optimization problems (Das and Suganthan, 2011).

3.3 Summary

This chapter presents the challenges of making effective material purchasing decisions for apparel manufacturers. To overcome the identified challenges, the SSOA model is developed to handle three different types of material purchasing problem. As the most important parts of this proposed solution mechanism, the FEAHP method and the differential evolution technique are described briefly in this chapter.

Chapter 4 Fuzzy-extended analytic hierarchy process-based supplier evaluation and ranking

Based on the methodology presented in Chapter 3, three material purchasing problems at the two levels of apparel purchasing are to be investigated. To reduce product costs and maintain excellent customer services and product quality, the most important purchasing decision is how to maintain close relationships with fewer selected reliable suppliers. In order to evaluate each supplier more reasonably, the decision maker should always use multiple criteria. However, the decision maker is not always able to be explicit about his preferences due to the fuzzy nature of comparison. This chapter adopts the fuzzy-extended analytic hierarchy process (FEAHP) to deal with supplier selection. Supplier selection involves multiple criteria, including cost, quality, risk, service performance, and supplier profiles. Experiments are conducted to validate the effectiveness of the proposed methodology.

4.1 The fuzzy-extended analytic hierarchy process (FEAHP)-based supplier ranking method

As discussed in the introduction, supplier ranking gives the decision maker an effective tool to choose suitable suppliers. In this research, supplier ranking is implemented by the FEAHP. The procedure is detailed as follows:

Step 1: Define criteria for supplier selection

To define effective criteria for supplier selection, this research collects promising candidate criteria based on existing research results (Dickson, 1966; Chan & Kumar, 2007), and additional criteria deemed important for manufacturers.

On the basis of the selected candidate criteria, structured interviews are used to evaluate these criteria by three senior specialists, including a senior designer and two purchasing managers denoted by (R1), (R2) and (R3) respectively. To evaluate candidate criteria, the respondents are requested to use the linguistic assessment of human feelings (Table 4-1). Upon receiving the inputs of the respondents, the criteria are identified and averaged. If there are too many criteria, the pair-wise comparison can become a difficult and time-consuming process. To overcome these problems, the top 5 criteria's average value is selected.

The 5 final criteria are 1) overall cost of products (C1); 2) quality of product delivery (C2); 3) risk factors (C3); 4) supplier profiles (C4); and 5) service performance of a supplier (C5).

Step 2: Define sub-criteria for supplier selection

To evaluate suppliers more precisely, each selected criterion in Step 1 needs to be further represented by several sub-criteria. The identification and selection of these sub-criteria can be implemented as described in Step 1. If the sub-criteria are still obscure, they can be re-represented by sub-sub-criteria using the same process.

Step 3: Structure the hierarchical model and each criterion's weight

In this step, the FEAHP hierarchy model is built and the weight of each supplier selection model is calculated. The developed FEAHP model, based on the identified criteria, sub-criteria and sub-sub-criteria, has five levels: goals, criteria, sub-criteria, sub-sub-criteria and candidates. Figure 3 shows the 5-level hierarchy for supplier selection. The goal of supplier selection for manufacturers is identified on the first level. The second level (criteria) contains 5 criteria mentioned in Step 1. The third and fourth levels consist of sub-criteria and sub-sub-criteria (sub-sub-criteria are not considered in this paper's numerical experimentation). The lowest level of the hierarchy contains alternatives. That is, different suppliers are evaluated in order to pick the best ones. As shown in Figure 4-3, different suppliers are used to represent the arbitrary ones which manufacturers wish to evaluate.

The FEAHP model (Figure 4-1) is generally applicable to any type of supplier selection by manufacturers as it covers many important factors and their related criteria, sub-criteria and sub-sub-criteria.

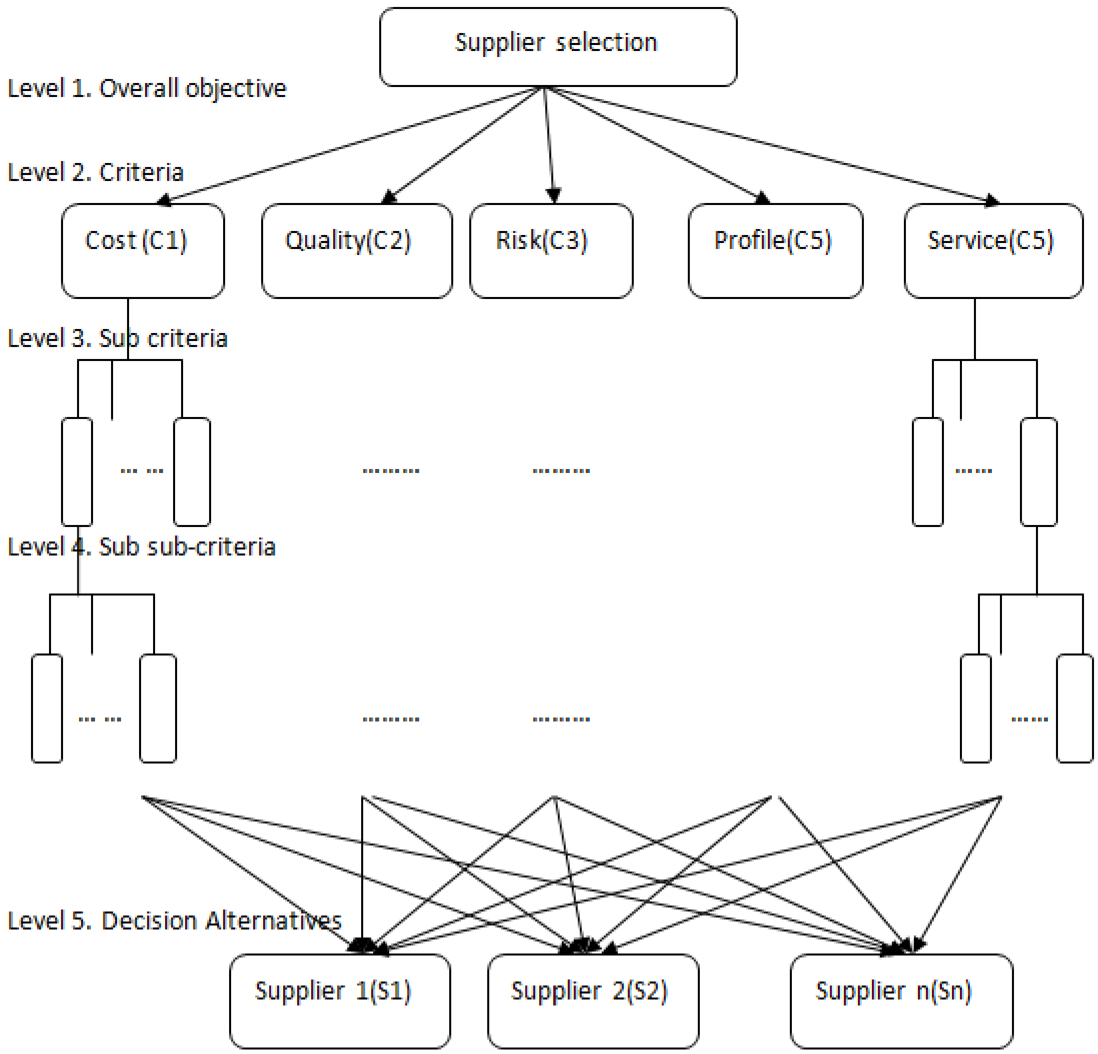

Figure 4-1: General hierarchy for supplier selection

In order to obtain the priority weight of each criterion on each level, a second structure is done in a similar manner to Step 1. The interview consisting of factors on each level of the FEAHP model is used to collect the judgments of pair-wise comparisons from all evaluation team members. These judgments are performed using pair-wise comparisons, which are elaborated in Section 4.1.1. An example of the pair-wise comparison matrix is shown in Table 4-1 in Section 4.2.1.

Step 4: Measure supplier performance and identify supplier priority

After obtaining the priority weight of each criterion and sub-criterion, the third structured interview is designed and modified. This interview collects the weights of alternatives to identify the best suppliers.

The priority weight is determined for alternatives in this step. The competitive rivals that are supposed to be suppliers are compared by each sub-criteria standard. After finding the local weight of each alternative in sub-criteria, the global weight of each alternative in each criterion can be calculated. The evaluation of the global weight of each alternative can be obtained by multiplying the global weights of sub-criteria and the local weight of each alternative. Based on the global priority, the weight of each alternative can be evaluated and summarized. An example of FEAHP-based supplier ranking is described in Section 4.2.2.

4.2 Experiment for FEAHP-based supplier ranking

The FEAHP starts from the pair-wise comparison matrices of five criteria (Table 4-1). Based on these matrices, the weights of suppliers and criteria are calculated and presented in Table 4-2.

The criteria for selection of material suppliers are as follows:

- Overall cost of products (C1): product price (A_1), freight cost (A_2), penalty for delayed payment (A_3), tariff and custom duties (A_4)

- Product quality (C2): rejection rate (A_5), response to changes (A_6), rate of warranty claims (A_7).

- Risk factors (C3): lead time (A_8), political stability (A_9), geographical location (A_{10}), inability to meet further requirements (A_{11})

- Supplier's profile (C4): financial status (A_{12}), performance history (A_{13}), production capacity (A_{14})

- Service performance of suppliers (C5): remedy for quality problems (A_{15}), delivery schedule (A_{16}).

These criteria can be found in the hierarchical structure (Figure 4-2).

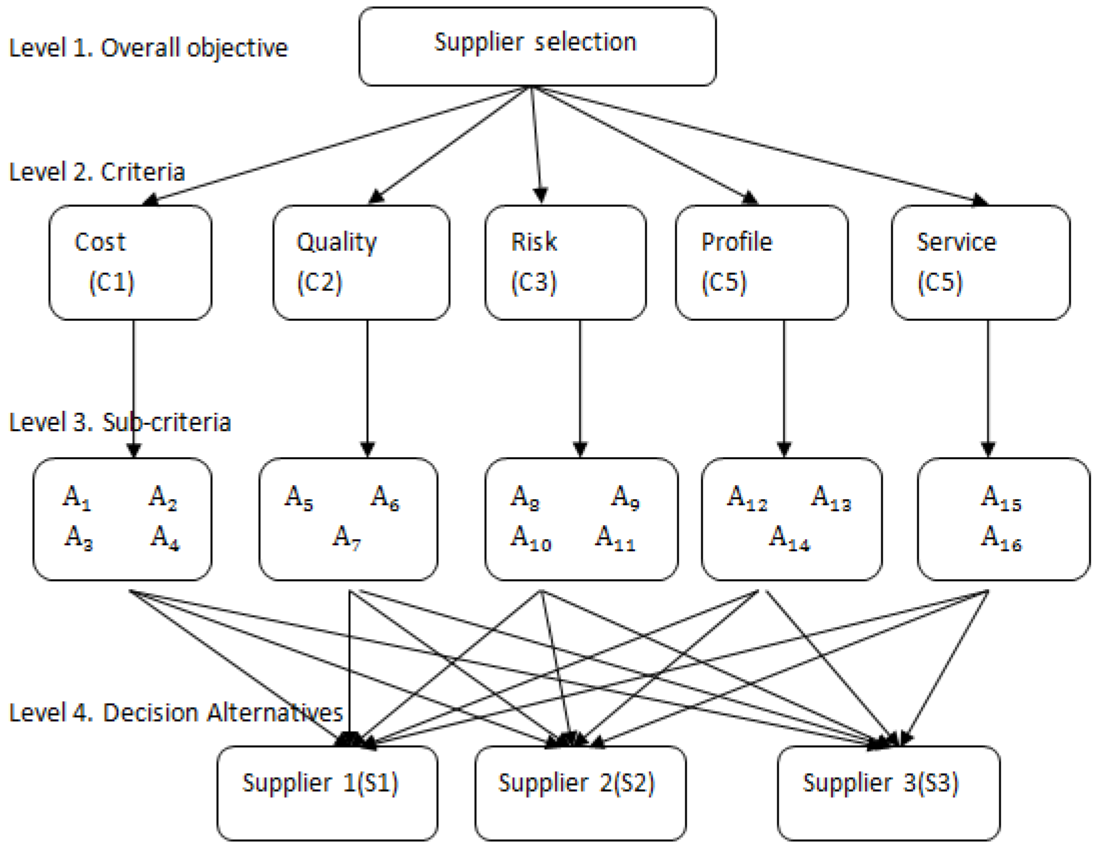

Figure 4-2: Hierarchy for supplier selection

4.2.1 Determination of criteria weights and sub-criteria weights

The example of the pair-wise comparison matrices shows that the fifth row and column attach importance to the row's criterion relative to the column's criterion (Table 4-1).

Table 4-1: The fuzzy evaluation of criteria of the overall objective

	C1	C2	C3	C4	C5	weights
C1	(1, 1, 1)	(2, 3, 4)	(3, 4, 5)	(5, 6, 7)	(2, 3, 4)	0. 43
C2	(0. 25, 0. 33, 0. 5)	(1, 1, 1)	(3, 4, 5)	(2, 3, 4)	(4, 5, 6)	0. 33
C3	(0. 2, 0. 25, 0. 33)	(0. 2, 0. 25, 0. 33)	(1, 1, 1)	(3, 4, 5)	(2, 3, 4)	0. 13
C4	(0. 14, 0. 17, 0. 2)	(0. 25, 0. 33, 0. 5)	(0. 2, 0. 25, 0. 33)	(1, 1, 1)	(2, 3, 4)	0. 02
C5	(0. 25, 0. 33, 0. 5)	(0. 17, 0. 2, 0. 25)	(0. 25, 0. 33, 0. 5)	(0. 25, 0. 33, 0. 5)	(1, 1, 1)	0. 09

Due to a good cost performance, the criterion for the first row is slightly preferred to the one on product quality, risk factors and service performance of suppliers (the fuzzy values of (2,3,4) and (3,4,5) and (2,3,4), respectively), and is strongly preferred to the supplier’s profile, (the value of (5,6,7)). Due to a good quality performance, the criterion for the second row and column is moderately more important than the service performance of suppliers (the value of (4,5,6)). Having fewer risk factors, the third row’s criterion is slightly preferred to a good profile (value of (3,4,5)). Decision makers only need to fill in the upper half of the comparison matrix by assuming that the pair-wise comparison of cost and service performance is (2,3,4), following the pair-wise comparison of service performance and cost (0.25,0.33,0.5). The value of (1,1,1) is assigned to diagonal elements.

Calculate various decision alternatives of fuzzy numbers based on Section 5.1:

$$S_{c_1} = (13\,,17\,,21) \times \left(\frac{1}{56.95},\frac{1}{45.78},\frac{1}{35.16}\right) = (0.23,0.37,0.60)$$

$$S_{c_2} = (10.25\ , 13.33, 16.5) \times \left(\frac{1}{56.95}, \frac{1}{45.78}, \frac{1}{35.16}\right) = (0.18, 0.29, 0.47)$$

$$S_{c_3} = (6.40\ , 8.50\ , 10.67) \times \left(\frac{1}{56.95}, \frac{1}{45.78}, \frac{1}{35.16}\right) = (0.11, 0.19, 0.30)$$

$$S_{c_4} = (3.59\ , 4.75\ , 6.03) \times \left(\frac{1}{56.95}, \frac{1}{45.78}, \frac{1}{35.16}\right) = (0.06, 0.10, 0.17)$$

$$S_{c_5} = (1.92\ , 2.20\ , 2.75) \times \left(\frac{1}{56.95}, \frac{1}{45.78}, \frac{1}{35.16}\right) = (0.03, 0.05, 0.08)$$

Comparison decision alternatives

$$V(S_{c_1} \geq S_{c_2}) = 1, V(S_{c_1} \geq S_{c_3}) = 1, V(S_{c_1} \geq S_{c_4}) = 1, V(S_{c_1} \geq S_{c_5}) = 1,$$

$$V(S_{c_2} \geq S_{c_1}) = 0.75, V(S_{c_2} \geq S_{c_3}) = 1, V(S_{c_2} \geq S_{c_4}) = 1, V(S_{c_2} \geq S_{c_5}) = 1$$

$$V(S_{c_3} \geq S_{c_1}) = 0.29, V(S_{c_3} \geq S_{c_2}) = 0.54, V(S_{c_3} \geq S_{c_4}) = 1, V(S_{c_3} \geq S_{c_5}) = 1$$

$$V(S_{c_4} \geq S_{c_1}) = 0.27, V(S_{c_4} \geq S_{c_2}) = 0.05, V(S_{c_4} \geq S_{c_3}) = 0.42, V(S_{c_4} \geq S_{c_5}) = 1$$

$$V(S_{c_5} \geq S_{c_1}) = 0.87, V(S_{c_5} \geq S_{c_2}) = 0.72, V(S_{c_5} \geq S_{c_3}) = 0.33, V(S_{c_5} \geq S_{c_4}) = 0.21$$

Calculate the decision alternatives' weights

$$d'(c_1) = \min(1,1,1,1) = 1,\ \ d'(c_2) = \min(0.75,1,1,1) = 0.75$$

$$d'(c_3) = \min(0.29, 0.54, 1, 1) = 0.29$$

$$d'(c_4) = \min(0.27, 0.05, 0.42, 1) = 0.05$$

$$d'(c_5) = \min(0.87, 0.72, 0.33, 0.21) = 0.21$$

Priority weights form $W' = (1, 0.75, 0.29, 0.05, 0.21)$ vector. After normalization of the values, the priority weights of the main goal are calculated as (0.43, 0.33, 0.13, 0.02, 0.09). The results (i.e. principal vectors) show that the criteria have the following approximate priority weights: cost (0.43), quality (0.33), risk (0.13), supplier profiles (0.02) and service performance of suppliers (0.09).

Different attributes are compared by each criterion separately with the same procedure as discussed above. The fuzzy evaluation matrices of attributes and the weight vectors of sub-criteria are shown in Tables 4-2 to 4-6.

Table 4-2: Fuzzy evaluation of attributes of criterion C1

	A1	A2	A3	A4	weights
A1	(1, 1, 1)	(2, 3, 4)	(3, 4, 5)	(3, 4, 5)	0. 49
A2	(0. 25, 0. 33, 0. 5)	(1, 1, 1)	(3, 4, 5)	(2, 3, 4)	0. 31
A3	(0. 2, 0. 25, 0. 33)	(0. 2, 0. 25, 0. 33)	(1, 1, 1)	(3, 4, 5)	0. 09
A4	(0. 2, 0. 25, 0. 33)	(0. 25, 0. 33, 0. 5)	(0. 2, 0. 25, 0. 33)	(1, 1, 1)	0. 12

Table 4-3: Fuzzy evaluation of attributes of criterion C2

	A5	A6	A7	weights
A5	(1, 1, 1)	(4, 5, 6)	(2, 3, 4)	0. 56
A6	(0. 17, 0. 2, 0. 25)	(1, 1, 1)	(3, 4, 5)	0. 19
A7	(0. 25, 0. 33, 0. 5)	(0. 2, 0. 25, 0. 33)	(1, 1, 1)	0. 26

Table 4-4: Fuzzy evaluation of attributes of criterion C3

	A8	A9	A10	A11	weights
A8	(1, 1, 1)	(4, 5, 6)	(4, 5, 6)	(1, 1, 2)	0. 59
A9	(0. 17, 0. 2, 0. 25)	(1, 1, 1)	(4, 5, 6)	(2, 3, 4)	0. 39
A10	(0. 17, 0. 2, 0. 25)	(0. 17, 0. 2, 0. 25)	(1, 1, 1)	(3, 4, 5)	0. 01
A11	(0. 5, 1, 1)	(0. 25, 0. 33, 0. 5)	(0. 2, 0. 25, 0. 33)	(1, 1, 1)	0. 01

Table 4-5: Fuzzy evaluation of attributes of criterion C4

	A12	A13	A14	weights
A12	(1, 1, 1)	(3, 4, 5)	(3, 4, 5)	0. 51
A13	(0. 2, 0. 25, 0. 33)	(1, 1, 1)	(3, 4, 5)	0. 18
A14	(0. 2, 0. 25, 0. 33)	(0. 2, 0. 25, 0. 33)	(1, 1, 1)	0. 30

Table 4-6: Fuzzy evaluation of attributes of criterion C5

	A15	A16	weights
A15	(1, 1, 1)	(3, 4, 5)	0. 52
A16	(0. 2, 0. 25, 0. 33)	(1, 1, 1)	0. 48

4.2.2 Calculate the suppliers' weights

Similarly, the fuzzy evaluation matrices of decision alternatives and the corresponding weight vector of each alternative with respect to the corresponding attributes are determined. The priority weights of suppliers with respect to each criterion are given by adding each supplier's weight to each corresponding attribute's weight. The results are shown in Tables 4-7 to 4-12.

Table 4-7: Fuzzy evaluation of sub-criteria of criterion C1

	A1	A2	A3	A4	Alternative priority
weight	0. 49	0. 31	0. 09	0. 12	weight
Alternatives					
S1	0. 51	0. 51	0. 69	0. 87	0. 57
S2	0. 23	0. 23	0. 08	0. 01	0. 19
S3	0. 26	0. 26	0. 23	0. 12	0. 24

Table 4-8: Fuzzy evaluation of sub-criteria of criterion C2

	A5	A6	A7	Alternative priority
weight	0. 56	0. 19	0. 26	weight
Alternatives				
S1	0. 42	0. 49	0. 53	0. 46
S2	0. 28	0. 23	0. 15	0. 24
S3	0. 30	0. 28	0. 32	0. 30

Table 4-9: Fuzzy evaluation of sub-criteria of criterion C3

	A8	A9	A10	A11	Alternative priority
weight	0.59	0.39	0.01	0.01	weight
Alternatives					
S1	0.51	0.53	0.69	0.68	0.52
S2	0.21	0.23	0.08	0.11	0.22
S3	0.28	0.24	0.23	0.21	0.26

Table 4-10: Fuzzy evaluation of sub-criteria of criterion C4

	A12	A13	A14	Alternative priority
weight	0.51	0.18	0.30	weight
Alternatives				
S1	0.39	0.49	0.51	0.44
S2	0.28	0.21	0.17	0.23
S3	0.33	0.30	0.32	0.32

Table 4-11: Fuzzy evaluation of sub-criteria of criterion C5

	A15	A16	Alternative priority
weight	0.52	0.48	weight
Alternatives			
S1	0.39	0.35	0.37
S2	0.33	0.41	0.37
S3	0.28	0.24	0.26

Finally, the priority weight of each supplier can be calculated by multiplying the weight of each corresponding criterion. The results are shown in Table 4-12.

Table 4-12: Relative weight of each supplier and criterion

	C1	C2	C3	C4	C5	Alternative priority
weight	0.43	0.33	0.13	0.02	0.09	weight
Alternatives						
S1	0.57	0.46	0.44	0.52	0.37	0.50
S2	0.19	0.24	0.23	0.22	0.37	0.23
S3	0.24	0.30	0.32	0.26	0.26	0.27

The summary of the overall attributes is shown in Table 4-12. It should be noted that among the four given suppliers, "S1" has the highest weight and therefore is selected as the best supplier to satisfy the goals and objectives of the manufacturing company. Table 13 also shows the final score of each supplier's results and rankings. As can be seen, S1 (0.5) scores higher than S2 (0.23) and S3 (0.23). The important results are shown in Figures 4-3 and 4-4.

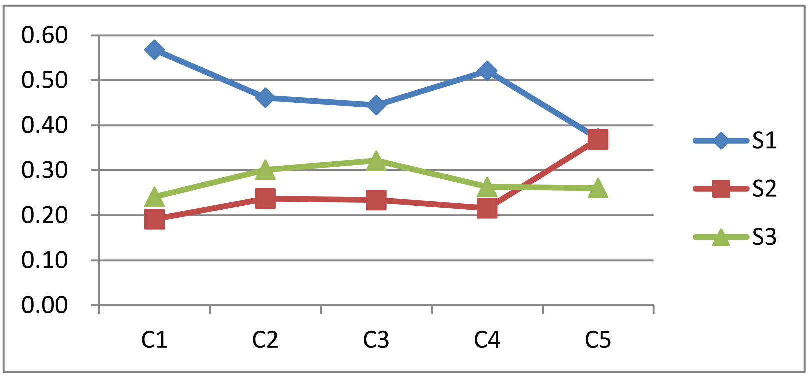

Figure 4-3: Suppliers based on criteria

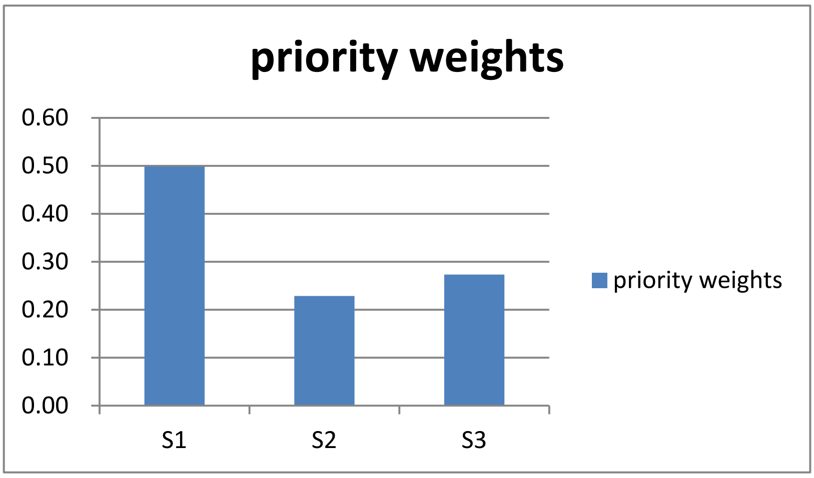

Figure 4-4: Final priority weights of suppliers

4.3 Summary

In this chapter, a fuzzy-extended AHP (FEAHP) method is presented to select reliable suppliers for an apparel company. The main criteria and attributes are discussed based on the literature review, business scenarios and experiences of decision makers in the respective fields.

The experiments prove that:

(1) The FEAHP model is simple, less time-consuming and costs less computationally.

(2) The FEAHP has the ability to deal with uncertainty and vagueness from subjective perception and human decision-making, and effectively solve multi-attribute decision-making problems.

(3) Each criterion weight can be easily attained by using the FEAHP method. The weight of each criterion greatly impacts on order allocation and is used in the following chapter.

Chapter 5 Supplier selection and order allocation for single-item purchasing

Chapter 4 discusses supplier selection at the first stage of purchasing. In the following two chapters, order allocation, which is the second stage of purchasing, will be discussed.

In the apparel industry, an apparel manufacturer usually needs to purchase two categories of material: (1) common materials (e.g. white fabric, cotton) and (2) fashion accessories of the current season. In general, common materials are characterized by large demand and high repurchase frequency.

The main purpose of this chapter is to develop a single-item purchasing optimization (SIPO) sub-model to provide effective decision solutions for single-item purchasing with consideration for multiple objectives, multiple periods and time-varying prices using multiple objectives dynamic programming, each selected supplier's weights and each criterion's weights. The detail will be presented in the following sub-section.

5.1 Problem formulation

Firstly, this chapter investigates a basic situation in the apparel industry. In the apparel industry, manufacturers always need to source common materials (e.g. white fabric) from suppliers over a planning horizon of different periods in order to encourage competition among suppliers and ensure access to a wide variety of goods or services. Therefore, the selection of suitable suppliers and an optimal order allocation plan become crucial. This study proposes a model to handle optimal order allocation based on supplier ranking.

The assumptions of this preliminary study are as follows:

1) Each supplier can provide materials for manufacturers and suppliers have different production capacities.

2) Manufacturers can get information on each supplier in terms of production capacity and price at the beginning of each planning horizon.

3) There is no inventory of materials and manufacturers need to purchase all materials for production.

Let I = $\{1, \ldots, N\}$ represent the set of N suppliers, J = $\{1, \ldots, M\}$ represent the set of M customer orders, and $T = \{1, \ldots, H\}$ represent the set of T planning periods. x_{it} denotes the order quantity from supplier i. c_{it} denotes the capacity of supplier i $(i \in I)$ in period t. p_{it} denotes the unit price of the material purchased from supplier i $(i \in I)$ in period $t \in T$. D_t represents manufacturers' demands for materials based on customers' orders, received before material purchasing. r_i represents the relative risk index of supplier i, which indicates that a higher value of r_i, can generate a higher real purchasing risk. Supplier ranking and order allocation investigated in this research can be formulated as follows.

$$\min E(x_{it}) = \min \left(\sum_{t=1}^{T} \sum_{i=1}^{n} p_{it}\ x_{it}\right) \tag{5-1}$$

$$\min F(x_{it}) = \min \left(\sum_{t=1}^{T} \sum_{i=1}^{n} r_i x_{it}\right) \tag{5-2}$$

s.t.,

$$0 \leq x_{it} \leq c_{it} \quad \forall\, i, t \tag{5-3}$$

$$\sum_{i=1}^{n} x_{it} = D_t \quad \forall\, i, \tag{5-4}$$

Formula (5-1) minimizes the total purchasing costs of materials for all customer orders. Formula (5-2) minimizes the total purchasing risks (e.g. delay risk, defect risk). Formula (5-3) shows that the order quantities are not more than the supplier's maximum capacity in any purchasing period. Formula (5-4) requires that the supply must satisfy the demands of manufacturers.

After presenting the mathematical model of optimal order allocation based on supplier rankings, a supply selection (ranking) and order allocation model is developed in Section 5.1. In Section 5.2, experiment results to validate the performance of the proposed model are presented. The summary is given in Section 5.3.

5.2 Dynamic programming-based optimization for supplier selection and order allocation

To solve the above problem formulated, we propose in this section an effective single-item purchasing optimization (SIPO) sub-model model based on FEAHP and DP. This model comprises two processes, including an FEAHP-based supplier/criteria ranking process and a DP-based order allocation process (Figure 5-1).

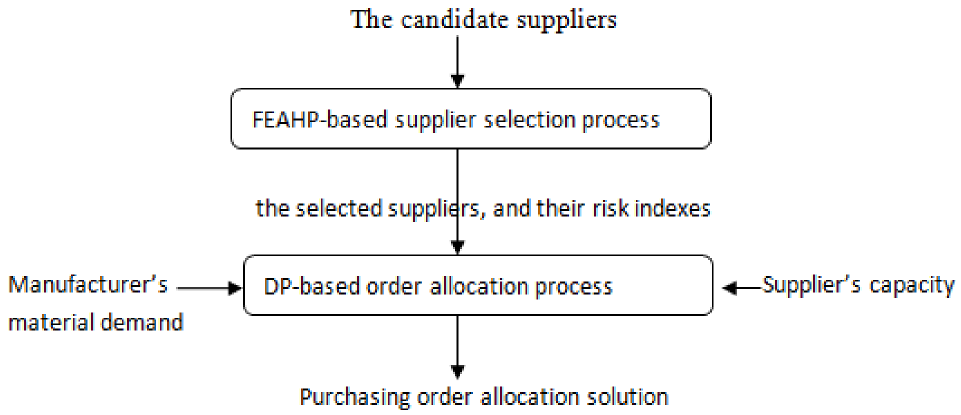

Figure 5-1: Processes of SIPO

The details of the single-item purchasing optimization (SIPO) sub-model are described as follows.

5.2.1 Dynamic programming

As purchasing price is time-varying in the model, the cost objective is judiciously captured by the dynamic value function below:

$$V_{1,t} = \min_{0\leq x_{it}\leq c_{it}}\left\{\sum_{i=1}^{n} p_{it}x_{it} + V_{1,t+1}\left(D_t - \sum_{i=1}^{n} x_{it}\right)\right\} \tag{5-5}$$

Where the stage is decision dates in time-periods, t = 1,2,…,T. The decision variable is the quantities ordered from supplier i , $x_{it} = 0,1,\ldots, c_{it}$.

To account for both objectives, a distance-to-ideal framework is employed to integrate risk and cost objective functions, using the optimal values of individual objectives obtained above.

To incorporate the ideal values of risk and cost, the sum (weights) of deviations from such ideal values is minimized. Hence, a dynamic value function is derived as follows:

$$V_{2,t} = \min_{0 \leq x_{it} \leq c_{it}} \left\{ w_{c_1} \sum_{i=1}^{n} p_{it} x_{it} + w_{c_3} \sum_{i=1}^{n} (r_i x_{it}) + V_{2,t+1}\left(D_t - \sum_{i=1}^{n} x_{it}\right) \right\} \quad (5\text{-}6)$$

where $V_{2,t}$ is the minimum total weighted deviation. w_{c_1} is the cost weight defined by decision-makers using FEAHP. w_{c_3} is the risk weight defined by decision-makers using FEAHP.

5.3 Numerical experiments

To validate the effectiveness of the proposed SSOA model, a series of experiments are conducted based on real industrial data of an apparel manufacturer which locates in Chinese Mainland making up fast fashion with rapid stock turnaround. For the reason of confidentiality, the name of the company is hidden.

The manufacturer needs to purchase a specified amount of raw fabric from 3 appropriate material suppliers for the production of its customers' orders. The 3 suppliers have been selected from its N collaborative suppliers. The manufacturer seeks to determine how much should be purchased from the 3 suppliers in order to minimize its overall cost and maximize its utility over a multi-period planning horizon.

A real apparel manufacture purchasing environment usually has the following four scenarios: 1) a manufacturer's demand for common materials is the same in all planning periods. In order to obtain orders steadily, suppliers reserve a certain capacity and charge a reasonable price; 2) demands for common materials are steady, but suppliers do not reserve a certain capacity, so price and capacity fluctuate in different planning periods; 3) suppliers' prices are different throughout the planning period; and 4) suppliers' capacities and prices are different throughout the planning period.

5.3.1 Scenario 1: Suppliers can reserve a certain capacity and charge a reasonable price in all planning periods.

Table 5-1: Demand

Period	1	2	3
Demand	6	6	6

Table 5-2: Price and capacity

Supplier	price (per unit)			Capacity
	Period 1	Period 2	Period 3	
S1	12	12	12	6
S2	10	10	10	6
S3	11	11	11	6

Table 5-3: Optimal order quantities with respect to minimum risk

Period	1	2	3	Total risk	Total cost
S1	6	6	6	30	216
S2					
S3					

Table 5-4: Optimal order quantities with respect to minimum cost

Period	1	2	3	Total risk	Total cost
S1				94.7	180
S2	6	6	6		
S3					

After getting the weight score of each vender and criterion in the first stage, $w_{c_1} = 0.43$ and $w_{c_3} = 0.13$. In addition to having information on each supplier's capacity and pricing, the dynamic approach mentioned in Section 5.1.2 can be rewritten as follows:

$$V_{2,t} = \min_{0\leq x_{it}\leq c_{it}}\left\{0.43\sum_{i=1}^{n} p_{it}x_{it} + 0.13\sum_{i=1}^{n}(r_i x_{it}) + V_{2,t+1}\left(D_t - \sum_{i=1}^{n} x_{it}\right)\right\} \quad (5\text{-}7)$$

Table 5-5: Optimal order quantities with respect to minimum cost and risk

Period	1	2	3	Total risk	Total cost
S1	4	3	2	58	205
S2	1	0	1		
S3	1	3	3		

Through the bi-objective dynamic value function, the trade-off solution incurs a cost 13% higher than its ideal value (minimum) and a risk value 93% higher than its ideal value (minimum). However, if there were only minimum cost, the manufacturer's risk would be 215% higher than its ideal value; if there were only minimum risk, the cost would be 20% higher than its ideal value. Given the conflicting nature of the two objectives, the manufacturer clearly achieves a better compromise by adopting the proposed bi-objective trade-off solution produced by the proposed dynamic programming approach.

5.3.2 Scenario 2: Suppliers have different capacities and charge different prices in different planning periods.

Table 5-6: Demand

Period	1	2	3
Demand	6	6	6

Table 5-7: Price and capacity

Supplier	Ordering price (per unit)			Capacity
	Period 1	Period 2	Period 3	
S1	12	11	14	5
S2	11	12	10	6
S3	9	11	10	4

Table 5-8: Optimal order quantities with respect to minimum risk

Period	1	2	3	Total risk	Total cost
S1	6	6	6	30	222
S2					
S3					

Table 5-9: Optimal order quantities with respect to minimum cost

Period	1	2	3	Total risk	Total cost
S1		5		72.24	184
S2	2		2		
S3	4	1	4		

After getting the weight score of each vender and criterion in the first stage, $w_{c_1} = 0.45$ and $w_{c_3} = 0.15$. In addition to having information on each supplier's capacity and pricing, the dynamic approach mentioned in Section 5.1.2 can be rewritten as follows:

$$V_{2,t} = \min_{0\leq x_{it}\leq c_{it}}\left\{0.43\sum_{i=1}^{n} p_{it}x_{it} + 0.13\sum_{i=1}^{n}(r_i x_{it}) + V_{2,t+1}\left(D_t - \sum_{i=1}^{n} x_{it}\right)\right\} \quad (5\text{-}8)$$

Table 5-10: Optimal order quantities with respect to minimum cost and risk

Period	1	2	3	Total risk	Total cost
S1	3	5	3	53.1	201
S2	0	0	3		
S3	3	1	0		

Through the bi-objective dynamic value function, the trade-off solution incurs a cost 70% higher than its ideal value (minimum) and a risk value 14% lower than its ideal value (minimum). However, if there were minimum cost, the manufacturer's risk would be 150% higher than its ideal value; if there were only minimum risk, the cost would be 21% higher than its ideal value. Given the conflicting nature of the two objectives, the manufacturer clearly achieves a better compromise by adopting the proposed bi-objective trade-off solution produced by the proposed dynamic programming approach.

Table 5-11: Demand

Period	1	2	3	4
Demand	6	6	6	6

Table 5-12: Price and capacity

Supplier	Ordering price (per unit)				Capacity
	Period 1	Period 2	Period 3	Period 4	
S1	12	11	14	10	5
S2	11	12	10	11	6
S3	9	11	10	11	4

Table 5-13: Optimal order quantities with respect to minimum risk

Period	1	2	3	4	Total risk	Total cost
S1	5	5	5	5	54.76	276
S2	0	0	0	0		
S3	1	1	1	1		

Table 5-14: Optimal order quantities with respect to minimum cost

Period	1	2	3	4	Total risk	Total cost
S1	0	5	0	0	88.21	246
S2	0	0	6	6		
S3	6	1	0	0		

Table 5-15: Optimal order quantities with respect to minimum cost and risk

Period	1	2	3	4	Total risk	Total cost
S1	5	5	0	5	64.48	256
S2	0	0	2	0		
S3	1	1	4	1		

Through the bi-objective dynamic value function, the trade-off solution incurs a cost 16% higher than its ideal value (minimum) and a risk value 26% lower than its ideal value (minimum). However, if there were only minimum cost, the manufacturer's risk would be 18% higher than its ideal value; if there were only minimum risk, the cost would be 7% higher than its ideal value. Given the conflicting nature of the two objectives, the manufacturer clearly achieves a better compromise by adopting the proposed bi-objective trade-off solution produced by the proposed dynamic programming approach.

5.3.3 Scenario 3: The manufacturer's demands and the supplier's prices are different throughout the planning periods.

Table 5-16: Demand

Period	1	2	3
Demand	11	9	10

Table 5-17: Price and capacity

Supplier	Ordering price (per unit)			Capacity
	Period 1	Period 2	Period 3	
S1	95	95	99	4
S2	87	87	89	4
S3	93	91	91	6

After getting the weight score of each vender and criterion in the first stage, $w_{c_1} = 0.43$ and $w_{c_3} = 0.13$. In addition to having information on each supplier's capacity and pricing, the dynamic approach mentioned in Section 5.1.2 can be rewritten as follows:

$$V_{2,t} = \min_{0\leq x_{it}\leq c_{it}}\left\{0.43\sum_{i=1}^{n} p_{it}x_{it} + 0.13\sum_{i=1}^{n}(r_i x_{it}) + V_{2,t+1}\left(D_t - \sum_{i=1}^{n} x_{it}\right)\right\} \quad (5\text{-}9)$$

Table 5-18: Optimal order quantities with respect to minimum risk

Period	1	2	3	Total risk	Total cost
S1	4	4	4	90.69	2802
S2	1	0	0		
S3	6	5	6		

Table 5-19: Optimal order quantities with respect to minimum cost

Period	1	2	3	Total risk	Total cost
S1	1	0	0	116.8	2706
S2	4	4	4		
S3	6	5	6		

Table 5-20: Optimal order quantities with respect to minimum cost and risk

Period	1	2	3	Total risk	Total cost
S1	4	4	0	105.21	2728
S2	4	4	4		
S3	3	1	6		

Through the bi-objective dynamic value function, the trade-off solution incurs a cost 1% higher than its ideal value (minimum) and a risk value 10% lower than its ideal value (minimum). However, if there were only minimum cost, the manufacturer's risk would be 16% higher than its ideal value; if there were only minimum risk, the cost would be 2% higher than its ideal value. Given the conflicting nature of the two objectives, the manufacturer clearly achieves a better compromise by adopting the proposed bi-objective trade-off solution produced by the proposed dynamic programming approach.

Table 5-21: Demand

Period	1	2	3	4
Demand	11	9	10	12

Table 5-22: Price and capacity

Supplier	Ordering price (per unit)				Capacity
	Period 1	Period 2	Period 3	Period 4	
S1	95	95	99	96	5
S2	87	87	89	90	4
S3	93	91	91	93	6

Table 5-23: Optimal order quantities with respect to minimum risk

Period	1	2	3	4	Total risk	Total cost
S1	5	5	5	5	121.38	3950
S2	0	0	0	1		
S3	6	4	5	6		

Table 5-24: Optimal order quantities with respect to minimum cost

Period	1	2	3	4	Total risk	Total cost
S1	1	0	0	1	158.29	3720
S2	4	4	4	4		
S3	6	5	6	6		

Table 5-25: Optimal order quantities with respect to minimum cost and risk

Period	1	2	3	4	Total risk	Total cost
S1	5	5	0	5	140.43	3853
S2	4	4	4	4		
S3	2	0	6	3		

Through the bi-objective dynamic value function, the trade-off solution incurs a cost 4% higher than its ideal value (minimum) and a risk value 11% lower than its ideal value (minimum). However, if there were only minimum cost, the manufacturer's risk would be 2% higher than its ideal value; if there were only minimum risk, the cost would be 16% higher than its ideal value. Given the conflicting nature of the two objectives, the manufacturer clearly achieves a better compromise by adopting the proposed bi-objective trade-off solution produced by the proposed dynamic programming approach.

5.3.4 Scenario 4: Demands, price and capacity are different throughout the planning period.

Table 5-26: Demand

Period	1	2	3
Demand	11	9	10

Table 5-27: Price and capacity

Supplier	Ordering price (per unit)			Capacity		
	Period 1	Period 2	Period 3	Period 1	Period 2	Period 3
S1	95	95	99	4	6	5
S2	87	87	89	4	7	7
S3	93	91	91	6	5	6

Table 5-28: Optimal order quantities with respect to minimum risk

Period	1	2	3	Total risk	Total cost
S1	4	6	5	85.7	2818
S2	1	0	0		
S3	6	3	5		

Table 5-29: Optimal order quantities with respect to minimum cost

Period	1	2	3	Total risk	Total cost
S1	1	0	0	103.5	2688
S2	4	7	7		
S3	6	2	3		

Table 5-30: Optimal order quantities with respect to minimum cost and risk

Period	1	2	3	Total risk	Total cost
S1	4	2	0	93.2	2708
S2	4	7	4		
S3	3	0	6		

Through the bi-objective dynamic value function, the trade-off solution incurs a cost 1% higher than its ideal value (minimum) and a risk value 10% lower than its ideal value (minimum). However, if there were only minimum cost, the manufacturer's risk would be 9% higher than its ideal value; if there were only minimum risk, the cost would be 4% higher than its ideal value. Given the conflicting nature of the two objectives, the manufacturer clearly achieves a better compromise by adopting the proposed bi-objective trade-off solution produced by the proposed dynamic programming approach.

5.4 Summary

This chapter investigates the topic of multi-objective order allocation based on supplier selection in the purchasing stage with single items and multiple suppliers taken into consideration. A mathematical model for investigation is established, which considers minimizing the total cost and risk in all purchasing processes. The effectiveness of the proposed optimization model is validated by the real data from a manufacturing company. The experiment results demonstrate that the proposed model can handle order allocation effectively.

Chapter 6 Supplier selection and order allocation for multi-item purchasing

Based on the results presented in Chapter 4, we decide on the set of prequalified suppliers. The main purpose of this chapter is to optimize multi-item purchasing of fashion accessories, which happens in the final choice stage of material purchasing. The general characteristics of fashion accessories of current seasons are 1) multiple-item purchasing, 2) one-time purchasing and 3) on-time delivery.

A mixed integer linear program is formulated under multiple objectives of minimum purchasing cost and delivery delay with constraints of demand, capacity and discounts. In order to solve the stochastic discrete multiple objective problem, a discrete composite differential evolution algorithm is proposed. The details will be presented in following sub-section.

6.1 Problem description

In order to maximize total profit, minimize purchasing cost and reduce total delivery delay, a manufacturer must select suitable suppliers from a set of candidates. When allocating orders to selected suppliers, the purchasing manager must consider materials costs, quantity-based discounts for multiple items, supplier candidates' capacities and the impact of delivery delay on product prices.

The proposed model is constrained by the following assumptions:

a. One or more items can be acquired from each supplier.

b. Quantity discounts are offered by each supplier.

c. There is no shortage of each item.

d. Demands of each item are determined.

e. Capacities of each supplier are finite.

f. Expected total delivery delay by each supplier can be assessed from statistics of historical data.

g. Expected discount of each product with respect to delivery delay can be assessed from statistics of historical sales data.

The model of multi-supplier order allocation in multi-item purchasing is proposed. The following notations are used in model formulation.

i : $\mathrm{i} = \{1, \dots, \mathrm{o}\} \in Z^+$ the type of products to be manufactured;

j : $\mathrm{j} = \{1, \dots, \mathrm{m}\} \in Z^+$ the type of materials to be purchased;

k : $\mathrm{k} = \{1, \dots, \mathrm{n}\} \in Z^+$ the number of candidate suppliers;

Inputs:

P_{jk} : The price of material j charged by supplier k ;

d_k: The discount offered by supplier k;

ξ_k: The random variables mean of supplier k's delivery delay, $\xi_k \in \{0,7,14\}$;

l_k: The lower bound of the discount offered by supplier k;

$rate_k$: The discount rate offered by supplier k based on the manufacturer's order size;

$PD_i(E(max(Y_i\xi_i))$: The discount expectation function of product i based on different delays of product i;

PD_i^1: The value of the expected price discount rate of product i if the delay of product i lasts longer than 14 days;

PD_i^2: The value of the price expectation discount rate of product i if the delay of product i spans 7- 14 days;

PP_i: The price of product i;

PN_i: The number of each product;

$Z(X_{jk}, Y_k)$: The cost function;

$F(X_{jk}, Y_k)$: The profit expectation function of all products.

Decision variables:

X_{jk} : The quantity of material j purchased from supplier k; (order allocation variable);

Y_k : 1 if choosing supplier k, otherwise 0 (supplier selection variable).

Objective 1: minimizing total purchasing cost

$$\min Z(X_{jk}, Y_k) = \sum_j \sum_k P_{jk} X_{jk} d_k Y_k + \sum_k (C_k * Y_k) \quad (6\text{-}1)$$

Objective 2: minimizing expectation of total delivery delay

$$\min E(g(Y_k \xi_k)) = \min E(\max(Y_k \xi_k)) \quad (6\text{-}2)$$

The objectives (6-1), (6-2) are established to minimize the total purchasing cost and the expectation of total delivery delay respectively. The first part of Eq.(6-1) denotes the purchasing cost concerning price and discount on any material, and the second part denotes that if a supplier is selected, there is a fixed cost related to its selection and assignment.

Constraint 1: Demand constraint

$$\sum_j X_{jk} = demand_j \quad (6\text{-}3)$$

$$X_{jk} \in Z^+ \quad (6\text{-}4)$$

Constraint 2: Capacity constraint

$$\sum_k X_{jk} \leq \text{capacity}_k \quad (6\text{-}5)$$

Constraint 3: Supplier selection constraint

$$Y_k = \begin{cases} 0 & X_{\cdot,k} = 0 \\ 1 & \text{other} \end{cases} \tag{6-6}$$

Constraint 4: Discount factor:

$$d_k = \begin{cases} \text{rate}_k \in [0,1) & \sum_j P_{jk} X_{jk} \geq l_k \\ 1 & \text{other} \end{cases} \tag{6-7}$$

Discount rate function: expectation of delivery delay

$$PD_i(E(\max(Y_k \xi_k)) = \begin{cases} PD_i^1 & 14 \leq E(\max(Y_i \xi_i)) \\ PD_i^2 & 7 < E(\max(Y_i \xi_i)) < 14 \\ 1 & 0 \leq E(\max(Y_i \xi_i)) \leq 7 \end{cases} \tag{6-8}$$

Trade-off function (fitness function): maximizing expectation of total profit

$$\max\Big(F\big(X_{jk}, Y_k\big)\Big) = \sum_i PD_i(E(\max(Y_k \xi_k))*PP_i * PN_i - Z\big(X_{jk}, Y_k\big) \tag{6-9}$$

Constraint 1(Eq.(6-3)-(6-4)) is a demand constraint, meaning that the demand for all materials must be satisfied. It should be noticed that, based on the discount rate offered by the supplier, it can be economical to buy more than the total demand, which, however, can also increase inventory cost. To take advantage of reductions in quantity discount and inventory cost, the total order quantity must equal the quantities demanded. Constraint 2 (Eq.(6-5)) provides integers and non-negativity conditions for the variables. The variables X_{jk} are integers as they represent the units of material j purchased from supplier k. Constraint 3 represents the restriction imposed by the capacity of the supplier. The total order placed with each supplier should not exceed the total capacity reserved by the supplier for the manufacturer. Constraint 3 (Eq.(6-6)) shows the binary nature of supplier selection decisions and the minimum order requirements to all selected suppliers for each item. In the model, the minimum quantity assigned to each supplier is one. Constraint 4 (Eq.(6-7)) describes the supplier’s discount schemes. Eq.(6-7) ensures that the quantity purchased from the supplier at a specific price break is in a discount interval and that only one discount level is finally used for the total amount of purchase if the material is purchased from supplier k.

If the manufacturer fails to deliver the product on time and thus delays the retailer’s launch of the product, the product will have to be sold at a discount. Eq.(6-8) determines the discount intervals of product i offered by the manufacturer.

The last function (6-9) is used for evaluation. We translate the objectives (6-1) and (6-2) into a single objective optimization problem. To maximize the total profit, the manufacturer selects the best compromised solution.

6.2 Composite Discrete Differential Evolutionary-based optimization model for multi-item purchasing

In this section, an enhanced Composite Discrete Differential Evolutionary (CODDE)-based optimization technique is presented for solving the suppler section and order allocation (SSOA) problem in multi-material purchasing. The steps in the CODDE algorithm are illustrated in Figure 6-1. The detailed mechanisms of the CODDE algorithm are described in the following subsections.

6.2.1 Structure of Composite Discrete Differential Evolutionary optimization model

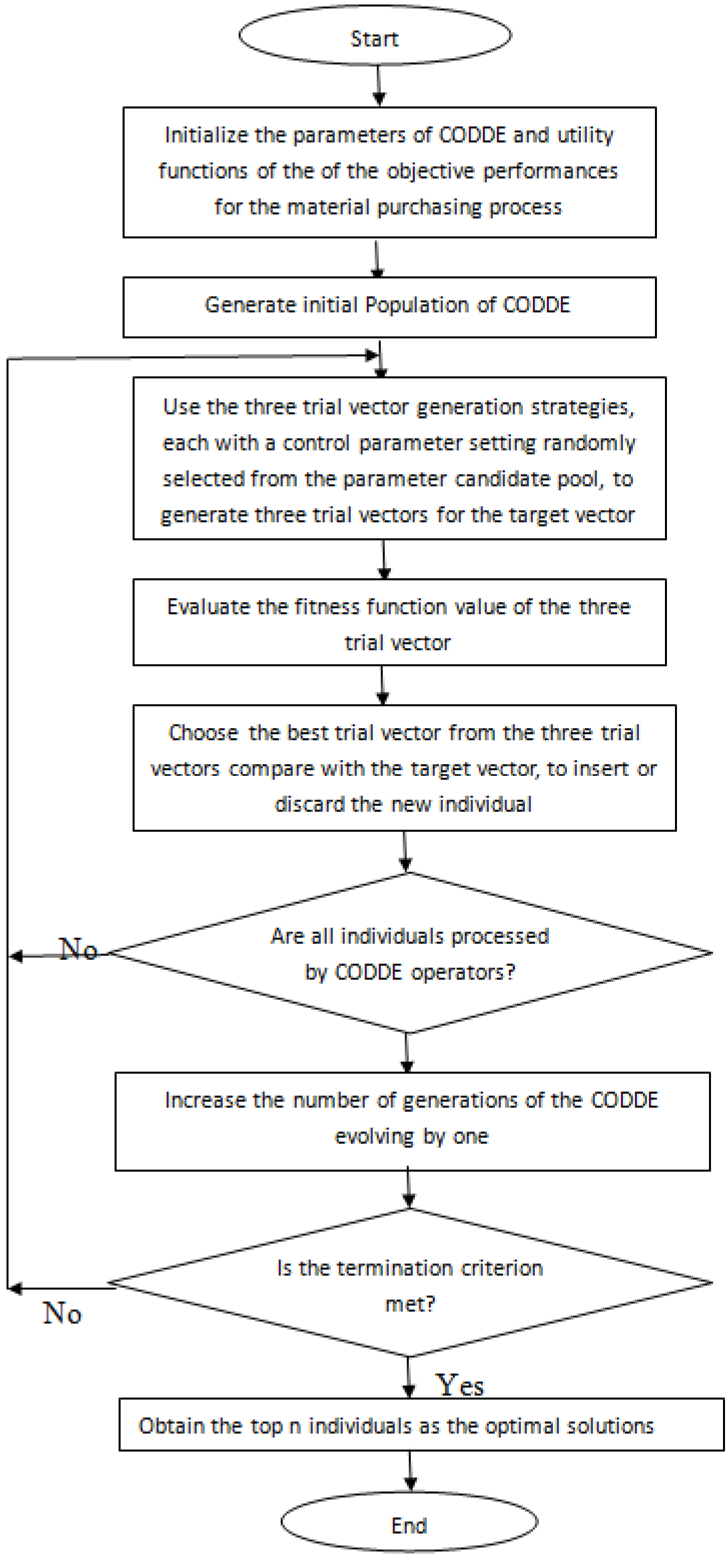

Figure 6-1: CODDE algorithm

The primary idea of CoDE (Tang et al. 2011) is randomly combining several trial vector generation strategies with several control parameter settings in each generation to create new trail vectors. CoDE is composed of three trial vector generation strategies and three control parameter settings. The three trial vector generation strategies are as follows:

"rand/1/bin" :

$$\mathrm{u}_{\mathrm{i,j,G}} = \begin{cases} \mathrm{x}_{\mathrm{r1,j,G}} + F * \left(\mathrm{x}_{\mathrm{r2,j,G}} - \mathrm{x}_{\mathrm{r3,j,G}}\right), & \text{if } rand < C_r \text{ or } j = j_{rand} \\ \mathrm{x}_{\mathrm{r,j,G}} & \text{otherwise} \end{cases} \tag{6-10}$$

"ran/2/bin":

$$\mathrm{u}_{\mathrm{i,j,G}} = \begin{cases} \mathrm{x}_{\mathrm{r1,j,G}} + F * \left(\mathrm{x}_{\mathrm{r2,j,G}} - \mathrm{x}_{\mathrm{r3,j,G}}\right) + F * \left(\mathrm{x}_{\mathrm{r4,j,G}} - \mathrm{x}_{\mathrm{r5,j,G}}\right), & \text{if } rand < C_r \text{ or } j = j_{rand} \\ \mathrm{x}_{\mathrm{r,j,G}} & \text{otherwise} \end{cases} \tag{6-11}$$

"current-to-rand/1"

$$\vec{\mathrm{u}}_{\mathrm{i,G}} = \vec{\mathrm{x}}_{\mathrm{i,G}} + rand * \left(\vec{\mathrm{x}}_{\mathrm{r1,G}} - \vec{\mathrm{x}}_{\mathrm{i,G}}\right) + F * (\vec{\mathrm{x}}_{\mathrm{r2,G}} - \vec{\mathrm{x}}_{\mathrm{r3,G}}) \tag{6-12}$$

Where *i*= 1,2,…,NP and *NP* is the population size ; *j* = 1, 2,...,*D* and *D* is the dimension size; *G* is the generation number; $x_{i,j,G}$ is the state of the *i*th individual in the *j*th dimension in generation *G*; *r*1, *r*2, *r*3, *r*4 and *r*5 are the distinct random integers from the interval [1, *NP*] and also different from *i*. *F* is the scaling factor, which amplifies the difference vectors; C_r is the crossover control parameter; j_{rand} is an integer from the interval [1, *D*]; *rand* is a uniformly distributed random number between 0 and 1.

The three control parameter settings are:

1) $[\mathrm{F} = 1.0, C_r = 0.1]$;

2) $[\mathrm{F} = 1.0, C_r = 0.9]$;

3) $[\mathrm{F} = 0.8, C_r = 0.2]$.

The first control parameter setting,$[\mathrm{F} = 1.0, C_r = 0.1]$, deals with separable problems; the second control parameter setting, $[\mathrm{F} = 1.0, C_r = 0.9]$, aims to maintain the population diversity and enhances the capacity for global exploration; the last control parameter setting, $[\mathrm{F} = 0.8, C_r = 0.2]$ exploits the three strategies and thus increases the convergence speed of the population. In each generation, each trial vector generation strategy in the strategy candidate pool (6-10)-(6-12) creates a new trial vector with a control parameter setting randomly chosen from the three parameter settings. Thus, three trial vectors are generated for each target vector and the best one is chosen to enter the next generation if it is better than its target vector

As a new optimization method, Composite Differential Evolution (CoDE) is more competitive in global optimization than other evolutionary algorithms. However, the original version of CoDE operates on real values. According to the characteristics of the SSOA, a discrete composite differential evolution algorithm is proposed in this study. The revised parts are described in the following subsections.

6.2.2 Representation

To represent these variables, the binary representation for integer variables is adopted. For the problem investigated, the decision variables include supplier selection and order alloction variables, which are all integer variables. To determine the values of these variables, one only needs to determine the quantities of materials purchased from suppliers 1 to n-1 because the material quantities from supplier n can then be determined based on the material demands. The number of genes (bits) for each variable is determined by the demand quantity of the corresponding material. For example, if the demand quantity of material 1 is 1000, then the number of genes for its corresponding variable is $\log_2(1000) + 1 = 10$.

Figure 2 shows a representation example of 2 decision variables, which indicate the order quantities of a material purchased from suppliers 1-2. Based on this representation, the order quantities from suppliers 1-2 are 617 and 421 respectively.

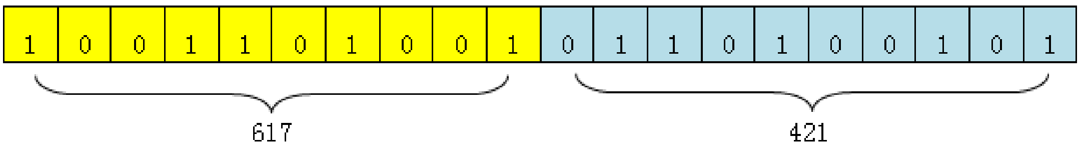

Figure 6-2: Representation of chromosomes for order allocation scheme

6.2.3 Initialization

Based on the constraints given in section 6.1, each chromosome can be generated by a set of heuristic procedures described as follows:

<u>Procedure</u>

Step 1. Randomly allocate material orders to each supplier.

Step 2. Test the sum of the order allocation strategy, regardless of whether the strategy meets the demands of the manufacturer or not.

6.2.4 Mutation

The mutation operator cannot be applied directly to the discrete-value vector chromosome based on Eq. (6-10)-(6-12) and the real-value CoDE must be extended to handle the discrete-value vector. In this research, two modified operators, namely subtraction and addition operators, are defined based on the proposed chromosome representation and their definitions are described as follows:

Definition 1: Subtraction operator of two individuals

s discussed above, each individual is composed of n parts and each part can be regarded as a set that contains a number of operations. Therefore, the subtraction between two individuals can be resolved into each corresponding part between two individuals. The subtraction of each part can be treated as a set difference operation. Figure 6-3 is an example of the subtraction operator between $X_{r_1,G}$ and $X_{r_2,G}$.

$X_{r_1,G}$	1	1	1	0
$X_{r_2,G}$	0	1	0	1
$D_{i,G}$	1	0	0	1

Figure 6-3: Example of subtraction operator

Definition 2: Addition operator of two individuals

Like the subtraction operator, the addition between two individuals can be resolved into the addition of each corresponding part between two individuals. The addition of each part can be treated as a set union operation. Figure 6-4 is an example of the addition operator between $X_{r_1,G}$ and $D_{i,G}$.

$X_{r_1,G}$	1	1	1	0
$D_{i,G}$	1	0	0	1
$V_{i,G-1}$	0	1	0	1

Figure 6-4: Example of addition operator

Unlike the subtraction operator, when the result of a set union operation makes the number of operations exceed the limit length of each part, a part of operations should be discarded randomly from the result.

Based on the above two operators, the mutation operator can be implemented after the proposed chromosome is represented by the discrete-value vector.

In order to facilitate the operation, the scaling factors in this paper are all equal to one, that is, F=1.

6.2.5 Crossover

The crossover operator is used to maintain the diversity and the convergence speed of the population. The standard CoDE is correspondingly extended to the discrete-value vector. An example of the crossover operator is shown in Figure 6-5.

$X_{r_1,G}$	1	1	1	0
$D_{i,G}$	1	0	0	1
$U_{i,G-1}$	1	0	1	0

Figure 6-5: Example of crossover operator

Based on the standard CoDE, we use different C_r to ensure the population diversity and convergence.

6.3 Numerical experiments

In order to investigate the effectiveness of the proposed model and optimization technique (CODDE) for the SSOA in multiple material purchasing, a series of experiments are conducted based on real industrial data of an apparel manufacturer which locates in Chinese Mainland making up fast fashion with rapid stock turnaround. For the reason of confidentiality, the name of the company is hidden.

Three of these experiments are highlighted in the following sections and the remaining ones are shown in Appendixes A, B and C. The experiments can be transformed into three scenarios:

1) The first scenario features two experiments. The apparel manufacturer purchases different kinds of material from a variety of suppliers for one product. Each supplier has the ability to provide at least one kind of raw material and has sufficient production capacity to satisfy the total material demand.

2) The second scenario features five experiments. The apparel manufacturer purchases different materials from a variety of suppliers for two products. Each supplier has the ability to provide at least one kind of raw material and has sufficient production capacity to satisfy the total material demand.

3) The third scenario features five experiments. The apparel manufacturer purchases different materials from a variety of suppliers for two or more products. Each supplier has the ability to provide at least one kind of raw material, but may not be able to satisfy the total material demand

6.3.1 Scenario 1: Apparel manufacturer purchases different materials from a variety of suppliers for one product

Experiment 6-1.1

In this scenario, the apparel manufacturer purchases many kinds of material for one product. Based on the historical sales data, the discount rate of the product related to delivery delay can be acquired as shown in Table 6-1.

Table 6-1: Production Information

Product	Quantity	Price	Discount rate related to delivery delay days
Item 1	500	200	$PP_i(E(\max(Y_i\xi_i)) = \begin{cases} 0.7 & 14 \leq E(\max(Y_i\xi_i)) \\ 0.8 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \leq E(\max(Y_i\xi_i)) \leq 7 \end{cases}$

To manufacture the product, the manufacturer needs to purchase three kinds of material from supplier candidates. Table 6-2 shows the information on each candidate in terms of material demands, price and capacity.

Table 6-2: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	
M 1	12	1000	10	1000	10	1000	1000
M 2	10	2000	8	2000	11	2000	2000
M 3	8	1000	9	1000	12	1000	1000

A data set is shown in Table 6-3, which concerns the supplier's cost (i.e. transportation cost and maintenance cost), the discount rate related to the total purchased amount and the probability distribution of delivery delay. $\mathrm{Sum(Sk)}, k = 1,2,3$ denotes a discount rate related to the total purchased amount provided by each supplier, and $\mathrm{Sum(Sk)} = \sum_{j=1}^{3} P_{jk} X_{jk}$.

Table 6-3: Probability distribution, order cost, discount rate information of supplier

supplier	delivery delay days			Order cost	Discount rate
	0	7	14		
S1	0.3	0.4	0.3	2000	IF Sum(S1)>=6000, 0.95
S2	0.1	0.7	0.2	1900	IF Sum(S2)>=5500, 0.96
S3	0.4	0.5	0.1	2100	IF Sum(S3)>=7000, 0.91

In this case, the problem originates from industrial practice. The purchasing manager usually allocates material orders using single-objective methods, that is, minimizing purchasing cost or delivery delay. The comparisons of allocation performances between industrial results and optimal solutions generated by the CODDE are shown in Table 6-4.

Table 6-4: Comparisons of allocation performances in terms of different objectives

	solution	1	2	3
weights	w1	1	0	
	w2	0	1	
objective	cost	38060	41940	40351.96
	delay	10.3	4.9	6.7
	profit	42140	57860	59448.04
supplier		1,2,3	3	1,3
order quantity	X11	0	0	113
	X12	0	0	0
	X13	1000	1000	887
	X21	0	0	1538
	X22	2000	0	0
	X23	0	2000	462
	X31	1000	0	983
	X32	0	0	0
	X33	0	1000	17

In this table, $x_{jk}, j, k = 1,2,3$ denotes the results of order quantities allocated to each supplier of each material item. The first two solutions in Table 6-4 are obtained by considering only one of the objectives. Solutions 1 and 2 minimize cost and delivery delay respectively. In solution 1, supplier 1 receives orders for the third material item; supplier 2 receives orders for the second item; supplier 3 receives orders for the first item. Based on the lowest price with consideration for the discount rate provided by each supplier (i.e. w1=0), the manufacturer can receive 42,140 in profit by spending 38,060 (cost) and endure 10.3 days of delivery delay. In solution 2 (i.e. a delivery delay dominating model), supplier 3 receives orders for each item under the lowest delivery delay (i.e. w2=0), the manufacturer expects to gain 57,860 in profit by spending 41,940 (cost) and endure 4.9 days of delivery delay. The third and final solution is generated by the proposed model. In this model, we focus on maximizing the total profit. In order to achieve this objective, we allocate the material orders to suppliers 1 and 3. The details of the order allocation strategy are shown in the last column of Table 4. Based on this strategy and the discount rate of products, the manufacturer expects to gain 40,351.96 in profit by spending 59,448.04 (cost) and endure 6.7 days of delivery delay.

Figure 6-6 shows the relationship between overall profits and generations. In this figure, the optimal solution is converged from the sixtieth generation, demonstrating that an optimal solution can be quickly achieved by applying the CODDE algorithm.

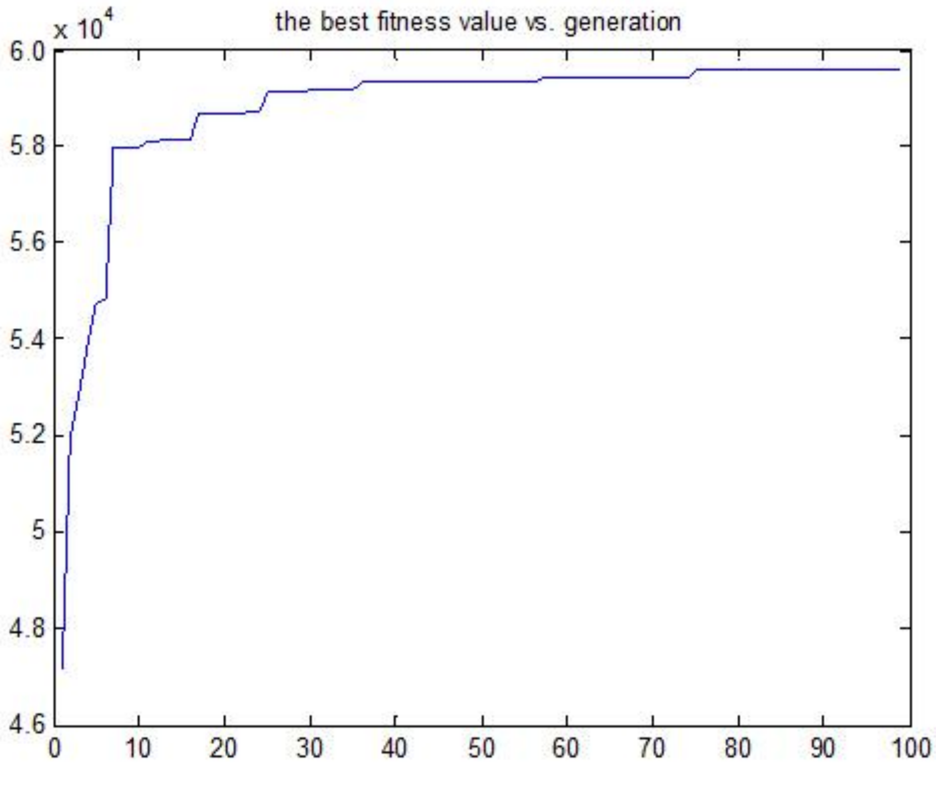

Figure 6-6: Relationship between overall profits and generations

In experiment 6-1.2 (Appendix A), the manufacturer purchases six kinds of material for one product. The information on each supplier in terms of probability distribution, order cost and discount rates is similar to the highlighted experiment. The differences in price and capacity between the suppliers are shown in Table A-1. The optimization solutions are shown in Table A-2.

6.3.2 Scenario 2: Apparel manufacturer purchases different materials from different suppliers for two products

Experiment 6-2.1

In this experiment, the manufacturer produces two products. Based on the historical sales data, the discount rate related to delivery delay can be acquired as shown in Table 6-5.

Table 6-5: Production Information

Product	Quantity	Price	Discount rate related to delivery delay days
Item 1	500	154	$PP_i(E(\max(Y_i\xi_i))=\begin{cases} 0.7 & 14 \le E(\max(Y_i\xi_i)) \\ 0.8 & 7 < E(\max(Y_i\xi_i))<14 \\ 1 & 0 \le E(\max(Y_i\xi_i))\le 7 \end{cases}$
Item 2	500	200	$PP_i(E(\max(Y_i\xi_i))=\begin{cases} 0.85 & 14 \le E(\max(Y_i\xi_i)) \\ 0.9 & 7 < E(\max(Y_i\xi_i))<14 \\ 1 & 0 \le E(\max(Y_i\xi_i))\le 7 \end{cases}$

To manufacture these two products, the manufacturer needs to purchase six kinds of material from supplier candidates. Table 6-6 shows material demands, price and capacity concerning each candidate. In this table, a supplier’s 0 capacity means that it cannot provide this material item.

Table 6-6: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Supplier 4		Supplier 5		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	
M 1	10	1000		0		0		0	12	1000	1000
M 2	10	2000	8	2000		0		0	9	2000	2000
M 3	10	1000	9	1000	8	1000		0	9	1000	1000
M 4		0	7	3000	13	3000	7	3000	8	3000	3000
M 5		0		0	12	1000	11	1000	10	1000	1000
M 6	10	2000		0	11	2000	12	2000	9	2000	2000

A data set is shown in Table 6-7, which involves the supplier's cost, the discount rate related to the total purchased account and the probability distribution of delivery delay. $\mathrm{Sum(Sk)}, \mathrm{k} = 1, \ldots, 6$ denotes a discount rate related to the total purchased amount provided by each supplier, and $\mathrm{Sum(Sk)} = \sum_{j=1}^{6} \mathrm{P_{jk}} \mathrm{X_{jk}}$.

Table 6-7: Information on each supplier in terms of probability distribution, order cost and discount rates

supplier	delivery delay days			Order cost	Discount rate
	0	7	14		
S1	0.3	0.4	0.3	2000	IF Sum(S1)>=6000, 0.95
S2	0.2	0.6	0.2	1500	IF Sum(S2)>=6500, 0.94
S3	0.1	0.7	0.2	1900	IF Sum(S3)>=5500, 0.96
S4	0.4	0.5	0.1	2100	IF Sum(S4)>=7000, 0.91
S5	0.25	0.4	0.35	2200	IF Sum(S5)>=7000, 0.91

In this case, the problem originates from industrial practice. The purchasing manager usually allocates material orders using single-objective methods, that is, minimizing purchasing cost or delivery delay. The comparisons of allocation performances between industrial results and optimal solutions generated by the CODDE are shown in Table 6-8.

Table 6-8: Comparisons of allocation performances in terms of different objectives

	solution	1	2	3
weights	w1	1	0	
	w2	0	1	
objective	cost	91334	96341	93712.99
	delay	14.3	6.9	11.66
	profit	50022	49749	55025
supplier		1,2,3,4,5	1,2,4	1,2,4,5
order quantity	X11	1000	1000	935
	X12	0	0	0
	X13	0	0	0
	X14	0	0	0
	X15	0	0	65
	X21	0	0	84
	X22	0	2000	32
	X23	0	0	0
	X24	0	0	0
	X25	2000	0	1884
	X31	0	0	0
	X32	0	1000	51
	X33	1000	0	0
	X34	0	0	0
	X35	0	0	949
	X41	0	0	209
	X42	2000	0	1846
	X43	0	0	0
	X44	1000	3000	0
	X45	0	0	945
	X51	0	0	0
	X52	0	0	0
	X53	0	0	0
	X54	0	1000	8
	X55	1000	0	992
	X61	0	0	133
	X62	0	0	0
	X63	0	0	0
	X64	0	2000	62
	X65	2000	0	1805

In this table, x_{jk}, $j = 1, \dots, 6. k = 1, \dots, 5$ denotes the results of order quantities allocated to each supplier of each material item. The first two solutions in Table 6-8 are obtained by considering only one of the objectives. Solutions 1 and 2 minimize cost and delivery delay respectively. In solution 1, supplier 1 receives orders for the first material item; suppliers 2 and 4 split orders for the fourth item; supplier 3 received orders for the third item; supplier 5 receives orders for the second, fifth, and sixth items. Under the lowest price discount rate provided by each supplier (i.e. w1=0), the manufacturer can receive 50,022 in profit by spending 91,334 (cost) and endure 14.3 days of delivery delay.

In solution 2 (a delivery delay dominating model), supplier 1 receives orders for the first material item, supplier 2 receives orders for the second and third items, and supplier 4 receives orders for the remaining material items as in doing so the manufacturer can enjoy the lowest delivery delay, that is, w2=0. Based on this allocation strategy and the discount rates of the products, the manufacturer expects to gain 49,749 in profit by spending 96,341 (cost) and endure 6.9 days of delivery delay.

The third and final solution is generated by the proposed model. In this model, we focus on maximizing the total profit. In order to achieve this objective, we allocate the material orders to suppliers 1, 2, 4 and 5. The details of the order allocation strategy are shown in the last column of Table 8. Based on this strategy and the discount rates of the products, the manufacturer expects to gain 55,025 in profit by spending 93,712.99 (cost) and endure 11.66 days of delivery delay.

Figure 6-7 shows the relationship between overall profits and generations. In this figure, the optimal solution is converged from the sixtieth generation. Once again the CODDE algorithm can achieve an optimal solution quickly.

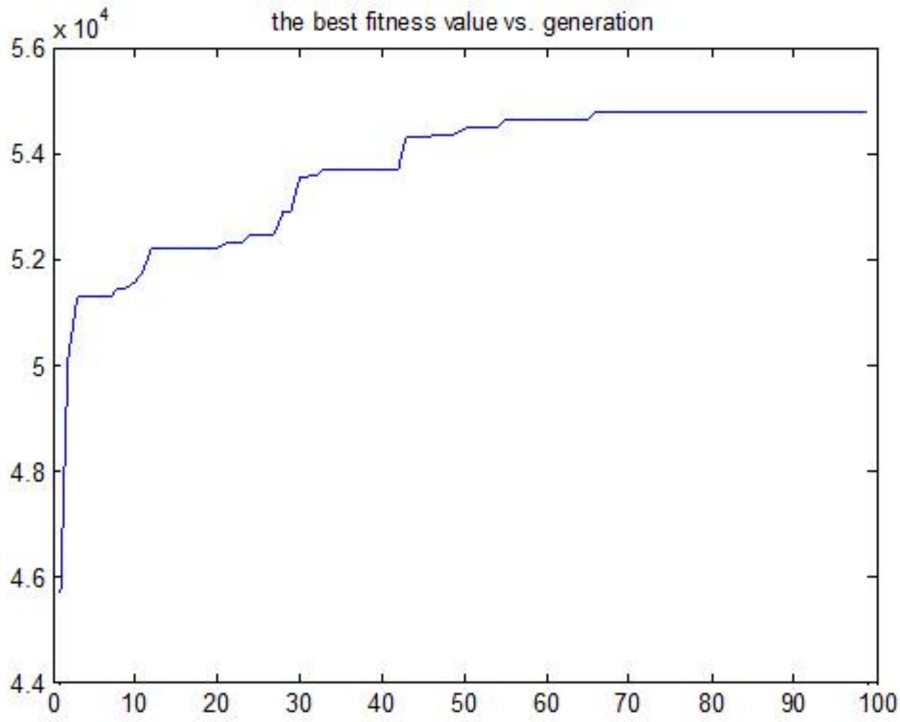

Figure 6-7: Relationship between overall profits and generations

As shown in Table 6-8, the solutions generated by the CODDE are clearly superior to the industrial results. The industrial results suggest longer delivery delays and higher costs, thus compromising the total profit. The CODDE method provides a far more efficient framework for the purchasing manager to choose suppliers and allocate orders.

The remaining experiments of this scenario (experiments 6-2.2 to 6-2.5) are shown in Appendix B. All the experiments share the information on each supplier in terms of probability distribution, order cost and discount rates. Based on assumption A, all needed materials can be provided by the same group of supplier candidates. Hence, the information on probability distribution; order cost and discount rates is the same as experiment 6-2.1 (Table 6-7). The information on different products is shown in Tables B-1, B-4, B-7 and B-10; the information on different material prices and capacities is shown in Tables B-2, B-5, B-8 and B-11. The optimization solutions are shown in Tables B-3, B-6, B-9 and B-12..

6.3.3 Scenario 3: Apparel manufacturer purchases different materials from different suppliers for two or more products

Experiment 6-3.1:

In the experiment, the supplier can provide one type of required material but cannot provide every type. Table 6-9 shows the information on each candidate supplier in terms of material demands, price and capacity. In this case, the capacity of each supplier may not be able to meet the demand of each type of required material. No changes are found in Tables 6-5 and 6-7 as information on products and suppliers is the same as experiment 2.

Table 6-9: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Supplier 4		Supplier 5		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	
M 1	10	600		0		0		0	12	600	1000
M 2	10	2000	8	1000		0		0	9	2000	2000
M 3	10	1000	9	800	8	700		0	9	1000	1000
M 4		0	7	3000	13	2000	7	3000	8	3000	3000
M 5		0		0	12	1000	11	1000	10	1000	1000
M 6	10	2000		0	11	2000	12	2000	9	2000	2000

As in experiment 2, the comparisons of allocation performances in terms of total cost, delivery delay and total sale profit are shown in Table 6-10.

Table 6-10: Comparisons of allocation performances in terms of different objectives

objective	cost	93123	98142.3	95150.99
	delay	14.3	6.9	11.66
	profit	48233	47947.7	53587
supplier		1,2,3,4,5	1,2,4	1,2,4,5
order quantity	X11	600	600	593
	X12	0	0	0
	X13	0	0	0
	X14	0	0	0
	X15	400	400	407
	X21	0	1000	664
	X22	1000	1000	336
	X23	0	0	0
	X24	0	0	0
	X25	1000	0	1000
	X31	0	200	0
	X32	300	800	141
	X33	700	0	0
	X34	0	0	0
	X35	0	0	859
	X41	0	0	0
	X42	0	0	1846
	X43	0	0	0
	X44	3000	3000	0
	X45	0	0	1154
	X51	0	0	0
	X52	0	0	0
	X53	0	0	0
	X54	0	1000	97
	X55	1000	0	903
	X61	0	0	243
	X62	0	0	0
	X63	0	0	0
	X64	0	2000	353
	X65	2000	0	1404

In Table 6-10, the solutions generated by the CODDE are superior to those by the industrial results. The industrial results suggest longer delivery delay and higher cost, thus compromising the total profit. Figure 6-8 shows the relationship between overall profits and generations. In this figure, the optimal solution is converged from the sixtieth generation, indicating that the CODDE is more profitable than its industrial counterparts. Once again the CODDE method proves to be superior when it comes to supplier selection and order allocation.

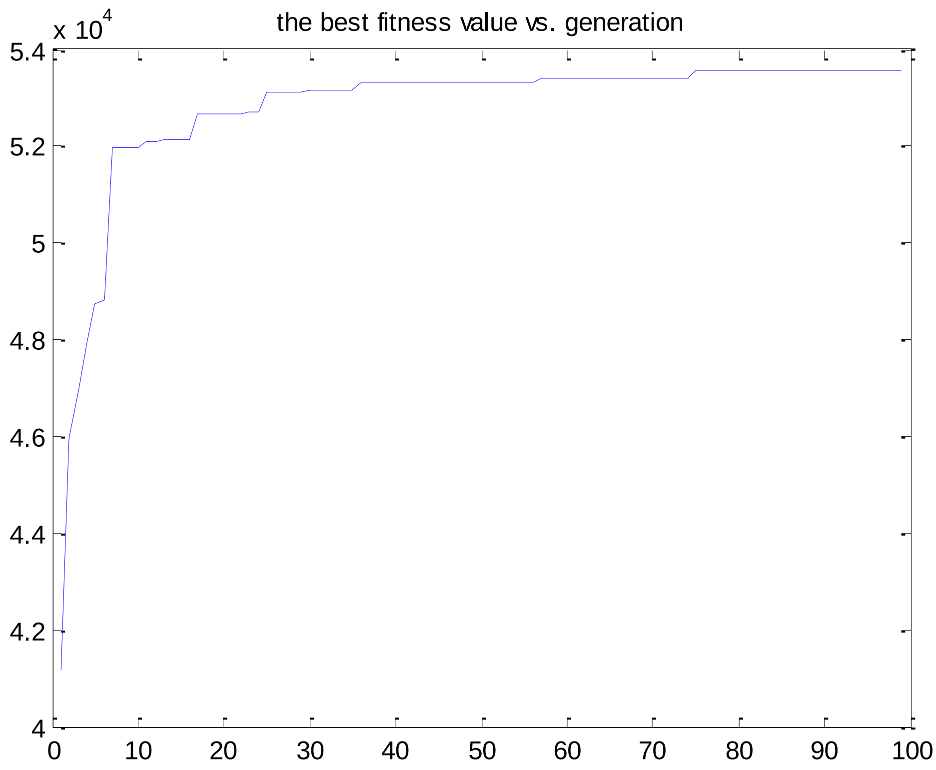

Figure 6-8: Relationship between overall profits and generations

The remaining experiments (i.e. 6-3.2 to 6-3.5) of scenario 3 are shown in Appendix C. All experiments share the information on each supplier in terms of probability distribution, order cost and discount rates. Based on assumption A, all needed materials can be provided by the same group of supplier candidates. Hence, the information on probability distribution, order cost and discount rates is the same as experiment 6-2.1 (Table 6-7). The information on different products is shown in Tables C-1, C-4, C-7 and C-10; the information on different material prices and capacities is shown in Tables C-2, C-5, C-8 and C-11. The optimization solutions are shown in Tables C-3, C-6, C-9 and C-12.

6.4 Conclusion

This chapter proposes a multiple mix integer expectation model to address the SSOA problem with consideration for a supplier's capacity, discount rate and delivery delay. The weighting method is widely used to deal with multiple-objective models because it is easy to implement; however, this method is biased heavily towards the experience of the decision maker. This chapter argues that such an unscientific approach can be rectified by translating the data on total cost and delivery delay under the manufacturer's profit-maximizing objective. The optimal solutions can be solved by the CoDDE algorithm.

Extensive experiments, including didactic examples and production data from industrial practice, have been conducted to validate the proposed optimization model and CoDDE algorithm. The experiment results demonstrate that the proposed model can effectively solve the multi-item purchasing problem. Compared with the industrial results, the solutions generated by the proposed optimization model are much better at gaining total profits for the manufacturer than conventional approaches. This paper also shows that the relationship between product price and delivery delay is an important factor in maximizing the manufacturer's total profit.

Chapter 7 Conclusion and Future Work

This chapter starts with the conclusions of this research and presents the contributions and limitations of this research as well as suggestions for future work.

7.1 Conclusion

The purpose of this research is to develop an effective intelligent supplier selection and order allocation (SSOA) model for material purchasing decision-making in the fast-fashion apparel supply chain. Based on real-world data, the SSOA model aims to give the purchasing decision maker an optimal purchasing strategy. This model consists of three sub-models, namely the SPER sub-model at the purchasing preparation stage, the SIOP sub-model and the MIOP sub-model at the final choice stage of material purchasing. The three decision-making optimal sub-models at different stages of material purchasing are investigated in depth in this research.

The SPER sub-model is developed to optimize supplier pre-evaluation and ranking at the purchasing preparation stage, which aims at helping the decision maker eliminate inefficient candidates and reduce the number of suppliers. Due to the multi-criteria nature of this decision and the fuzzy information involved in human decision-making, the FEAHP method is adopted as the basis of the optimal sub-model. The experiments prove that the FEAHP-based SPER sub-model has the ability to deal with uncertainty and vagueness from subjective perception and human decision-making and deal with multi-attribute decision-making effectively. Each supplier's weight and criterion weight can be easily attained using the FEAHP method. The weight of each criterion greatly impacts on order allocation and can be used to solve single-item purchasing optimal problems.

In the final choice stage of material purchasing, this research investigates common material (e.g. white fabric) purchasing (i.e. single-item multi-period purchasing). There are two things complicating the decision-making. The first one is that some objectives may conflict with each other; for example, minimizing purchasing cost always means high purchasing risk. The other one is that a purchasing planning horizon covers several periods, resulting in solution spaces becoming larger and more complex. The SIPO sub-model, which integrates the FEAHP method, multi-objective programming (MOP) and dynamic programming (DP), is developed to help the decision maker identify ultimate suppliers and define optimum quantities among selected suppliers in minimizing the risk of material purchasing and the total material purchasing costs, with the constraints of customer demand, supplier capacity and material price. In this model, the multi-objective problem is formulated as MOP and solved by a novel technique which integrates the FEAHP and the linear weighting sum method. The multi-period decision problems are solved by the DP method. Extensive experiments based on industrial data are conducted to validate the proposed SIPO sub-model. The results demonstrate that the SIPO sub-model can effectively handle common material purchasing in the final choice stage of material purchasing

Fashion accessories purchasing at the final choice stage of material purchasing is also investigated. Various real-world factors in fast-fashion purchasing are considered, such as discount rates offered by suppliers enjoying economies of scale, uncertain delivery delay and uncertain product discount rates offered by manufacturers. As a result, purchasing becomes a discrete, stochastic, multi-objective, NP-hard problem. In order to tackle the problem, this research proposes an MIPO sub-model, which integrates the probability theory and an improved DE algorithm. In this model, the relationship between delivery delay and selling price is studied. By using this relationship, the multi-objective problem transforms into a stochastic discrete single-objective problem. Then uncertain delivery delay and uncertain product discount are determined by the probability theory. Finally, the composite discrete differential evolution (CoDDE) algorithm is applied to the discrete single-objective NP-hard problem. The CoDDE algorithm is an improved composite differential evolution (CoDE) algorithm, which extends the real-value CoDE algorithm to the discrete-value vector by introducing two modified operators, namely subtraction and addition operators. Extensive experiments based on industrial data are conducted to validate the proposed MIPO sub-model. The results demonstrate that the MIPO sub-model can effectively deal with fashion accessories purchasing in the final choice stage of material purchasing.

7.2 Contributions of this Research

This research enriches our understanding of apparel material purchasing from both academic and industrial perspectives.

The proposed SSOA is the first intelligent material purchasing decision-making architecture for fast-fashion apparel manufacturers with consideration for various real-world factors. It can overcome the shortcomings of material purchasing decision-making in the apparel industry. On the basis of the proposed architecture, material purchasing decision-making can be integrated in a systematic and effective manner.

Few studies have investigated material purchasing by integrating supplier pre-selection and final choice stages. Some real-world production characteristics are considered in this research, such as material price, supplier evaluation, multi-period purchasing optimization, order allocation and material delivery. These considerations are necessary and have significant impact on solutions to apparel material purchasing. The objectives discussed in this research are particularly useful for helping the apparel purchasing decision maker optimize material purchasing.

In this research, several SSOA methodologies are developed to deal with material purchasing decision-making.

In order to tackle multi-objective problems in material purchasing, the linear weighting sum method is used because it is easy to implement; however, this method is biased heavily towards the experience of the decision maker. This research argues that such an unscientific approach can be rectified in two ways. One is integrating the FEAHP technique because it can calculate each objective's weight scientifically. The other is using the reality relationship because it can convert multi-objective problems into single objective problems scientifically. The experiment results show that the improved linear weighting sum method is highly effective.

In order to tackle the discrete NP-hard problem in material purchasing, the improved CoDE method (CoDDE) is proposed. Owing to the CoDE's capacity for global optimization, the proposed CoDDE is able to obtain 'near optimal' solutions even though it does not always guarantee optimal solutions. In this research, some effective modifications to the CoDE are made to deal with material purchasing decision-making with consideration for various realistic features. A binary representation is introduced in the CoDE to deal with discrete supplier selection variables in material purchasing decision-making. A novel mutation operator is proposed to deal with the discrete NP-hard supplier final selection and order allocation in material purchasing. The experiment results show that the proposed methodologies are effective.

7.3 Limitations of this Research and Suggestions for Future Work

While this research can serve to facilitate development of methodologies for material purchasing in the apparel industry, it has its limitations and there are a number of promising avenues for future research.

This research is focused on apparel manufacturers and suppliers. However, in order to further enhance the performance of the apparel supply chain, the decision maker should take into account the new problems associated with soft issues such as relationship management and conflict resolution between potential supply chain partners (e.g. manufacturers and suppliers). The tackling of these issues is left for future research.

In fashion accessories material purchasing, this research defines delivery delay as a discrete probability distribution function, but uncertain delivery delay can be a probabilistic cumulative distribution function. Which probabilistic cumulative distribution function can describe the uncertain delivery delay of each pre-selected supplier better? And which mathematical expressions can describe the relationship (defined as equation (6-8) in Chapter 6) between the apparel manufacturer's product price and delivery delay more practically? I will attempt to answer these questions in future research. On the other hand, this research neglected the influence of the order with minimum quantity. However, this factor cannot be ignored in real-world purchasing, which directly decided what order allocation strategy should be selected. To investigate the order with minimum quantity, future research should improve the CODDE algorithm and MIPO sub-model to deal with the order with minimum quantity.

Some uncertain real-world factors, such as retailer orders, supplier failure and shortages of material, are also not considered in this research. These factors often occur in real-world purchasing and can have a great influence on purchasing decision-making. Future research should investigate the effects of these factors on material purchasing decision-making.

In this research, it is assumed that real-life industrial data are accurate. The proposed methodology provides effective material purchasing decision-making on the basis of these accurate industrial data. However, incomplete or wrong data also exists in real-life databases. Some data can be inaccurate due to input error by manual effort. However, this research ignores these effects. Further research should focus on seeking an effective data-filtering mechanism to sort out incomplete or wrong data, analyzing the fault tolerance of the proposed methodology and exploring intelligent and highly fault-tolerant methodologies.

7.4 Related publication

The author demonstrated the originality of this research through the following publications.

Refereed Journal Paper

Zhi Li, W. K. Wong, C.K Kwong, (2013). "An Integrated Model of Material Supplier Selection and Order Allocation Using Fuzzy Extended AHP and Multiobjective Programming." Mathematical Problems in Engineering 2013.

Zhi Li, W. K. Wong, C.K Kwong, (2013). "An integrated CODDE-MOP model for multi-material supplier selection and order allocation problem." International Journal of Advanced Manufacturing Technology (Under review).

Conference Paper

Zhi Li, W. K. Wong, C.K Kwong, (2013). "An Integrated Model of Material Supplier Selection and Order Allocation Using FEAHP-MOP for Apparel Industry." European Busines s Research Conference 2013.

Appendix A

Experiment 1.2

Table A-1: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	
M 1	10	500			11	500	500
M 2			8	700	9	700	700
M 3	10	200	9	200	11	200	200
M 4			11	800	13	800	800
M 5	11	900			12	900	900
M 6	11	400			13	400	400

Table A-2: Comparisons of allocation performances in terms of different objectives

	solution	1	2	3
weights	w1	1		
	w2		1	
objective	cost	52117	63431	56639
	delay	10.3	4.9	6.7
	profit	9748	6430	10043
supplier		1,2,3	3	1,3
order quantity	X11	500	0	406
	X12	0	0	0
	X13	0	500	94
	X21	0	0	0
	X22	700	0	0
	X23	0	700	700
	X31	0	0	121
	X32	200	0	0
	X33	0	200	79
	X41	0	0	0
	X42	800	0	0
	X43	0	800	800
	X51	900	0	835
	X52	0	0	0
	X53	0	900	65
	X61	400	0	312
	X62	0	0	0
	X63	0	400	88

Appendix B

Experiment 2.2

Table B-1: Production Information

Product	Quantity	Price	Discount rate related to delivery delay days
Item 1	250	270	$PP_1(E(\max(Y_i\xi_i)) = \begin{cases} 0.68 & 14 \leq E(\max(Y_i\xi_i)) \\ 0.75 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \leq E(\max(Y_i\xi_i)) \leq 7 \end{cases}$
Iterm 2	150	200	$PP_2(E(\max(Y_i\xi_i)) = \begin{cases} 0.65 & 14 \leq E(\max(Y_i\xi_i)) \\ 0.79 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \leq E(\max(Y_i\xi_i)) \leq 7 \end{cases}$

Table B-2: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Supplier 4		Supplier 5		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	
M 1	10	500	0	0	0	0	12	500	0	0	500
M 2	0	0	8	1000	0	0	9	1000	0	0	1000
M 3	10	200	9	200	11	200	9	200	0	0	200
M 4	0	0	11	1300	13	1300	7	1300	8	1300	1300
M 5	0	0	0	0	0	0	10	100	11	100	100
M 6	13	1500	0	0	11	1500	12	1500	9	1500	1500

Table B-3: Comparisons of allocation performances in terms of different objectives

	solution	1	2	3
weights	w1	1		
	w2		1	
objective	cost	40800	46000	45364
	delay	11.56	4.9	6.7
	profit	24600	28325	28961
supplier		1,2,4,5	4	1,4,5
order quantity	X11	500	0	488
	X12	0	0	0
	X13	0	0	0
	X14	0	500	0
	X15	0	0	12
	X21	0	0	0
	X22	1000	0	0
	X23	0	0	0
	X24	0	1000	1000
	X25	0	0	0
	X31	0	0	0
	X32	200	0	0
	X33	0	0	0
	X34	0	200	200
	X35	0	0	0
	X41	0	0	0
	X42	0	0	0
	X43	0	0	0
	X44	0	1300	816
	X45	1300	0	484
	X51	0	0	0
	X52	0	0	0
	X53	0	0	0
	X54	100	100	100
	X55	0	0	0
	X61	0	0	0
	X62	0	0	0
	X63	0	0	0
	X64	0	1500	1500
	X65	1500	0	0

Experiment 2.3

Table B-4: Production Information

Product	Quantity	Price	Discount rate related to delivery delay days
Item 1	250	270	$PP_1(E(\max(Y_i\xi_i))=\begin{cases}0.68 & 14 \le E(\max(Y_i\xi_i)) \\ 0.75 & 7 < E(\max(Y_i\xi_i))<14 \\ 1 & 0 \le E(\max(Y_i\xi_i))\le 7\end{cases}$
Iterm 2	150	200	$PP_2(E(\max(Y_i\xi_i))=\begin{cases}0.65 & 14 \le E(\max(Y_i\xi_i)) \\ 0.79 & 7 < E(\max(Y_i\xi_i))<14 \\ 1 & 0 \le E(\max(Y_i\xi_i))\le 7\end{cases}$

Table B-5: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Supplier 4		Supplier 5		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	
M 1	10	500	0	0	0	0	0	0	12	500	500
M 2	0	0	8	1700	0	0	6	1700	9	1700	1700
M 3	10	200	9	200	11	200	0	0	10	200	200
M 4	0	0	11	1300	13	1300	8	1300	7	1300	1300
M 5	11	900	0	0	0	0	11	900	10	900	900
M 6	13	1500	0	0	11	1500	12	1500	9	1500	1500

Table B-6: Comparisons of allocation performances in terms of different objectives

	solution	1	2	3
weights	w1	1		
	w2		1	
objective	cost	43317	50405	47501
	delay	11.66	6.4	6.7
	profit	22941	25920	26824
supplier		1,2,4,5	4,5	1,4,5
order quantity	X11	500	0	369
	X12	0	0	0
	X13	0	0	0
	X14	0	0	0
	X15	0	500	131
	X21	0	0	0
	X22	0	0	0
	X23	0	0	0
	X24	1700	1700	1167
	X25	0	0	533
	X31	0	0	0
	X32	200	0	0
	X33	0	0	0
	X34	0	0	200
	X35	0	200	0
	X41	0	0	0
	X42	0	0	0
	X43	0	0	0
	X44	0	1300	616
	X45	1300	0	684
	X51	0	0	0
	X52	0	0	0
	X53	0	0	0
	X54	900	900	344
	X55	0	0	556
	X61	0	0	0
	X62	0	0	0
	X63	0	0	0
	X64	0	1500	0
	X65	1500	0	1500

Experiment 2.4

Table B-7: Production Information

Product	Quantity	Price	Discount rate related to delivery delay days
Item 1	500	176	$PP_1(E(\max(Y_i\xi_i)) = \begin{cases} 0.68 & 14 \le E(\max(Y_i\xi_i)) \\ 0.75 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \le E(\max(Y_i\xi_i)) \le 7 \end{cases}$
Iterm 2	300	157	$PP_2(E(\max(Y_i\xi_i)) = \begin{cases} 0.65 & 14 \le E(\max(Y_i\xi_i)) \\ 0.79 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \le E(\max(Y_i\xi_i)) \le 7 \end{cases}$

Table B-8: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Supplier 4		Supplier 5		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	
M 1	13.1	1000							12.5	1000	1000
M 2			7.3	500			7.1	500	7.7	500	500
M 3	7.6	500			8.3	500			7.9	500	500
M 4			11	3000	13	3000	8	3000	7	3000	3000
M 5	9.7	1000					10.5	1000	10	1000	1000
M 6					11	2000	12	2000	9	2000	2000

Table B-9: Comparisons of allocation performances in terms of different objectives

solution	1	2	3
w1	1		
w2		1	
cost	47501	72123	67110.5
delay	12.35	5.9	6.7
profit	26824	42977	36098.5
	1,3,4,5	1,4	1,4,5
X11	0	1000	539
X12	0	0	0
X13	0	0	0
X14	0	0	0
X15	1000	0	461
X21	0	0	0
X22	0	0	0
X23	0	0	0
X24	500	500	500
X25	0	0	0
X31	0	500	167
X32	0	0	0
X33	500	0	0
X34	0	0	0
X35	0	0	333
X41	0	0	0
X42	0	0	0
X43	0	0	0
X44	0	3000	1994
X45	3000	0	1006
X51	1000	1000	464
X52	0	0	0
X53	0	0	0
X54	0	0	0
X55	0	0	536
X61	0	0	0
X62	0	0	0
X63	0	0	0
X64	0	2000	665
X65	2000	0	1335

Experiment 2.5

Table B-10: Production Information

Product	Quantity	Price	Discount rate related to delivery delay days
Item 1	500	165	$PP_1(E(\max(Y_i\xi_i)) = \begin{cases} 0.68 & 14 \leq E(\max(Y_i\xi_i)) \\ 0.75 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \leq E(\max(Y_i\xi_i)) \leq 7 \end{cases}$
Iterm 2	700	200	$PP_2(E(\max(Y_i\xi_i)) = \begin{cases} 0.65 & 14 \leq E(\max(Y_i\xi_i)) \\ 0.79 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \leq E(\max(Y_i\xi_i)) \leq 7 \end{cases}$

Table B-11: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Supplier 4		Supplier 5		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	
M 1			11.7	1000			12.5	1000	12.5	1000	1000
M 2	14	1000	15	1000			17	1000	12	1000	1000
M 3	7.6	500			8.3	500	7.9	500	6.9	500	500
M 4			11	3000	13	3000	11.9	3000			3000
M 5	9.7	1000					10	1000	9.7	1000	1000
M 6		2000	11	2000			9	2000	9	2000	2000

Table B-12: Comparisons of allocation performances in terms of different objectives

	solution	1	2	3
weights	w1	1		
	w2		1	
objective	cost	68472.5	75123	73684.4
	delay	11.66	4.9	6.9
	profit	53537.5	46977	61325.6
supplier		1,2,4,5	4	2,4,5
order quantity	X11	0	0	0
	X12	1000	0	769
	X13	0	0	0
	X14	0	1000	231
	X15	0	0	0
	X21	0	0	0
	X22	0	0	0
	X23	0	0	0
	X24	0	1000	239
	X25	1000	0	761
	X31	0	0	0
	X32	0	0	0
	X33	0	0	0
	X34	0	500	0
	X35	500	0	500
	X41	0	0	0
	X42	3000	0	1874
	X43	0	0	0
	X44	0	3000	1126
	X45	0	0	0
	X51	1000	0	0
	X52	0	0	0
	X53	0	0	0
	X54	0	1000	375
	X55	0	0	625
	X61	0	0	0
	X62	0	0	0
	X63	0	0	0
	X64	2000	2000	1239
	X65	0	0	761

Appendix C

Experiment 3.2

Table C-1: Production Information

Product	Quantity	Price	Discount rate related to delivery delay days
Item 1	250	270	$PP_1(E(\max(Y_i\xi_i)) = \begin{cases} 0.68 & 14 \le E(\max(Y_i\xi_i)) \\ 0.75 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \le E(\max(Y_i\xi_i)) \le 7 \end{cases}$
Iterm 2	150	200	$PP_2(E(\max(Y_i\xi_i)) = \begin{cases} 0.65 & 14 \le E(\max(Y_i\xi_i)) \\ 0.79 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \le E(\max(Y_i\xi_i)) \le 7 \end{cases}$

Table C-2: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Supplier 4		Supplier 5		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	
M 1	10	500							12	500	500
M 2			8	800			9	1700	7	1100	1700
M 3	10	200	9	200	11	200			10	200	200
M 4			11	500	8	500	13	1300	7	900	1300
M 5	11	900					11	900	10	900	900
M 6	13	900			11	500	12	1500	9	1300	1500

Table C-3: Comparisons of allocation performances in terms of different objectives

	solution	1	2	3
weights	w1	1		
	w2		1	
objective	cost	42700	56100	49711
	delay	14.3	5.9	6.7
	profit	22700	18225	25229
supplier		1,2,3,4,5	1,4	1,4,5
order quantity	X11	500	500	369
	X12	0	0	0
	X13	0	0	0
	X14	0	0	0
	X15	0	0	131
	X21	0	0	0
	X22	600	0	0
	X23	0	0	0
	X24	0	1700	1167
	X25	1100	0	533
	X31	0	200	0
	X32	200	0	0
	X33	0	0	0
	X34	0	0	200
	X35	0	0	0
	X41	0	0	0
	X42	0	0	0
	X43	400	0	0
	X44	0	1300	616
	X45	900	0	684
	X51	0	0	0
	X52	0	0	0
	X53	0	0	0
	X54	0	900	344
	X55	900	0	556
	X61	0	0	0
	X62	0	0	0
	X63	200	0	0
	X64	0	1500	305
	X65	1300	0	1195

Experiment 3.3

Table C-4: Production Information

Product	Quantity	Price	Discount rate related to delivery delay days
Item 1	250	270	$PP_1(E(\max(Y_i\xi_i))=\begin{cases}0.68 & 14 \le E(\max(Y_i\xi_i)) \\ 0.75 & 7 < E(\max(Y_i\xi_i))<14 \\ 1 & 0 \le E(\max(Y_i\xi_i))\le 7\end{cases}$
Iterm 2	150	200	$PP_2(E(\max(Y_i\xi_i))=\begin{cases}0.65 & 14 \le E(\max(Y_i\xi_i)) \\ 0.79 & 7 < E(\max(Y_i\xi_i))<14 \\ 1 & 0 \le E(\max(Y_i\xi_i))\le 7\end{cases}$

Table C-5: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Supplier 4		Supplier 5		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	
M 1	13.1	1000							12.5	1000	1000
M 2			7.3	500		500	7.1	500	7.7	500	500
M 3	7.6	500			8.3	500			7.9	500	500
M 4			11	3000	13	3000	8	3000	7	3000	3000
M 5	9.7	1000		1000		1000	10.5	1000	10	1000	1000
M 6				2000	11	2000	12	2000	9	2000	2000

Table C-6: Comparisons of allocation performances in terms of different objectives

	solution	1	2	3
weights	w1	1		
	w2		1	
objective	cost	67110.5	77201.25	73971.152
	delay	14.3	11.66	11.66
	profit	36098.5	26007.75	39237.848
supplier		1,2,3,4,5	1,2,4,5	1,2,4,5
order quantity	X11	500	700	539
	X12	0	0	0
	X13	0	0	0
	X14	0	0	0
	X15	500	300	461
	X21	0	0	0
	X22	0	0	0
	X23	0	0	0
	X24	500	500	500
	X25	0	0	0
	X31	500	500	167
	X32	0	0	0
	X33	0	0	0
	X34	0	0	0
	X35	0	0	333
	X41	0	0	0
	X42	800	800	1038
	X43	0	0	0
	X44	1000	1000	946
	X45	1200	1200	1016
	X51	550	550	464
	X52	0	0	0
	X53	0	0	0
	X54	0	0	0
	X55	450	450	536
	X61	0	0	0
	X62	0	0	0
	X63	900	0	0
	X64	0	2000	927
	X65	1100	0	1073

Experiment 3.4

Table C-7: Production Information

Product	Quantity	Price	Discount rate related to delivery delay days
Item 1	250	270	$PP_1(E(\max(Y_i\xi_i)) = \begin{cases} 0.68 & 14 \le E(\max(Y_i\xi_i)) \\ 0.75 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \le E(\max(Y_i\xi_i)) \le 7 \end{cases}$
Iterm 2	150	200	$PP_2(E(\max(Y_i\xi_i)) = \begin{cases} 0.65 & 14 \le E(\max(Y_i\xi_i)) \\ 0.79 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \le E(\max(Y_i\xi_i)) \le 7 \end{cases}$

Table C-8: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Supplier 4		Supplier 5		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	
M 1			11.7	700			12.5	1000	12.5	1000	1000
M 2	14	1000	15	1000			17	1000	12	1000	1000
M 3	7.6	500			8.3	500	7.9	500	6.9	300	500
M 4			11	2550	13	3000	11.9	3000			3000
M 5	9.7	600					10	1000	9.7	700	1000
M 6			11	2000			9	1000	9	1100	2000

Table C-9: Comparisons of allocation performances in terms of different objectives

	solution	1	2	3
weights	w1	1		
	w2		1	
objective	cost	74295.1	81656.5	76625.195
	delay	11.66	6.4	8.1
	profit	48714.9	41353.5	68384.805
supplier		1,2,4,5	4,5	2,4,5
order quantity	X11	0	0	0
	X12	700	0	700
	X13	0	0	0
	X14	0	1000	300
	X15	300	0	0
	X21	0	0	0
	X22	0	0	0
	X23	0	0	0
	X24	0	1000	239
	X25	1000	0	761
	X31	0	0	0
	X32	0	0	0
	X33	0	0	0
	X34	200	500	209
	X35	300	0	291
	X41	0	0	0
	X42	2550	0	1874
	X43	0	0	0
	X44	450	3000	1126
	X45	0	0	0
	X51	600	0	0
	X52	0	0	0
	X53	0	0	0
	X54	0	1000	375
	X55	400	0	625
	X61	0	0	0
	X62	0	0	337
	X63	0	0	0
	X64	1000	1000	900
	X65	1000	1000	763

Experiment 3.5

Table C-10: Production Information

Product	Quantity	Price	Discount rate related to delivery delay days
Item 1	500	265	$PP_1(E(\max(Y_i\xi_i)) = \begin{cases} 0.68 & 14 \le E(\max(Y_i\xi_i)) \\ 0.75 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \le E(\max(Y_i\xi_i)) \le 7 \end{cases}$
Item 2	800	240	$PP_2(E(\max(Y_i\xi_i)) = \begin{cases} 0.65 & 14 \le E(\max(Y_i\xi_i)) \\ 0.79 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \le E(\max(Y_i\xi_i)) \le 7 \end{cases}$
Iterm 3	700	275	$PP_2(E(\max(Y_i\xi_i)) = \begin{cases} 0.65 & 14 \le E(\max(Y_i\xi_i)) \\ 0.87 & 7 < E(\max(Y_i\xi_i)) < 14 \\ 1 & 0 \le E(\max(Y_i\xi_i)) \le 7 \end{cases}$

Table C-11: Information on each supplier in terms of price and capacity

	Supplier 1		Supplier 2		Supplier 3		Supplier 4		Supplier 5		Demands
	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	
M 1			11.7	700			12.5	1000	12.5	1000	1000
M 2	14	1000	15	1000			17	1000	12	700	1000
M 3	7.6	500			8.3	500	8.8	500	6.9	500	500
M 4			11	2550	13	3000	13.9	5000			5000
M 5	9.7	1000					10	1000	9.7	1000	1000
M 6			11	2000			12	2000	9	1100	2000
M 7					15.3	3350	17.3	3350			3350
M 8	6	1350	6.5	900			9	1350	7	1350	1350

Table C-12: Comparisons of allocation performances in terms of different objectives

	solution	1	2	3
weights	w1	1		
	w2		1	
objective	cost	925306.4	997304.77	95575.195
	delay	14.3	4.9	11.66
	profit	67948.9	69943.5	70324.791
supplier		1,2,3,4,5	4	1,2,4,5
order quantity	X11	0	0	0
	X12	700	0	700
	X13	0	0	0
	X14	0	1000	300
	X15	300	0	0
	X21	0	0	0
	X22	0	0	0
	X23	0	0	0
	X24	0	1000	418
	X25	1000	0	582
	X31	0	0	0
	X32	0	0	0
	X33	0	0	0
	X34	200	500	323
	X35	300	0	177
	X41	0	0	0
	X42	2550	0	2174
	X43	2450	0	2826
	X44	0	5000	0
	X45	0	0	0
	X51	600	0	633
	X52	0	0	0
	X53	0	0	0
	X54	0	1000	0
	X55	400	0	367
	X61	0	0	0
	X62	0	0	805
	X63	0	0	0
	X64	1000	2000	227
	X65	1000	0	968
	X71	0	0	0
	X72	0	0	0
	X73	3350	0	3218
	X74	0	3350	132
	X75	0	0	0
	X81	1350	0	1350
	X82	0	0	0
	X83	0	0	0
	X84	0	1350	0
	X85	0	0	0

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