DOKUZ EYLÜL UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

MULTI-CRITERIA BASED NOVEL STRATEGIC SOURCING METHODOLOGIES

by

Ceyhun ARAZ

January, 2007

İZMİR

MULTI-CRITERIA BASED NOVEL STRATEGIC SOURCING METHODOLOGIES

A Thesis Submitted to the

Graduate School of Natural and Applied Sciences of Dokuz Eylül University

In Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in

Industrial Engineering, Industrial Engineering Program

by

Ceyhun ARAZ

January, 2007

İZMİR

Ph.D. THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"MULTI-CRITERIA BASED NOVEL STRATEGIC SOURCING METHODOLOGIES"** completed by **CEYHUN ARAZ** under supervision of **PROF. DR. IREM OZKARAHAN** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

Prof. Dr. Irem OZKARAHAN

Supervisor

Thesis Committee Member

Thesis Committee Member

Examining Committee Member

Examining Committee Member

Prof. Dr. Cahit HELVACI
Director
Graduate School of Natural and Applied Sciences

ACKNOWLEDGMENTS

I owe the greatest dept of gratitude to my advisor, Prof. Dr. İrem Özkarahan, for her continuous support, guidance, encouragement and patience. This dissertation could not have been written without Prof. Dr. İrem Özkarahan who was not only a dedicated advisor but also encouraged and challenged me throughout my academic life. It is my great pleasure and honor to be associated with her.

I would like to thank my committee members Prof. Dr. Miraç Bayhan and Prof. Dr. Tatyana Yakhno for their helpful comments and advice. Special thanks go to Prof. Dr. Hasan Eski who encouraged me throughout the progress of this dissertation.

I also want to thank Dr. Jose Rui Figueira for his valuable comments and supports. A special thank must go to my friend Dr. Derya Eren Akyol for her friendship and helps. I would also like to thank my friends Dr. Gökalp Yıldız, Özgür Eski, Dr. Özcan Kılınççı, Dr. Hasan Selim, Pınar M. Özfırat, Rahime and Emrah Edis, Özgür Armaneri and all my colleagues for their encouragement, friendship and helps.

Very special thanks would be given to my parents, Emine and Muhsin Araz, and my brother, Seyhun, for their forever love, confidence in me and understanding. Finally, I would like to express my special gratitude to my wife, Özlem Uzun Araz, for her love, endless support, understanding and sacrifices.

Ceyhun Araz

MULTI-CRITERIA BASED NOVEL STRATEGIC SOURCING METHODOLOGIES

ABSTRACT

Due to increasing competitive pressure, companies have been forced to focus on supply chain management (SCM). Supplier selection is one of the most vital actions of companies in a supply chain. With the recent trend in JIT philosophy, there is an emphasis on strategic sourcing that establishes long-term relationship with fewer but better suppliers.

Strategic sourcing decisions not only include the evaluation and selection of the potential strategic suppliers but also deal with developing the long-term strategic partnership with these suppliers, increasing the supplier performance by involving in supplier development programs and providing continuous feedback to the suppliers.

This research presents two methodologies for strategic sourcing problems. The first methodology helps the decision maker to classify suppliers into different categories, identify the differences in performances across supplier classes, monitor the suppliers' performances and make decisions about necessary development programs. The proposed methodology offers to use a multi-criteria sorting (MCS) procedure to determine supplier classes and reduce the number of suppliers to a manageable number. This research also proposes a new MCS methodology, which is named as PROMSORT. In this dissertation, another focus is placed on developing a fuzzy MCS methodology which is an extension of PROMSORT.

Secondly, this dissertation presents an integrated multi-criteria decision making methodology for strategic sourcing that enables the decision maker to reflect his/her fuzzy objectives into the sourcing process. The proposed methodology introduces an interactive fuzzy goal programming model for the order allocation problem.

In order to demonstrate the applicability of the proposed methodologies for the strategic supplier selection and order allocation problem, numerical strategic sourcing problems are presented. The results of the computational experiments indicate that the proposed methodologies are useful tools for firms to select the strategic partners, manage their supplier base and allocate the orders to the most appropriate suppliers.

Keywords: Strategic sourcing, Supplier evaluation and selection, Multi-criteria classification, Fuzzy goal programming.

ÇOK KRİTER TABANLI ÖZGÜN STRATEJİK TEDARİK METODOLOJİLERİ

ÖZ

Artan rekabet baskısı firmaları tedarik zinciri yönetimi konusuna odaklanmaya zorlamaktadır. Tedarikçi seçimi tedarik zinciri içerisinde bulunan bir firmanın en önemli kararlarından biridir. Tam zamanında üretim felsefesinin yaygınlaşmasının bir sonucu olarak, günümüzde daha az fakat daha iyi tedarikçilerle uzun dönemli işbirliğine imkan veren stratejik tedarik kavramının önemi artmıştır.

Stratejik tedarik kavramı yalnızca potansiyel stratejik tedarikçilerin seçimi ve değerlendirilmesi kararlarını içermez, bunun yanında, seçilen tedarikçilerle uzun dönemli stratejik ortaklık kurma, tedarikçi geliştirme programları ile mevcut tedarikçilerin performanslarını arttırma ve onlara devamlı geri bildirimde bulunma gibi kararlarla da ilgilenir.

Bu tezde stratejik tedarik problemleri için iki yöntem önerilmektedir. İlk yöntem karar vericiye tedarikçilerini belirli kategorilere ayırma, tedarikçi kategorilerinin performansları arasındaki farkları tanımlama, tedarikçilerin performanslarını zaman içerisinde izleme ve gerekli geliştirme programlarına karar verme konularında yardımcı olmaktadır. Önerilen yöntem tedarikçi kategorilerinin belirlenmesinde ve tedarikçi sayısının azaltılmasında bir çok kriterli sınıflandırma (ÇKS) algoritması kullanılmasını önermektedir. Bu nedenle, bu çalışmada PROMSORT olarak adlandırılan yeni bir ÇKS yöntemi önerilmiştir. Ayrıca bu çalışmada, önerilen PROMSORT metodunun geliştirilmiş versiyonu olan, bir bulanık ÇKS yöntemi de sunulmuştur.

İkinci olarak, bu çalışmada, stratejik tedarik problemleri için, karar vericilerin hedef değerlerindeki belirsizliğin tedarik sürecine dahil edilmesine imkan sağlayan bir bütünleşik çok kriterli karar verme yöntemi sunulmuştur. Bu yöntemde, hangi

tedarikçiye hangi üründen ne kadar sipariş verilmesi gerektiğini bulmak için, interaktif bulanık amaç programlama modeli geliştirilmiştir.

Önerilen yöntemlerin stratejik tedarikçi seçimi ve sipariş miktarı belirleme problemlerinde uygulanabilirliğini göstermek amacıyla sayısal stratejik tedarik problemleri sunulmuştur. Bu çalışmada sunulan sayısal örnekler, önerilen yöntemlerin firmalar için stratejik ortaklarını belirlemede, tedarikçileri ilişkilerini yönetmede ve siparişleri en uygun tedarikçilere atamada faydalı olacağını ortaya koymuştur.

Anahtar Kelimeler: Stratejik tedarik, Tedarikçi değerlendirme ve seçimi, Çok-kriterli sınıflandırma, Bulanık amaç programlama.

CONTENTS

Page

CHAPTER ONE
INTRODUCTION

In this chapter, the background, motivation and objectives of this work are stated, and the organization of this dissertation is outlined.

1.1 Background and Motivation

The growth in globalization, and the additional management challenges it brings, has motivated both practitioner and academic interest in global supply chain management (SCM) (Meixell and Gargeya, 2005). In general, a supply chain consists of all links from suppliers to customers: suppliers (and/or outsourcers), manufacturing plants, warehouses, distribution centers and retailers (Chopra and Meindl, 2004). Supplier selection and evaluation is one of the most vital actions of companies in a supply chain. Selecting the wrong supplier could be enough to deteriorate the whole supply chain's financial and operational position. In today's highly competitive, global operating environment, it is impossible to produce low cost, high quality products successfully without satisfactory suppliers (Vokurka et. al., 1996).

In the past decade or so, increasing competitive pressure, the rapid pace of technological change and the recent trend on just-in-time (JIT) manufacturing philosophy are motivating the firms to focus on strategic sourcing that establishes long-term relationship with a selected group of competent suppliers (Andersen and Rask, 2003). This strategic and long-term relation developed between the manufacturer and suppliers are expected to provide the opportunity for improving performance (Choy et al., 2003). By increasingly leaving marginal activities to selected suppliers and focusing their core competencies, the firms are enhancing their innovative and competitive ability (Andersen and Rask, 2003).

Strategic sourcing decisions not only include the evaluation and selection of the potential strategic suppliers but also deal with developing and implementing the long-term strategic partnership with these suppliers. Strategic sourcing strategy also helps to increase supplier performance by involving in supplier development programs and providing continuous feedback to the suppliers (Talluri and Narasimhan, 2004).

With the increasing significance of strategic sourcing, four important decisions describe a company's purchasing function: (a) criteria determination for selection of the suppliers; (b) selecting strategic partners in the long-term (c) managing the supplier base and (d) allocating orders to the appropriate suppliers.

Supplier selection problem inherently has a multiple criteria nature. Therefore, such decisions are complex because of the conflicting criteria to be considered in the decision making process. The changing nature of relationships between manufacturers and suppliers and the necessity of supplier involvement have raised the fact that strategic supplier selection and evaluation decisions must not be solely based on traditional selection criteria, such as cost, quality and delivery. The approach to traditional criteria has been changed to reflect the new requirements according to the role of suppliers in the supply chain (Choy et al., 2005). For instance, instead of price, total cost of ownership is considered, instead of quality, total quality and certification issues become the major concern etc. (Choy et al., 2005). In strategic sourcing, many other criteria should be considered with the aim of developing a long-term supplier relationship such as quality management practices, long-term management practices, financial strength, technology and innovativeness level, suppliers' cooperative attitude, supplier's co-design capabilities, and cost reduction capabilities (Mandal and Deshmukh, 1994; Dowlatshahi, 2000; De Toni and Nassimbeni, 2001; Choy et al. 2002; Dulmin and Mininno, 2003; Choy et al. 2003; Talluri and Narasimhan, 2004).

Especially, the strategic role of suppliers in a supply chain has been changing as a result of increasing use of suppliers in innovation, more specifically in the product design stage (Croom, 2001). Today, in many industries, companies give suppliers increasing responsibilities relating to the product design, development and engineering (Wynstra et al., 2001). Several researches have pointed out the benefits of starting long-term relationship with the suppliers at the product/process design and development stages such as fast project development times, lower development and product cost, increased the level of motivation of suppliers, increased supplier-originated innovation and better product quality (Bonaccorsi and Lipparini, 1994; De toni and Nassimbeni, 2001; Valk and Wynstra, 2005). However, it is clear that these expected benefits can only be obtained with competent suppliers which have strong long-term capabilities on product design. Therefore, concurrent design teams should select the suppliers that can effectively meet the varying conditions from the perspective of new product development, design, manufacturing processes and manufacturing capability (Talluri and Narasimhan, 2004). In other words, the supplier selection decision needs to incorporate design criteria into the assessment process (Humphreys et al., 2005).

In strategic sourcing, besides long-term strategic relationship and suppliers' involvement in product development and design, reduction of supplier base should be one of the main tasks of concurrent design teams. Several important factors have caused the current shift to a reduced supplier base such as (Shin et al., 2000):

- multiple sourcing prevents supplier from achieving the economies of scale based on order volume and learning curve effect,
- worldwide competition forces firms to find the best suppliers in the world.

Dowlatshahi (2000, p.117) also emphasized the importance of the reduced supplier base with the following words:

- "*Supplier development is costly – so suppliers must be limited to a manageable number,*

- *A close and long-term relationship is only achievable with a limited number of suppliers,*
- *Suppliers can be expected to be involved in the developmental efforts of concurrent design teams only when the number of suppliers is reduced etc.*".

As for flexible and efficient purchasing decisions, there is a growing trend that companies sort supplier bases into two or more categories (Choy et al., 2005): "competitive or collaborative" (Choy et al., 2005) and "strategic partners, candidates for supplier development program or pruning suppliers" (Talluri and Narasimhan, 2004).

As more firms become interested in developing and implementing strategic partnership with their suppliers during product development, it is necessary to have a supplier management system for companies to manage their supplier base and to address the managerial decisions about supplier groups and individual suppliers. The roles of the supplier management systems should be to identify differences in performances across supplier groups, to provide feedback to supplier groups about their weaknesses, to assist suppliers by providing knowledge, skills and experience via various supplier development programs, and to monitor suppliers' performance after providing support (See Talluri and Narasimhan (2004) and Lee et al. (2001)).

Lastly, among the selected strategic partners, the specific subset of suppliers which will actually receive an order must be determined. Once the selected set of suppliers is determined, the firm must allocate orders to them (Burke, 2005). Since all suppliers in the base have necessary overall performance in terms of companies' long term expectations and design based capabilities and abilities, allocation decisions of the orders should be based on their score of strategic partnership and the item-specific criteria. Briefly, besides supplier management system, evaluation of existing outsourcers in terms of company's product specific goals, selecting the most appropriate suppliers among the strategic partners and allocating the ordered quantities to them are also important purchasing decisions.

Although many methods have been proposed and used for selection and evaluation of suppliers, most of them try to rank the suppliers from the best to the worst or to choose the best supplier among others. In addition, the use of design-related criteria to assess supplier performance has largely been ignored, although it is essential in assessing the role of suppliers in product development (Humphreys et al., 2005). Up to date, comparison of the suppliers and identification of the potential reasons for differences in supplier performance have not been fully explored in the literature (Talluri and Narasimhan, 2004). Furthermore, although order allocation and strategic sourcing decisions, such as selecting the potential strategic suppliers, implementing the strategic partnership with these suppliers and providing continuous feedback to the suppliers, have been studied in the literature separately, few researches have been dedicated to solve these problems together.

In addition to these facts, up do date, in supplier classification problems, it has mostly been assumed that the performances of alternative suppliers have been known in advance or companies are able to evaluate their suppliers exactly. However, especially in the early product development stages, this is not a realistic assumption.

In the light of the above discussions, it can be seen easily that as more firms become interested in developing and implementing strategic partnership with their key suppliers during product development, effective tools and methodologies are needed to help purchasing teams in classifying their suppliers based on their performances with the capability of continually monitoring and assessing both fuzzy and crisp performances of their suppliers and in allocating the orders to the most suitable partners. This fact is the major motivator of this study.

1.2 Research Objectives

Motivated by the fact that increasing importance of strategic sourcing decisions in enhancing performance of supply chain, this research aims to propose novel methodologies for effective strategic sourcing decisions. Selecting strategic suppliers from a large number of possible suppliers with various levels of capabilities and potential is inherently a multi-criteria decision making (MCDM) problem (Kahraman et al., 2003; Dahel, 2003). Therefore, the proposed strategic supplier evaluation and management systems should be based on the multi-criteria evaluation of the suppliers.

Considering these facts, the main objectives of this research are:

- to propose a strategic supplier evaluation and management system which can assist the concurrent design teams in assessing suppliers involved in the design process, in identifying supplier groups, in selecting potential partners using design criteria, in developing and implementing the partnership, in identifying the differences among the supplier groups, in monitoring the performance of suppliers and in providing feedback to ineffective suppliers regarding the necessary improvements. Furthermore, it offers a quantitative evaluation of the support given by suppliers in new product development activities.

- to propose an integrated MCDM methodology for outsourcing management which can select the most appropriate outsourcers suitable to be strategic partners with the company and simultaneously allocates the quantities to be ordered to them by the help of interactive fuzzy goal programming (IFGP) approach. The methodology also identifies the differences in performances across outsourcers, and assists in monitoring the outsourcers' performances.

While this research focuses on novel methodologies for evaluating and managing suppliers for the strategic partnership, it also deals with the multi-criteria sorting (MCS) problem. Because of the multiple criteria nature of the supplier selection and evaluation problems, a MCS method may be efficient in order to sort suppliers into the predefined ordered classes, to compare suppliers and to identify potential reasons for differences in supplier performance. Therefore, this research also aims to propose a new MCS procedure based on PROMETHEE methodology and to investigate the applicability of the proposed MCS method for other real world problems besides supplier selection.

Another focus is placed on developing a fuzzy MCS procedure to solve supplier classification problems at the early product development stages. As an extension of proposed MCS method, to develop a new fuzzy MCS procedure in assigning alternatives to predefined ordered categories where the performance of alternatives can be defined as fuzzy numbers is another aim of the research proposed in this thesis.

To summarize, the main objectives of this research are twofold. The first one is to develop novel methodologies for strategic sourcing problems. The second one is to develop a MCS procedure that can handle both fuzzy and crisp input data and that can be used to solve many real world classification problems besides supplier selection.

1.3 Original Contributions

We contribute the both of supplier selection and MCDM literature in many ways.

- A new MCS method named as PROMSORT (Araz and Ozkarahan, 2005, 2006), which is an extension of well-known PROMETHEE (Brans et al., 1986) method, is proposed.

- A new supplier evaluation and management methodology is proposed, in which suppliers are categorized and compared according to their performances on several design based criteria, potential reasons for differences in supplier performance are identified, and performances of the suppliers are improved by applying supplier development programs. To the best of our knowledge, MCS methods have not yet been applied for strategic sourcing problems. The application of the proposed methodology, PROMSORT, in strategic sourcing problem is the first time a MCS methodology is utilized for such problem.

- An integrated MCDM methodology for outsourcing management is proposed. For the first time, an integrated approach that incorporates a MCS procedure and IFGP is used to select the strategic partners and to allocate the appropriate orders to them simultaneously.

- A new fuzzy MCS Procedure, Fuzzy-PROMSORT, is proposed. We extend PROMSORT so that it can handle fuzzy input data.

  In most of the MCS methods, it is assumed that the performances of an alternative on a set of criteria are known exactly. The MCDM literature involves numerous fuzzy approaches to the ranking problems but few studies, which apply fuzzy set theory (FST) (Zadeh, 1965), have been proposed to solve sorting problems (see Belacel and Boulasses, 2004).

- F-PROMSORT was applied to the strategic supplier selection problem. To the best of our knowledge, it is the first attempt to use a fuzzy MCS procedure for the pre-qualification phase of supplier selection problem considering the fuzzy performances of suppliers.

- In order to validate the effectiveness of the proposed sorting methodology, PROMSORT was also applied to financial classification problems besides supplier selection.

1.4 Organization of the Thesis

The organization of this dissertation is as follows.

Chapter 2 gives an overview of SCM and strategic sourcing. A detailed literature review concerning supplier selection metrics and an overview of solution approaches used for solving supplier selection problem are also provided in this chapter.

In Chapter 3, taxonomy of MCDM problems is described and some methods used for solving these problems are reviewed. Chapter 3 also provides a comprehensive overview of multi-criteria classification (MCC) problem and reviews some methods to solve MCC problems. PROMETHEE based sorting methods from which our methodology is inspired are also explained in this chapter.

Chapter 4 presents a brief overview of fuzzy sets used to build the proposed methodologies in this research. A general overview of how fuzzy sets are used in solving MCDM problems and what makes them appropriate tools for solving these problems are given.

Chapter 5 is devoted to explain the proposed MCS methodology, PROMSORT. By means of a financial classification example, characteristics and features of the methodology are illustrated and the results of the methodology are compared with the results of other similar MCS methodologies. The development of an extended version of proposed methodology based on fuzzy sets is also discussed in Chapter 5. Additionally, in Chapter 5, a basic software coded in Visual Basic 6.0 that allows decision maker to sort alternatives into the predefined ordered classes by using PROMSORT methodology is presented.

In Chapter 6, the proposed supplier evaluation and management system that utilizes PROMSORT in assessing, classifying and monitoring suppliers is presented. The proposed approach is illustrated by the case of strategic supplier selection in the new product development phase. The robustness of PROMSORT methodology is also investigated by using the case problem.

Chapter 7 proposes an integrated MCDM methodology for outsourcing management that incorporates PROMSORT and IFGP approaches for the selection of strategic partners and order allocation. An illustrative case study on testing and benchmarking the proposed methodology is also presented and in-depth discussion and analysis of the results are given.

Chapter 8 contains the concluding remarks of this research and identifies future research directions.

CHAPTER TWO
SUPPLY CHAIN MANAGEMENT AND STRATEGIC SOURCING

2.1 Introduction

Purpose of this chapter is three-fold. The first purpose is to provide an overview of supply chain management (SCM). The second purpose is to explain the strategic sourcing and to emphasize the importance of suppliers' involvement on new product development and the reduced number of suppliers on effective sourcing strategies. This chapter also reviews the key criteria used in the literature on supplier selection. The last purpose of this chapter is to present a detailed review on supplier selection and evaluation methods that exist in the literature.

This chapter is further organized as follows: Firstly, it introduces the basics of SCM starting with a definition of supply chain and SCM and emphasizes the role of sourcing decisions in a supply chain. Section three describes the general structure of strategic sourcing in detail. The design collaboration, supply base reduction and determination of supplier selection criteria decisions underlying the strategic sourcing concept are also discussed in greater detail. In section four, the literature review on methods in support of supplier selection is given. Section 5 sums up our findings and presents a general overlook on the gap in the existing literature, the research questions to be studied on this research and the expected contribution of this research to the purchasing literature.

2.2 Supply chain management – An overview

In today's highly competitive and global operating environment, due to the high variety of customer demands, advances in technologies and the increasing importance of communication and information systems companies have been forced to focus on SCM (Andersen and Rask, 2003). A supply chain consists of two or more separated organizations which include not only manufacturer and suppliers but also transporters, warehouses, retailers and customers.

The SCM literature presents different definitions of supply chain as follows:

For Christopher (1998), "*a supply chain is a network of organizations that are involved, through upstream and downstream linkages, in the different process and activities that produce value in the form of products and services in the hands of the ultimate customer*".

As stated by Beamon (1998), "*a supply chain is an integrated process wherein a number of various business entities work together in an effort to: (i) acquire raw materials/components, (ii) covert these raw materials into final products, (iii) deliver these final products to retailers*".

In the light of these definitions, some researchers express the term SCM in different ways. According to Stadtler (2002, p.9), the term SCM can be defined as *"the task of integrating organizational units along a supply chain and coordinating material, information and financial flows in order to fulfill (ultimate) customer demands with the aim of improving competitiveness of a supply chain as a whole"*. As stated by Wang et al. (2004, p.1), "*SCM is the use of information technology to endow automated intelligence to the planning and the flow of supply chain to speed time to market, reduce inventory levels, lower overall costs and, ultimately, enhance customer service and satisfaction*".

As mentioned above, a typical supply chain may involve a variety of stages and the structure of most supply chains can be described as shown in Figure 2.1. It is obvious that a supply chain need not contain all stages or contains an extra stage.

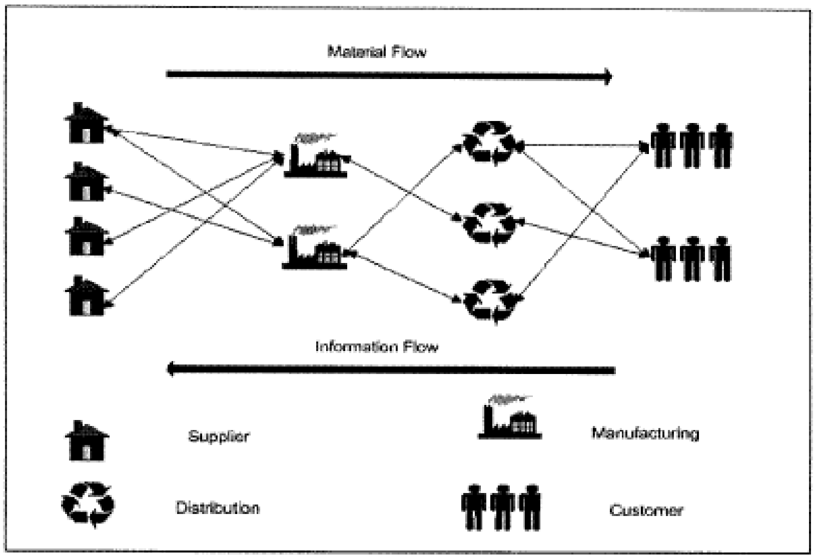


Figure 2.1 Supply Chain Stages (Chuang, 2004, p. 5)

Regardless of which member of supply chain is involved, the primary purpose for the existence of any supply chain is to meet the customer demands in the process of generating maximum value for itself (Chopra and Meindl, 2004). The objectives of every supply chain are to maximize the overall value generated and to increase the competitiveness of whole chain. Competitiveness can be improved in many ways, e.g., by reducing costs, increasing flexibility with respect to changes in customer demands or by providing superior quality of products and services (Stadler, 2002). In order to achieve these objectives, the appropriate management of all flows of information, product, or funds, which generate costs within the supply chain, is a key action and requires many decisions (Chopra and Meindl, 2004). These decisions are discussed in the next sub-section.

2.2.1 Planning tasks and decision phases along the supply chain

The whole supply chain network can be divided into interval supply chains for every partner in the network, each consisting of four main supply chain processes with substantially different planning tasks and decisions (Fleischmann et al., 2002):

- Procurement,

- Production,
- Distribution,
- Sales.

Procurement process provides all resources (e.g. materials, personnel etc.) necessary for production. The limited capacity of the resources is the input of the production process. The distribution process includes sub processes, such as order management, warehouse management, transportation management, which ensure the moving of products from manufacturer to customers. All of these processes requires demand forecast determined by sales process as inputs (Fleischmann et al., 2002).

Successful management of all processes require many decisions which are usually classified three decision phases depending on the frequency of each decision and the time frame over which a decision phase has an impact (Chopra and Meindl, 2004). Rodhe et al. (2000) classify the planning tasks and decisions in the two dimensions "planning horizon" (decision phases) and "supply chain process" using a matrix representation named as the *Supply Chain Planning Matrix* (SCP-Matrix). SCP-Matrix (see Figure 2.2) illustrates typical tasks which take place in most supply chain types, but with various contents in the particular businesses (Fleischmann et al., 2002).

Strategic planning deals with the decisions about the supply chain structure over the next several years. These decisions typically concern the design and structure of a supply chain and have long-term effects, noticeable over several years (Fleischmann et al., 2002). Examples of strategic planning decisions include, but not limited to:

- "*site selection*(Ganeshan et al.,2002),
- *new product introductions* (Ganeshan et al.,2002),
- *decisions on new production/distribution decisions* (Ganeshan et al.,2002),
- *the modes of transportation to be made available along different shipping legs* (Chopra and Meindl, 2004, p.7),

- *the type of information system to be utilized* (Chopra and Meindl, 2004, p.7),
- *long-range sales planning* (Fleischmann et al., 2004),
- *supplier evaluation and qualification* (Fleischmann et al., 2004),
- *strategic cooperation with suppliers of A-class items*" (Fleischmann et al., 2004).

Tactical planning reflects decisions for a time frame from a quarter to a year. Since the higher level (strategic planning) decisions have already been determined, the tactical level decisions (Ganeshan et al., 2002):

(i) *"should focus on the implementation of strategic decisions,*

(ii) *are functional in nature, and may deal with only a few players in the overall chain,*

(iii) *may involve systems necessary to manage the supply chain*."

In the tactical planning phase, the decisions made by the companies include, but not limited to,

- "*which market will be supplied from which locations* (Chopra and Meindl, 2004, p.7),
- *the subcontracting of manufacturing* (Chopra and Meindl, 2004, p.7),
- *the inventory policies to be followed* (Chopra and Meindl, 2004, p.7),
- *forecasting the potential sales for product groups* (Fleischmann et al., 2002),
- *the planning of transports between the warehouses and determination of the necessary stock levels* (Fleischmann et al., 2002),
- *basic agreements with strategic suppliers on the price, the total amount and other conditions for the materials to be delivered during the next planning horizon"* (Fleischmann et al., 2002).

The lowest planning level, which is operational planning, has to identify all activities as detailed instructions for instantaneous implementation and control. The planning horizon is between a few days and three months (Fleischmann et al., 2002). Planning phase includes decisions regarding (Chopra and Meindl, 2004, p.7):

- *"allocation of inventory or production to individual orders,*
- *setting a date that an order is to be filled,*
- *allocating an order to a particular shipping mode and shipment,*
- *placing replenishment orders".*

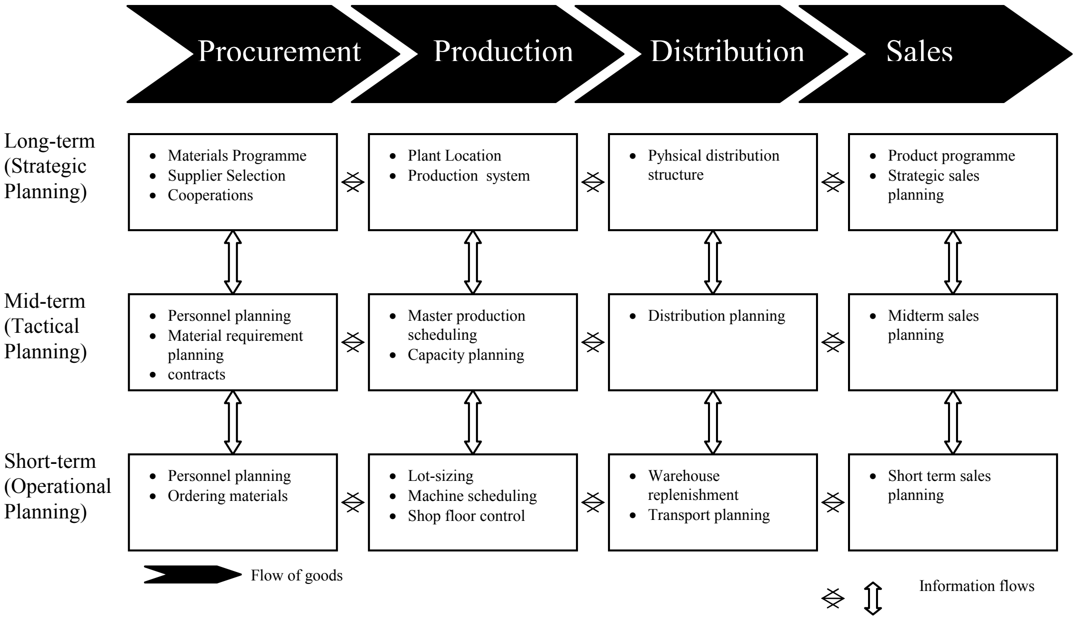


Figure 2.2 The Supply Chain Planning Matrix (Fleischmann et al., 2002, p. 77)

2.2.2 The role of sourcing decisions in a supply chain

Like any other chain structure, a supply chain is only as strong as its weakest link. Total performance of entire supply chain can only be enhanced when all links in the chain are simultaneously optimized (Burke, 2005). Procurement, also known as purchasing, is one of these important links. Chopra and Meindl (2004) defines the purchasing as a process by which companies acquire raw materials, components, products, services, and other resources from suppliers to execute their operations. On the other hand, they define sourcing as the entire set of business processes required to purchase goods and services. With the increasing significance of Just-in-Time (JIT) philosophy, purchasing has become a vital function for a supply chain. In today's global and open innovation economy, it is almost impossible to achieve a competitive position in the market, to reduce the overall cost of the chain and to increase the responsiveness of the chain without well-managed sourcing decisions. As has been stated in the previous section, the sourcing decisions have to be made in each phase of the supply chain decisions: strategic, operational and tactical.

Sourcing processes involve several main steps as shown in Figure 2.3 (Chopra and Meindl, 2004):

- the selection of suppliers,
- design of supplier contracts,
- product design collaboration,
- procurement of material,
- the evaluation of supplier performance.

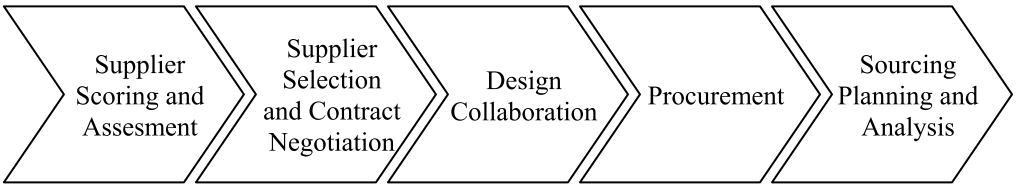


Figure 2.3 Key sourcing related processes (Chopra and Meindl, 2004, p. 388)

Besides these steps, Aissaoui et al. (2006) included a new initial step named as 'make or buy'. As shown in Figure 2.4, 'make or buy' is defined as a step in which a company would decide on whether a certain part or service should be 'produced' internally or outsourced. They use the term 'outsourcing' for the case when a finished/semi-finished part or service is being procured and the term 'purchasing' for the case when a raw material is being procured. In the outsourcing, suppliers carry out processes that add value to the item (Aissaoui et al., 2006). If it is assumed that company has already determined which parts or services should be purchased or outsourced, the remaining processes of searching the appropriate suppliers for both of purchasing and outsourcing cases are the same. Therefore, as in supplier selection literature, purchasing and outsourcing terms are used interchangeably in the remaining of the thesis.

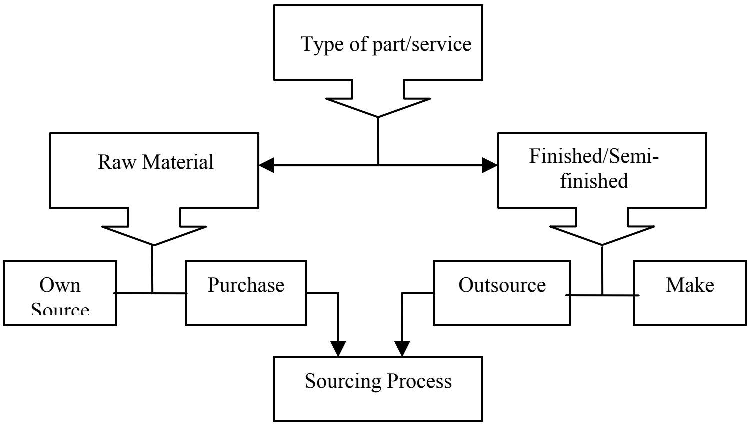


Figure 2.4 Purchasing and Outsourcing (Aissaoui et al., 2006)

Chopra and Meindl (2004) explain the steps in sourcing process as follows. The objective of supplier scoring and assessment is to rate supplier performance. These ratings are used to select most suitable suppliers. A supply contract is then negotiated with the selected suppliers. It is crucial that the selected suppliers should be actively involved at product design stages. Once the product has been designed, procurement is the process in which supplier sends product in response to orders placed by the buyer. Finally, continuous evaluation of the performance of selected suppliers is needed to identify opportunities for decreasing the total cost (Chopra and Meindl, 2004).

Effective strategic sourcing decisions contribute the effective SCM in a variety of ways. Researchers have frequently emphasized the benefits of effective strategic sourcing decisions, including, but not limited to, (Bonaccorsi and Lipparini, 1994; De Toni and Nassimbeni, 2001; Talluri and Narasimhan, 2004; Chen et al., 2005; Valk and Wynstra, 2005):

- reduce the cost of total supply chain,
- help to achieve sustainable competitive advantage,

- ensure fast project development times,
- increase economies of scale based on order volume and the learning curve effect,
- improve communication within supply chain,
- reduce development and product cost,
- increase the level of motivation of suppliers,
- increase supplier originated innovation and better product quality,
- etc.

Traditionally, companies are formed their sourcing strategy based on price of the product with the purpose of obtaining the lowest possible price in the short run, ignoring the fact that suppliers may differ on other important dimensions that impact the total cost of using a supplier (Freytag and Kirk, 2003; Chopra and Meindl, 2004). In the light of the aforementioned benefits, it is clear that short-term and price focused sourcing strategy is too narrow, and that a more effective sourcing strategy, in which a long-term relationship with fewer but better suppliers is preferred and suppliers are wanted to involve in product development activities, is needed. Hence companies should continuously develop a sourcing strategy that involves the strategy of supply base reduction and long-term supplier relationships development (Sarkar and Mohapatra, 2006). In the next section, we explain strategic sourcing process in greater detail.

2.3 Strategic sourcing in supply chain

As has been stated above, strategic sourcing strategy is one of the most vital actions of companies in a supply chain. Selecting the wrong sourcing strategy or managing it badly could be enough to deteriorate the whole supply chain's financial and operational position. In today's competitive and global business environment, it is impossible to improve supply chain performance without well-managed sourcing strategy.

In the mid-1980s, buyer supplier relationships tended to rely on arms-length agreements based on market prices, while relations in the 1990s were based on trust derived from collaboration and information sharing (Choy et al., 2005). With the growing importance of sourcing strategy as an essential step of supply chain improvement, many companies are adopting the sourcing strategies that allow developing long-term relationship with their suppliers (Andersen and Rask, 2003). Figure 2.5 shows the evolution of strategic sourcing within the last century.

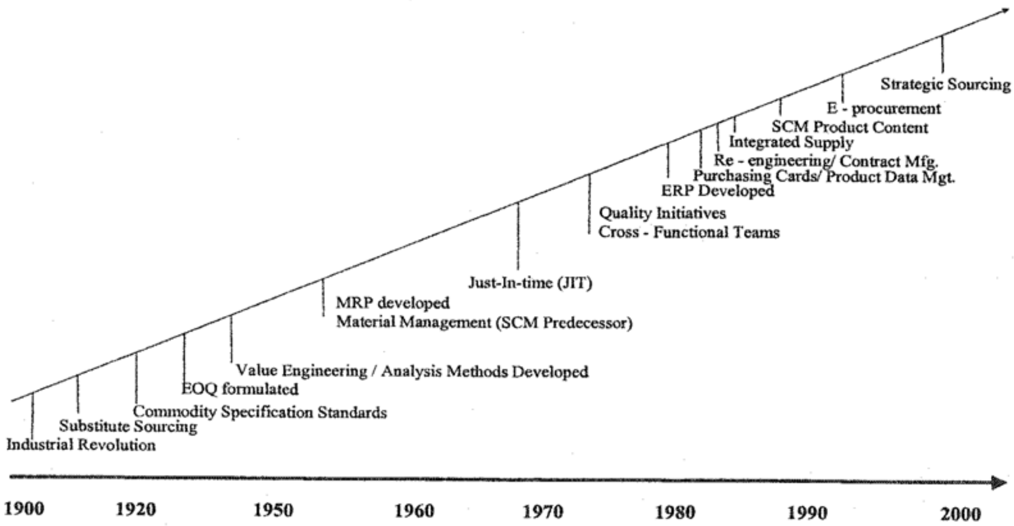


Figure 2.5 Evolution of strategic sourcing (Choy, 2004, p.38)

Over the past several years, with the recent trend on JIT manufacturing philosophy, there is an emphasis on strategic sourcing that establishes long-term mutually beneficial relationship with fewer but better suppliers. (Vokurka et al., 1996; Talluri and Narasimhan, 2004; Prahinski and Benton, 2004). This long term expectation developed between the manufacturer and suppliers can provide the opportunity for improving performance (Choy et al., 2003). As companies are increasingly outsourcing more and more activities to suppliers in order to focus their core competences, the suppliers are pushed to co-operate (Choy et al., 2005).

The long-term buyer and supplier relationships have received much attention from practitioners and researchers who frequently emphasize the necessity of integration between supply chain members. Dowlatshahi (2000) noted that, at the strategic level, the focus should be on the strategic development of suppliers and the crucial financial and confidential relationships with suppliers. They also indicated that the confidential partnership cannot be realistically developed and maintained if the relationship is short-term, limited, or a one-time event. Sheth and Sharma (1997) highlighted that the developing long term relationships with suppliers is critical for functioning of firms. Talluri and Narasimhan (2004) reported that strategic sourcing that establishes a long-term relationship with suppliers has become even more important and vital for enhancing organizational performance and strategic relationship with suppliers is a key ingredient to the success of a supply chain. Shin et al. (2000) stated that, through a well-developed long-term relationship, a supplier becomes part of a well-managed supply chain and it will have a lasting effect on the competitiveness of the entire supply chain. Chopra and Meindl (2004) pointed out that a long-term relationship encourages the supplier to expend greater effort on issues that are important to a particular buyer and improves communication and communication between two parties.

Strategic sourcing decisions are generally related with evaluating and selecting the potential strategic suppliers that can effectively meet the long-term expectations of companies, developing and implementing the strategic partnership with these suppliers by involving in supplier development programs to increase supplier performance and providing continuous feedback to the suppliers (Talluri and Narasimhan, 2004).

In order to develop collaborative, long-term, strategic relationships with suppliers, three crucial interconnected decisions should be realized:

- supplier involvement in product development,
- supply base reduction and development,
- determination of supply source selection criteria.

2.3.1 Supplier involvement in product development

After 1980s, with the increasing global competition, changing customer requirements and technological changes were forced the firms to be more and more innovative. Innovation is a critical strategic process central to the development of competitive advantage (Croom, 2001). In response to these pressures, the firms needed to acquire new scientific and technological knowledge from outside organizations (Chung and Kim, 2003). Active involvement of both manufacturing and supplier on product development project teams and pulling suppliers into a manufacturer's workplace are frequently offered by researchers as one of the important tools to solve these challenges (Maffin and Braiden, 2001; Chung and Kim, 2003).

Chopra and Meindl (2004) reported that it is generally accepted that about 80 percent of the cost of a product is determined during design and thus, it is vital for a manufacturer to collaborate with suppliers during the design stage if product costs are to be kept low. Various benefits of design collaboration between manufacturers and suppliers have been reported:

- *Reduced development costs:* Chopra and Meindl (2004) reported that suppliers' involvement at design stage can lower the cost of purchased material and also lower logistics and manufacturing costs. If manufacturer gives greater responsibility for design activities of logistics, supplier's helps may reduce transportation, handling, and inventory costs during distribution. They also emphasized that active involvement of suppliers in design for manufacturing (DFM) and design for assembly (DFA) activities can reduce manufacturing costs. Bonaccorsi and Lipparini (1994) stated that, by anticipating the involvement of suppliers in the innovative process, all firms can reduce their development costs. In this direction, they listed some relevant points as follows:

    - Early availability of prototypes,
    - Standardization of components,
    - Providing the design team with alternative technical proposal,

  - Ensuring the consistency between design and suppliers' process capabilities,
  - Reduced engineering changes.

  The importance of supplier involvement in product development on cost reduction have also emphasized by some other researchers: Wynstra et al. (2001), Chung and Kim (2003), De Toni and Nassimbeni (2001) etc.

- *Reduced product development time*: Several researchers have stated that suppliers can reduce product development time. De Toni and Nassimbeni (2001) stated that one of the preliminary advantages of early involvement of suppliers in design stage is that the time to market can be shortened. Chopra and Meindl (2004) indicated that collaborative partnership with suppliers in design phase can significantly speed up product development time. Bonaccorsi and Lipparini (1994) have reported that the early involvement of suppliers in new product development (NPD) helps to reduce the time to market by ensuring collaboration with suppliers in concurrent engineering practices, identifying the technical problems earlier, and reducing the suppliers' process engineering time.

- *Improved product quality*: Purchasing literature is generally agree on the fact that manufacturers may have an opportunity to improve the product quality by combining supplier's technical capability and enhancing their drawbacks with their suppliers (Chopra and Meindl, 2004). Chopra and Meindl (2004) stated that integrating the supplier into product development stage allows the manufacturer to focus on system integration, and it results in a higher quality product at lower cost. It is also clear that the early identification of technical problems leads to higher quality with fewer defects (Bonaccorsi and Lipparini, 1994).

- *Increased innovation*: It is clear that the innovation capability of a manufacturer is highly depend on its suppliers' technical ability. The use

> of technically competent suppliers in design stages creates opportunities to increase the innovation capability of manufacturers. Incorporating suppliers on design teams enhances the information and expertise regarding new ideas and technology (Humspery et al., 2005). Chung and Kim (2003) stated that manufacturers can create stronger competitive synergies by combining supplier's technical know-how and supplementing their weak points with their suppliers having a common cooperative goal.

Besides these major advantages, some researchers have emphasized additional benefits of the involvement of suppliers in design stages, such as increased level of motivation of suppliers (De Toni and Nassimbeni, 2001), reduced internal complexity of projects, improved communication and information exchanges (Humspery et al., 2005), improved market adaptability and reduced market risks (Chung and Kim, 2003) etc.

Although the importance of suppliers' contribution in product development stages have highlighted in the literature, the literature have also frequently emphasized that the success of involving suppliers in product development depends on the suppliers' design based capabilities and practices. Primo and Amundson (2002) stated that poor supplier performance can have negative effects. Ideally, manufacturers will try to select for involvement the suppliers that do have sufficient knowledge and skills (Wynstra et al., 2001). Therefore, concurrent design teams should select the suppliers that can effectively meet the varying conditions from the perspective of new product development, design, manufacturing processes and manufacturing capability (Talluri and Narasimhan, 2004). In other words, the supplier selection decision needs to incorporate design criteria into the assessment process (Humphreys et al., 2005). The design based criteria used in supplier selection problems will be briefly discussed in the following sections.

2.3.2 Supply base reduction

In strategic sourcing, besides long-term strategic relationship and suppliers' involvement in product development and design, reduction of supplier base should be one of the main tasks of purchasing teams. As an emerging management philosophy of today's global environment, JIT offers purchasing strategies in which the long-term strategic relationships are developed with a reduced number of suppliers. Some researchers underlined the main reasons to reduce the number of suppliers. Shin et al. (2000) listed several important factors have caused the current shift to a reduced supply base:

- Multiple sourcing prevents suppliers from achieving the economies of scale based on order volume and learning curve effect,
- Multiple sourcing can be more expensive and lowers overall quality level because of the increased variation in incoming quality among suppliers,
- A reduced suppliers base helps eliminate mistrust between buyers and suppliers due to lack of communication,
- Worldwide competition forces firms to find the best suppliers in the world.

Dowlatshahi (2000) emphasized in his paper that the long-term partnership and design collaboration should be the main concern of firms and stated that purchasing teams should reduce the number of suppliers in every part category to establish long-term partnerships and strategic alliances. In this direction, Dowlatshahi (2000, p.117) listed three main reasons to reduce the number of suppliers:

- "*supplier development is costly – so suppliers must be limited to a manageable number,*
- *a close and long-term relationship is only achievable with a limited number of suppliers,*
- *suppliers can be expected to be involved in the developmental efforts of concurrent design teams only when the number of suppliers is reduced*".

Many researchers have pointed out the importance of reduced supply base. Vokurka et al. (1996) stated that closer and more collaborative ties can only be maintained if firms work with a reduced set of suppliers and firms should abandon old habits such as having multiple suppliers for products and seeking multiple bids for purchases. Chuang (2004) pointed out that the reduction of supplier base is considered as a step towards strategic purchasing. However, little research has been devoted on how to reduce the supplier base (Chuang, 2004). As stated before, strategic sourcing methodologies proposed in this thesis helps purchasing teams in making decisions about reduction of supply base by sorting the suppliers into classes based on performances. By this way, it aims to fill the gap existing in supply chain literature.

2.3.3 Supply source selection criteria

Supplier selection decisions are complicated by the fact that various criteria must be considered in the decision making process (Choy et al., 2002). In one of the pioneer works on supplier selection, Dickson (1966) identified 23 supplier criteria used for selecting a supplier. Dickson indicated that cost, quality, and delivery performance were the three most important criteria in supplier selection process. In a wide-ranging review of supplier selection methods, Weber et al., (1991) reported that quality was considered to be the most important selection criterion. The quality is followed by delivery and cost.

In today's global and open innovation economy where concurrent product and supplier development are often the rule, strategic supplier selection and evaluation decisions must not be solely based on traditional selection criteria, such as cost, quality and delivery. Up to date, the criteria for assessing supplier performance in the supplier selection process have been widened (Choy et al., 2005). A comprehensive list of supplier selection criteria can be found in the recent work of Huang and Keskar (2006).

With the increasing significance of strategic sourcing and competition of global environment, the approach to traditional criteria has been changed to reflect the new requirements according to the role of suppliers in the supply chain (Choy et al., 2005). Strategic evaluation of suppliers requires consideration of supplier practices (managerial, quality and financial etc.) and supplier capabilities (co-design capabilities, cost reduction capabilities, technical skills, etc.) (Dowlatshahi, 2000; Talluri and Narasimhan, 2004).

In strategic sourcing, many other criteria should be considered with the aim of developing a long-term supplier relationship, such as quality management practices, long-term management practices, financial strength, technology and innovativeness level, suppliers' cooperative attitude, supplier's co-design capabilities, and cost reduction capabilities, information coordination capabilities, supplier viability (Mandal and Deshmukh, 1994; Dowlatshahi, 2000; De Toni and Nassimbeni, 2001; Choy et al., 2002; Dulmin and Mininno, 2003; Choy et al., 2003; Talluri and Narasimhan, 2004; Chopra and Meindl, 2004).

Due to the importance of concurrent engineering and supplier involvement in product development, several works are focused on suppliers' design capability in assessing the performance. Dulmin and Mininno (2003) define the co-design criteria as supplier's effort within the project team. In another work, De Toni and Nassimbeni (2001) present a framework for the evaluation of supplier's co-design effort. They suggest capabilities in co-design activities, most of them are concurrent engineering techniques, offered by suppliers in the development stages as evaluation criteria such as support in product simplification, support in component selection, and support in DFM / DFA activities etc. It has been stated in the literature that the use of these techniques lead to substantial improvement in quality, cost and delivery performance (Maffin and Braiden, 2001; De Toni and Nassimbeni, 2001; Talluri and Narasimhan, 2004). Hence, it is essential to consider these factors in supplier evaluation.

2.4 Methods in support of supplier selection

Supplier selection and evaluation is one of the most critical activities of companies, since supply performance can have a direct financial and operational impact on the business (Croom, 2001). Because of its increasing importance, supplier selection and evaluation have received a lot of attention in the literature. Many methods have been suggested for supporting supplier selection decisions.

Some researchers have tried to give an overview of the different supplier selection problems and methods: (Weber et al., 1991; Degraeve et al., 2000; De Boer et al., 2001; Aissaoui et al., 2006). Weber et al. (1991) studied on 74 articles and classified them in terms of the criteria used in the selection process, the decision environment and the methods used in the study. Degreave et al. (2000) reviewed some vendor selection models and used the total cost of ownership (TCO) approach to compare them. De Boer et al. (2001) presented a review of decision models reported in the literature for supporting the supplier selection process. They dealt with all supplier selection process, rather than only focusing the ultimate supplier selection stage. De Boer et al. (2001) reported that a supplier selection problem typically consists of four phases:

- problem definition,
- formulation of criteria,
- qualification of suitable suppliers (or Pre-qualification),
- final selection.

They explained all the stages in detail and classified the articles reviewed with regard to abovementioned stages. Recently, Aissaoui et al. (2006) have presented a new review paper which extends and updates previous reviews. Although, all stages are investigated in their study, they give more attention to the final stage especially in multiple sourcing contexts.

In the problem definition phase, the following questions should be answered (De Boer et al., 2001): “what is the ultimate problem?” and “why does selecting one or more suppliers seem the best way to handle it?”. On the other hand, formulation of criteria phase deals with obtaining suggestions as to which criteria to use in a particular situation (De Boer et al., 2001). Regarding available methods, there is a lack in the purchasing literature for the problem definition and the formulation of criteria. In their review paper, De Boer et al. (2001) didn't mention any method about the problem definition phase, while only following two studies were presented for the formulation of criteria phase: Mandal and Deshmukh (1994) and Vokurka et al. (1996).

Contrarily to the problem definition and formulation of criteria phases, pre-selection and final selection phases have received much attention from the purchasing literature. However, it should be noted that the vast majority of the models developed deals with the final selection of suppliers. In the next sub-sections, we will explain both stages in detail and review the decision models available at present.

2.4.1 Pre-selection of potential suppliers

As stated before, today manufacturers are taking more attention to JIT management philosophy in order to gain a competitive advantage in global markets. JIT philosophy generally imposes some requirements on suppliers including long-term relationships with a reduced number of capable suppliers (Tsai, 1999). De Boer et al. (2001) define the pre-selection step as "sorting" process rather than "ranking" process. Despite of the its increasing importance, the decision models dealt with reducing the set of all suppliers to a smaller set of acceptable suppliers have received far less attention from researchers than the models used in final selection of suppliers. The most of the pre-qualification models in the literature can be classified into four categories (De Boer et al., 2001): elimination methods, categorical methods, cluster analysis (CA), and data envelopment analysis (DEA).

In the elimination methods, some selection rules are determined by defining so-called thresholds (i.e. minimum quality standards, maximum price for parts) or on/off variables (i.e. presence or absence of quality certifications). Then the suppliers that do not satisfy the predefined selection rules are pruned from the supply base. Aissaoui et al. (2006) only mentioned two studies that use elimination methods: Crow et al. (1980) (conjunctive rule) and Wright (1975) (lexicographic rule). In the conjunctive rule, decision maker determines a minimal threshold for each criterion. If a supplier cannot satisfy one of these requirements, it is eliminated. On the other hand, the lexicographic rule requires the determination of priority structure of the criteria selected. Suppliers are firstly compared with respect to the criterion which has highest priority. If we find suppliers that outperform other suppliers with respect to this criterion, these are selected. Otherwise, the remaining criteria are taken into consideration.

Categorical method (see Timmerman (1986)) is one of the simplest decision models in the purchasing literature. In this method, buyer evaluates its suppliers on a set of criteria by assigning some categorical terms such as “positive”, “neutral” or “negative”. Considering all evaluation matrix, buyer gives a final rating using the same categorical terms to each of the suppliers. In this way, suppliers are categorized into three classes (De Boer et al., 2001). It should also be noted as drawbacks that the categorical methods imply a high-level of subjectivity and do not take the criteria weights into consideration (Tsai, 1999).

Clustering algorithms try to regroup the alternatives into classes in order to make the distances between the alternatives within a same class the shortest and the distances between the different classes the longest (Leger and Martel, 2002). Hinkle et al. (1969) reported that CA can be utilized to categorize the suppliers into homogenous classes. Holt (1998) stated that the use of CA can be very beneficial in the pre-selection of suppliers. However, it should be noted that CAs are distance based and do not allow multi-criteria evaluation of suppliers. Additionally, although it is possible to specify the number of categories priori, we cannot fix the number of suppliers to be selected for strategic partnership (Sarkar and Mohapatra, 2006).

DEA is a multi-factor analysis tool that measures the relative efficiencies of a set of alternatives. In supplier selection problems, the input factors (e.g. supplier capabilities) and output factors (performance metrics) are considered effectively in evaluating the efficiency scores of suppliers (Talluri and Narasimhan, 2004). The efficiency score of a supplier is defined as the ratio of the weighted sum of its outputs to the weighted sum of its inputs. For each supplier, the DEA method finds the most favorable set of weights. In this way it helps to classify the supplier as the efficient suppliers and inefficient suppliers (De Boer et al., 2001).

Only few works have used DEA in support of supplier selection. Weber and Desai (1996) used DEA to measure the vendor performance and efficiency. In order to display the efficiency of vendors on multiple criteria, parallel coordinates graphical representation was used. By means of a JIT purchasing example, they showed that the proposed approach can flexibly be used to negotiate with inefficient vendors. Then Weber et al. (1998) have combined multi-objective programming (MOP) and DEA in order to select and negotiate with vendors who were not selected. Liu et al. (2000) extended the work of Weber and Desai and evaluated different suppliers for an individual product using DEA. More recently, Talluri and Narasimhan (2004) proposed a methodology for strategic sourcing, which considers multiple strategic and operational factors in the supplier evaluation process. They utilized a combination of DEA to categorize the suppliers into groups and investigated the differences among supplier groups.

About the disadvantages of DEA based methods, Sarkar and Mohapatra (2006) stated that the suppliers with the highest efficiency score have relatively the best performance with the least long-term capability, since DEA tries to maximize the relative output-input measure. They also pointed out that this makes DEA questionable because the supply base reduction process, with the aim of establishing long-term relationship, should select suppliers who are both highly capable and high performers.

Case-based reasoning (CBR), which is one of the well-known artificial intelligence (AI) techniques, has also been applied to supplier selection problems by some researchers. Two of them deal with the pre-qualification of suppliers. Ng et al.

(1995) proposed a CBR based decision support system (DSS) for the pre-qualification of suppliers. More recently, Choy et al. (2005) presented a case-based supplier selection and evaluation system in which the potential suppliers are evaluated and categorized based on suppliers' past practices into two classes: collaborative and competitive. Despite of its strong ability to differentiate the suppliers, the main drawback of CBR techniques is that it requires a set of samples sometimes impossible to obtain (Sarkar and Mohapatra, 2006).

In a recent paper, Sarkar and Mohapatra (2006) develop a systematic framework for carrying out the supply base reduction process. In order to deal with uncertainty and imprecision involved in performances of suppliers, they use fuzzy set approach to rank a potential list of suppliers against their performance and capability. The suppliers in decreasing order of preference are determined by using a 'capability–performance matrix'. Finally, the desired numbers of suppliers are selected on the basis of this ordered list. In their study, Sarkar and Mohapatra (2006) classify suppliers into three classes: motivated, demotivated and balanced.

2.4.2 Final selection of suppliers

As stated earlier, the vast majority of the researches on the purchasing literature have been devoted to solve final supplier selection problem. De Boer et al. (2001) stated that it is not very surprising because the final choice phase is the most visible one in the purchasing process. Therefore, up to date, numerous decision models have been developed and presented for the final choice phase. The methods used can be categorized in different ways such as "single criterion or multiple criterion", " single sourcing or multiple sourcing", " inventory management considered or not", etc. In the remaining subsections of this chapter, we will distinguish the models with regard to the specific technique used in modeling the problem. Specific comments on the papers about the aforementioned properties will also be provided.

2.4.2.1 Linear Weighting Methods and Outranking Techniques

In linear weighting models, a weight is assigned to each criterion in order to distinguish between criteria with different importance. The suppliers' grades are multiplied by these weights and a weighted score is computed for each. The higher the weighted score, the better the supplier (De Boer et al., 2001). Simple multiattribute rating technique (SMART) is one of the simple linear weighting techniques. In a recent study, Olson (2006) suggests the use of SMART technique in selecting ERP outsourcing strategy. He states that formal cost evaluation methods are difficult to apply in such a decision involves significant risks while a linear weighting methods, in this case SMART, can be efficiently used to support this critical decision. Aissaoui et al. (2006) pointed out that linear weighting method is also suitable for the pre-selection phase of suppliers by choosing a set of supplier having the highest scores. The vast majority of the linear weighting methods are used to solve the single sourcing problems.

Analytical hierarchy process (AHP) (Saaty, 1980) is a linear weighting technique that has been most frequently applied to the supplier selection problem. Some publications which firstly utilize AHP in supplier selection are: (Narasimhan, 1983; Nydick and Hill, 1992; Barbarosoglu and Yazgaç, 1997). Up to date, many researchers have used AHP in the supplier selection process.

Yahya and Kingsman (1999) proposed a vendor rating approach based on AHP. They also described a case study into vendor rating for a government sponsored Entrepreneur development program in Malaysia. Massella and Rangone (2000) proposed four different vendor selection systems depending on the time frame (short-term or long-term) and the content (logistic or strategic) of the cooperative customer/supplier relationship based on AHP.

Lee et al. (2001) presented a systematic framework that can help in managing the suppliers and in supporting with the managerial criteria identified during the supplier selection process. The managerial criteria for each part and each supplier are determined according to the results of AHP analysis. Tam and Tummala (2001) presented an AHP-based model in order to solve vendor selection problem of a telecommunications. A real case study was presented to examine the feasibility of the proposed methodology. They tried to show that AHP can be very useful in the group decision-making process.

In order to systemize the processing steps before the implementation of AHP such as the determination of buyer-supplier relationship and formulation of selection criteria, an interactive selection model was proposed by Chan (2003). Liu and Hai (2005) proposed a new procedure in place of AHP's paired comparison in order to drive the weights to be used and score the performance of suppliers. Jharkharia and Shankar (2006) proposed a comprehensive methodology for the selection of a logistic service provider based on analytic network process (ANP), which is a more sophisticated version of AHP.

Although AHP has received much more attention than any method used, researchers who study on operations research frequently discusses the some features of it such as the limitations of 9 point scale, difficulties on the paired comparison step etc. Therefore, some authors utilized different multi-criteria decision making (MCDM) methods in support of supplier selection. Dulmin and Mininno (2003) stated that, like other linear weighting techniques, AHP is fully compensatory. As reported in (De Boer et al., 1998) in many real-world supplier selection problems the full comparability between any two alternatives might not always be very realistic. Suppose supplier a scores much better than supplier b on all criteria except j^{th} criterion. De Boer et al., (1998) indicated that it is not necessarily true that the decision maker accepts that good scores on almost all criteria are worth the difference with respect to criterion j.

Contrary to linear weighting methods, outranking techniques are only partially compensatory. As reported in (Dulmin and Mininno, 2003), outranking techniques are particularly suitable to resolving problems of supplier selection, because of their ability to deal with qualitative and quantitative variables, to manage compensatory effects and understand relations between criteria. To our knowledge, there are four important applications of outranking methods - ELECTRE (De Boer et al., 1998;

Almeida, 2006) and PROMETHEE (Dulmin and Mininno, 2003; Wang and Yang, 2006) in supplier selection.

De Boer et al. (1998) discussed about the application of outranking methods in supplier selection problem. One specific outranking method, ELECTRE, was discussed and used. They have illustrated it with an example of supplier selection that an outranking approach may be very well suited as a decision making tool for the initial purchasing decisions.

Almeida (2006) utilized ELECTRE approach to the contract selection problem of service outsourcing. In the proposed approach, using utility theory each criterion is represented by a utility function, incorporating the probabilistic structure of the problem. Then, theses utility functions are integrated into the ELECTRE framework in order to obtain multi-criteria evaluation within a non-compensatory approach.

Dulmin and Mininno (2003) tried to explain how an outranking method, in this case PROMETHEE technique, provides powerful tools to solve supplier selection problems. In their model, PROMETHEE integrated with a Monte Carlo simulation to generate weights at random and a high dimensional sensitivity analyses were performed. They have illustrated it with an example that the model presented seems to be additional tool inside the final choice phase of a supplier selection process.

Wang and Yang (2006) propose a hybrid MCDM method for the information system (IS) outsourcing. The proposed method integrates two well known MCDM methods, AHP and PROMETHEE. AHP method is used to analyze the structure of the outsourcing problem and determine the weights of criteria, and the PROMETHEE method is used for final ranking, together with changing weights for a sensitivity analysis. They try to show by means of an application that the hybrid method is very well suited as a decision-making tool for the IS outsourcing decision.

In linear weighting methods, deriving the criteria weights is a crucial step. A variety of different statistical techniques have been suggested in order to obtain the weights of criteria. In the surveys proposed by De Boer et al. (2001) and Aissaoui et al. (2006), three applications which have the same propose are mentioned: Williams (1984), Min (1994) and Petroni and Braglia (2000).

2.4.2.2 Mathematical programming models

Mathematical programming (MP) allows the decision maker to formulate the decision problem in terms of mathematical objective function that wants to be maximized (e.g. maximize profit) or minimized (e.g. minimize cost) subject to the predefined constraints (e.g. capacity of supplier X) by vary the values of variables in the objective function (e.g. the amount ordered with supplier X) (De Boer et al., 2001). MP models have received a lot of attention from the purchasing literature. Aissaoui et al. (2006) divide the published works into two groups as in Figure 2.6: (1) single objective and (2) multiple objectives.

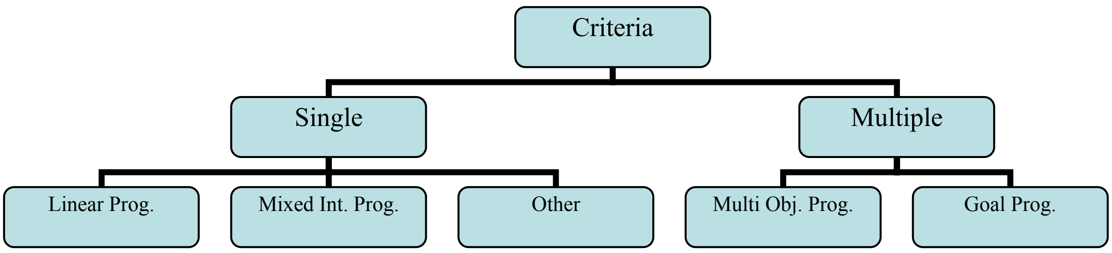


Figure 2.6 Technique oriented classification (Aissaoui et al., 2006)

Single objective programming methods generally want to minimize total purchasing costs (Aissaoui et al., 2006). Aggregated cost function used in the literature mainly includes following items (Aissaoui et al., 2006): purchasing price, fixed cost of establishing a vendor, price breaks, and inventory costs for multi-period models. In some models, penalty costs of poor quality, shortage or insufficient utilization of supplier capacities are also taken into consideration (Aissaoui et al., 2006).

In the single objective models, other criteria apart from cost-based objectives such as quality and delivery performance are included into the models as constraints

(Ghodsypour and O'Brien, 1998). Most of the single objective programming models are modeled as linear programming (LP) and mixed integer linear programming (MILP).

Anthony and Buffa (1977) proposed a single objective programming model to solve the purchasing problem. The model minimizes the total purchasing and storage cost. Pan (1989) developed a LP model, in which quality, service level and delivery criteria are considered in the constraints, to minimize the aggregate cost function.

Chaudhry et al. (1993), Rosenthal et al. (1995) and Sadrian and Yoon (1994) are also considered the levels on quality, service and delivery in the constraints. Additionally, in the Chaudhty et al. (1993)'s model, suppliers offer price breaks which depend on the amount of the order quantity, on the other hand, in the Sadrian and Yoon's (1994) model, suppliers offer discounts on the total dollar volume of business.

Narasimhan and Stoynof (1986) develop a MILP for a large manufacturing firm. The sum of shipping and penalty costs constitutes the objective of the model to be minimized. Jayaraman et al. (1999) developed a MILP model to select a set of suppliers and allocate the order quantities to them under the storage space, lead-time and quality level constraints. Recently, Crama et al. (2004) proposed a nonlinear mixed 0-1 programming model for a multi-plant company. The model is focused on a strategy in which suppliers offer a variety of discounts based on the order quantity, rather than total business volume. They also propose various ways to convert the nonlinear model developed to a linear one. More recently, Basnet and Leung (2005) proposed a mixed integer programming (MIP) model for a multi-period inventory lot-sizing scenario, where there are multiple products and multiple suppliers. The model developed determines what products to order in what quantities with which suppliers in which periods. They solved the model via an enumerative search algorithm and a heuristic.

A limited number of researchers used nonlinear programming and stochastic programming to model the decision problem such as Hong and Hayya (1992), Rosenblatt et al. (1998), and Bonser and Wu (2001).

The major disadvantage of single objective MP models is that the construction of an aggregated cost function is a difficult task because of the incommensurable nature of some terms such as units undelivered on time and the number of defective items. Aissaoui et al. (2006) stated that the use of multi-objective MP models eliminate the necessity of transforming them to a common unit of measurement, present the decision maker with a set of nondominated solutions and allows the decision maker to make final decisions by considering personnel judgments.

The most commonly used multi-objective MP technique is goal programming (GP). Buffa and Jackson (1983) proposed a GP model which includes price, quality and delivery objectives. Sharma et al. (1989) also considered service objective besides price, quality and delivery in their non-linear GP formulation. Chaudhry et al. (1993) developed a mixed integer linear GP model which includes three objectives (price, delivery and quality) and considers price discounts which depend on the sizes of the order quantities.

Karpak et al. (1999) used visual interface GP for purchasing materials. The proposed model considers minimization of costs and maximization of quality and delivery reliability objectives in order to select suppliers and allocate orders to them. Wadhva and Ravindran (2006) modeled the vendor selection problem as a multi-objective optimization problem assuming price, lead-time and quality to be the most important objectives. To solve the proposed model, they used three solution approaches; weighted objective method, GP and compromise programming. They stated that preemptive GP is a more suitable method for vendor selection problem. Some integrated and fuzzy approaches based on GP are also proposed to solve supplier selection problem. As can be seen later, these approaches will be discussed in the following sections.

Weber and Ellram (1993) and Weber and Current (1993) proposed a MOP approach to solve supplier selection problem. Weber et al. (2000) presented an approach for evaluating the number of vendors to utilize via MOP and DEA.

Degraeve and Roodhooft (1999) proposed a model that uses activity based costing (ABC) and TCO information in an MP model to simultaneously select vendors and determine order quantities for multiple items over a multi period time horizon. Ghodsypour and O'Brien (2001) present a mixed integer nonlinear programming model to solve the multiple sourcing problem, which takes into account the total cost of logistics, including net price, storage, transportation and ordering costs.

2.4.2.3 Integrated approaches

In order to better represent the multi-criteria nature of the supplier selection decision, recently, some researchers has paid increasing attentions to develop the integrated models. In general, the first phase of such approaches deal with the rating of the suppliers, then the selecting the appropriate suppliers and allocating the order quantities to them are performed by using MP techniques.

Ghodsypour and O’Brien (1998) developed an integrated AHP and LP model to help managers consider both qualitative and quantitative factors in the purchasing activity in a systematic approach. They, as a first time, used AHP ratings as the total value of purchase and integrated in an additive fashion into a goal. They also proposed an algorithm for sensitivity analysis to consider different scenarios in this decision making model. Çebi and Bayraktar (2003) proposed an integrated model with lexicographic GP and AHP for supplier selection. Similar to that of Ghodsypour and O’Brien (1998), their methodology also uses AHP ratings as utility scores of suppliers. In addition, quality, delivery and cost factors have been selected as the objective functions. Wang et al. (2004) developed an integrated AHP and preemptive GP-based MCDM methodology to take into account both qualitative and quantitative factors in supplier selection. Besides the total value of purchase objective, minimization of the total purchasing cost was also considered. Their methodology follows this philosophy but has a distinctive feature; it is guided by product driven supply chain design strategy.

Hong et al. (2006) suggested a MP model that considers the change in suppliers' supply capabilities and customer needs over a period in time. They designed a model which not only maximizes revenue but also satisfies customer needs. They used data mining techniques for prequalification of the alternative suppliers and a MILP model to select the optimal set of suppliers and to assign orders to them.

Demirtas and Üstün (2006) proposed an integrated approach of ANP and multi-objective MILP to allocate the optimum quantities to the selected suppliers while maximizing the total value of purchasing and minimizing the budget and defect rate. The priorities are calculated for each supplier by using ANP.

Shyur and Shih (2006) proposed a hybrid model for supporting the vendor selection process in new task situations. ANP is used to determine the criteria weights. A well-known MCDM method, TOPSIS, is then employed to create a decision matrix to help ease and finalize the selection process. In this paper, the authors also modified TOPSIS method for group decision making.

Wang and Che (2006) proposed an integrated model for evaluating the alternative suppliers for each part. The proposed model is focused on finding the appropriate supplier combination that will best minimize the cost–quality score by integrating the fuzzy theory, T transformation technology, and genetic algorithm.

2.4.2.4 Fuzzy sets based methods

As stated earlier, a supplier selection decision inherently is a multi-criterion problem and complicated because a set of criteria must be considered simultaneously (Kahraman et al., 2003; Choy et al., 2005). In the vast majority of the decision models developed, it is assumed that the performances of suppliers on different criteria are known exactly. However, as Kahraman et al. (2003) stated, some criteria may be impractical to evaluate during selection, information may be difficult to obtain or complex to analyze, or there may not be sufficient time to perform these tasks. MCDM literature have often emphasized that decision making becomes difficult when the available information is incomplete or imprecise. In order to better model the uncertainty and imprecision involved in supplier selection problem, some researchers proposed decision models based on fuzzy set theory (FST). In the review paper of De Boer et al. (2001), it is pointed out that FST can be combined with other techniques to improve the quality of the final tools (De Boer et al., 2001).

Some researchers have looked fuzzified versions of known methods as tools for supplier selection. Kahraman et al. (2003) presented a method that uses fuzzy AHP to select best supplier firm providing the most satisfaction for the criteria determined. They have illustrated it with an example of supplier selection for a white good manufacturer that Fuzzy AHP may be very well suited as a decision making tool in a fuzzy environment. In the same way, Chan and Kumar (2007) have recently presented a fuzzy extended AHP approach to select the best global supplier for a manufacturing firm.

Dogan and Sahin (2003) used ABC approach to select the best supplier. In their study, the factors that affect the selection process were considered as fuzzy numbers. Bevilacqua and Petroni (2002) developed a methodology for supplier selection using fuzzy logic. They carried out a case study to test the effectiveness and applicability of the approach. Kwong et al. (2002) introduced a combined scoring method with fuzzy expert systems approach in order to perform supplier assessment.

Chen et al. (2006) proposed an extension of TOPSIS methodology in a fuzzy environment for the problem of supplier selection. In the same way, Bottani and Rizzi (2006) utilized fuzzy TOPSIS methodology for the selection and ranking of the most suitable third-party logistics (3PL) service provider. In a recent paper, Işıklar et al. (2006) proposed an intelligent decision support framework for effective 3PL evaluation and selection. In order to deal with uncertain and imprecise decision situations, three decision techniques, CBR, rule-based reasoning and compromise programming are integrated in a fuzzy environment. They also provide a real industrial application to demonstrate the potential of the proposed framework.

More recently, a variety of fuzzy MP models have been suggested for supplier selection. Kumar et al. (2003) represented a fuzzy MIP GP to capture the uncertainty related to the vendor selection problem. They considered only the ambiguity of the decision situation due to imprecise information concerning the minimization of the three objectives related to the net cost, the net rejections and the net late deliveries. They assumed that only one item is purchased from one vendor and demand of the item is constant and known with certain. Kumar and his colleagues also presented a slightly different paper in 2006 (Kumar et al., 2006). Differently form previous paper; various input parameters have been treated as vague with a linear membership function of fuzzy type. In a similar fashion, Amid et al. (2006) developed a fuzzy multiobjective model for the supplier selection problem. Apart from the similar papers, in which the goals have equal importance, an asymmetric fuzzy-decision making technique is applied to enable the decision-maker to assign different weights to various criteria.

2.4.2.5 Artificial Intelligence based methods

Up to date, various AI techniques such as Neural Networks (NNs), CBR, expert systems etc. have been used in developing DSS for supplier selection.

Albino and Garavelli (1998) proposed a Neural Network (NN) based DSS which has capability of rating subcontractors for construction firms. In the proposed approach, an adaptive backpropagation network is used. The main advantage of the proposed methodology is that it does not require the decision maker expertise directly. It learns to rate subcontractors from the samples.

CBR is another AI techniques utilized in supplier selection. De Boer et al. (2001) stated that some characteristics of CBR systems, such as the capability to use information from previous negotiations and the easy training of the system, make them interesting in connection with supplier selection. As one of the first applications, Cook (1997) proposed a CBR system for supplier selection. Choy et al. (2003) presented an intelligent supplier relationship management system based on CBR technique. The proposed system integrates company's customer relationship management system, supplier rating system, and product coding system in order to select suppliers in new product development phase. More recently, Choy et al. (2005) also proposed a CBR DSS for outsourcing operations working under a hybrid inductive-nearest indexing approach through which suppliers are categorized according to their market competitiveness. In another study, Choy et al. (2002) present an intelligent supplier management tool using CBR and NN techniques to select and benchmark suppliers.

Apart form aforementioned AI techniques, Vokurka et al. (1997) developed a prototype expert system for the evaluation and selection of potential suppliers. The proposed system incorporates the strategic partnership considerations of supplier selection rather than the more traditional quantitative selection criteria.

2.4.2.6 Other methods

In addition to the aforementioned methods, some researchers developed and utilized alternatives methods for supplier selection problem such as TCO, stochastic models etc.

TCO based methods consider many other purchase-related costs besides the price of a purchase when making a decision on supplier selection. Bhutta and Hug (2002) stated that this approach has become increasingly important, as organizations look for ways to better understand and manage their costs. TCO is not an easy method to utilize, because it requires the determination of cost items to be considered in the supplier selection process and is more costly than traditional approaches (Aissaoui et al., 2006). Some researchers have proposed TCO-based models to select suppliers. Some of them are: Timmerman (1986), Monczka and Trecha (1988), Smytka and

Clemens (1993), Handfield and Pannesi (1994), and Ellram (1995). Recently, Bhutta and Hug (2002) have illustrated AHP and TCO approaches and provided a comparison.

As mentioned earlier, like any other decision making problem, supplier selection also involves uncertainty and imprecision in decision process. However, the vast majority of the supplier selection models used in the literature assumes that the parameters are exactly known priori. Only few researchers have paid attention to consider the imprecision and uncertainty via stochastic models. Some of them are: Soukoup (1987), Liao and Rittscher (2006), etc.

Existing approaches in support of supplier selection neglect some special situations which may arise during the selection process. Some researchers have been motivated from these shortcomings. Sean (2006) proposed a mathematical approach based on AHP for selecting slightly non-homogenous suppliers. Suck (2006) proposed a dynamic strategic vendor selection by considering the interdependencies in time arising from investment costs of selecting a new vendor and costs of switching from an existing vendor to a new one.

2.5 Gaps in the existing literature and the need for the proposed research

As evidenced by the explosion of research on SCM and purchasing literature, the importance of strategic sourcing on a company's competitive strategy is now widely accepted. Overall, there exist two silent viewpoints in the purchasing literature (Aissaoui et al., 2006, p.3):

- "*The most important purchasing decision is undoubtedly selecting and maintaining close relationship with a few, albeit reliable and high quality suppliers. The firms can only achieve a competitive position in the market by this way.*

- *There is a strong need for a systematic approach to purchasing decision making especially in the area of identifying appropriate suppliers and allocating order quantities to them*".

A synthesis of the literature review presented reveals that there are five important and emerging decisions in the current purchasing literature and leads to the determination of several research questions that related to the gaps in the literature:

Design collaboration: Almost all of the papers surveyed stated that it is crucial for a firm to collaborate with suppliers during the design stage in order to gain various benefits of design collaboration reported such as reduced the time to market, lower product costs and higher quality. The literature also pointed out that strategic supplier selection and evaluation decisions must not be solely based on traditional selection criteria, such as cost, quality and delivery and needs to incorporate design criteria into the assessment process. However, little research has been devoted on how to analytically evaluate the support given by suppliers in new product development activities.

These facts raise the following research questions:

1) Which decision criteria should be included into the selection process by taking into account the design collaboration between manufacturers and suppliers?
2) How can we analytically assess the support given by suppliers in new product development activities?

Supplier evaluation and selection: The literature review reveals that a lot of researchers have paid considerable attention to develop different methodologies for supplier evaluation and selection. Although the numerous methods have been proposed, supplier evaluation and management systems that compare suppliers, identify potential reasons for differences in supplier performance and helps in monitoring supplier performances have not been fully explored in the literature (Talluri and Narasimhan, 2004). This fact leads to following research question:

3) How can we develop effective supplier evaluation and management systems which can help the purchasing teams in assessing and monitoring the suppliers' performance and identifying the differences between suppliers?

Supply base reduction: It is clear from the literature review that there is a strong need for firms on the reduction of the number of suppliers. With the growing importance of JIT philosophy, the necessity of reducing supply base has been frequently reported in the literature and there is an emerging trend to classify supplier into two or more categories (Choy et al., 2005). Although a number of methods have been proposed for supply base reduction, as discussed in previous sections, there are some limitations and disadvantages of them. The major shortcoming of the existing methods is that the most of them is not based on the multi-criteria evaluation of suppliers. Because of the multiple criteria nature of the supplier selection and evaluation problems, we believe that a multi-criteria sorting (MCS) method will be more efficient in order to reduce supply base. To the best of our knowledge, MCS methods have not yet been applied for supplier selection and evaluation problems. Consequently, the research question of interest is:

4) How can we develop an effective MCS methodology for supply base reduction?

Order allocation: The research survey reveals that the large attention has been paid to develop effective order allocation models using MP techniques for both single objective and multiple objectives cases. In the literature, some researchers enhanced the MP models with fuzzy sets to better model the imprecision and uncertainty involved in the decision problem. On the other hand, there is an emerging trend in the purchasing literature to develop integrated methods which simultaneously consider prequalification and order allocation decisions. However, to the best of our knowledge, fuzzy MP approaches and MCS methods have not yet been utilized in the integrated models. As discussed earlier, MCS methods and fuzzy modeling approaches can be combined to improve the quality of the final tool. Considering this fact and the aforementioned gap in the existing literature, the research question of interest is:

5) How can we develop an integrated supplier management methodology that combines proposed MCS methodology and fuzzy MP in order to select the appropriate suppliers and assigning order among them?

Modeling uncertainty in strategic sourcing: It is clear form the literature review that the imprecision and uncertainty involved in the final supplier selection and order allocation decisions have been taken into consideration by embedding the FST into the decision models. The purchasing literature is abound with numerous fuzzy approaches to the ranking suppliers from the best to the worst or choice the best one but any sorting method, which applies FST, has not yet been developed to classify the suppliers based on their fuzzy performances. The last research question arises; when one consider possible extension of the proposed MCS methodology:

6) How can we extent the proposed MCS methodology so that it can deal with fuzzy input data?

As discussed in the first chapter, the main aim of this research is to propose novel methodologies for effective strategic sourcing decisions. The chapters 6 and 7 of this dissertation are devoted to explain proposed sourcing methodologies and to explain these research issues in great detail. However, in summary, the methodologies presented in the proposed research differ from the studies reviewed above in the following aspects:

- Apart from classical classification algorithms such as DEA, CA and CBR, as a first time, a new MCS method which allows the multi-criteria evaluation of suppliers is presented for supplier classification and supply base reduction purposes.

- As stated earlier, even though a lot of studies have been dedicated to develop decision methods for sourcing problems, most of them deal with the selection of ultimate supplier. Different form these studies, a new supplier evaluation and management methodology based on the proposed MCS method is presented for managing the supply base, rather than only focusing the final selection phase.

- Different from the integrated approaches presented in the literature, as a first time, an integrated sourcing management system that incorporates a MCS procedure and interactive fuzzy goal programming (IFGP) is proposed to select the strategic partners and to allocate the appropriate orders to them simultaneously.

- A fuzzified extension of the proposed MCS method is proposed, and, to the best of our knowledge, it is the first time that a method, which can handle fuzzy performances of the suppliers, has been suggested as a tool for solving fuzzy ordinal classification problem of suppliers.

As stated above, the proposed strategic sourcing methodologies and the computational experiments will be presented in Chapter 6 and 7. Since MCS problem is also focused in this research, we give an overview of MCS methods in the next chapter.

CHAPTER THREE
MULTI-CRITERIA DECISION MAKING: SORTING PROBLEMATIC

3.1 Introduction

Purpose of this chapter is two-fold. Because the supplier selection is a multi-criteria decision making (MCDM) problem in nature, the first objective is to provide an overview of MCDM problems and techniques used in supplier selection problems. On the other hand, since this research offers the use of multi-criteria sorting (MCS) methods in supplier classification and proposes a new MCS method, the second objective then is to provide a brief discussion of multi-criteria classification (MCC) problem, to review the existing techniques and explain the rationales behind the MCS methodology to be presented in the next chapter.

This chapter is further organized as follows: in section 2, a brief description of MCDM is given and taxonomy of MCDM problems is described. Section 3 provides a brief introduction to the main concept and features of some methods used for solving these problems. Section 4 gives an overview of MCC problem. Section 5 reviews some methods used to solve MCC problems. PROMETHEE based sorting methods from which our methodology is inspired are also described in this section. Section 6 sums up our findings and presents a general overlook on the gap in the existing literature and the research questions to be studied on this research.

3.2 Brief overview of multi-criteria decision making

MCDM is one of the most important fields of operations research and deals with the problems that involve multiple and conflicting objectives. It is obvious that when more than objective exists in the problem, making a decision becomes more complex.

In the literature, to define the methods that allow decision maker to solve the decision problems that involve multiple factors, two different terms are used: MCDM and multi-criteria decision aid (MCDA). Although both are often confused, some researchers pointed out the differences between MCDA and MCDM. Roy and Vanderpotten (1996) stated that MCDM methods tries to obtain an ideal solution, derived from a set of actions, on the other hand, MCDA seeks to give recommendation. On the other hand, this distinction also lies in the answer of that question: “which researchers did develop the method?”. Multi-criteria approaches have been developed generally by European operations researchers (the European school of MCDA) and United States (US) operations researchers (American school of MCDM). Henceforth, as in the operations research literature, MCDA and MCDM terms are used interchangeably in the remaining of the thesis.

MCDM’s scope and objective is to support decision makers during the problem solving to tackle with the decision problems that involve multiple criteria. Different from other simple decision models, MCDM approaches are focused on the model development aspects that are associated with the modeling and representation of the decision makers’ preferences, values and judgment policy (Doumpos and Zopounidis, 2002).

Zimmermann (1994) classified the MCDM into two categories: multi-objective decision making (MODM) and multi-attribute decision making (MADM). Some researchers (Doumpos and Zopounidis, 2002) performed this classification based on the problem type: discrete or continuous. Doumpos and Zopounidis (2002) graphically represented the discrete and continuous problems which are dealt with MADM and MODM methods, respectively, in Figure 3.1.

Discrete Problems

m alternatives
n criteria

		Criteria			
		g_1	g_2	. . .	g_n
Alternatives	x_1	g_{11}	g_{12}	. . .	g_{1n}
	x_2	g_{21}	g_{22}	. . .	g_{2n}
	x_3	g_{31}	g_{32}	. . .	g_{3n}
	.	.	.	. . .	.
	.	.	.	. . .	.
	.	.	.	. . .	.
	x_m	g_{m1}	g_{m2}	. . .	g_{mn}

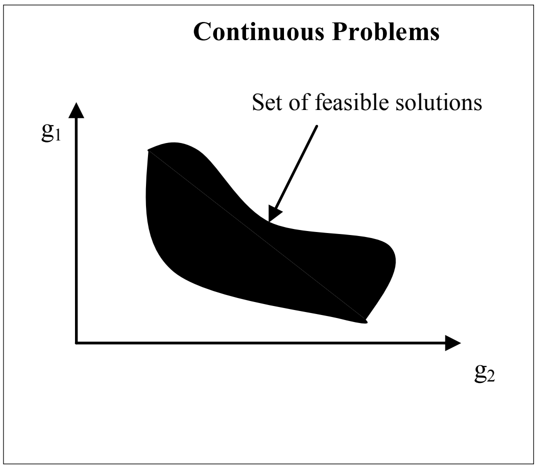


Figure 3.1 Discrete and continuous decision making problems (Doumpos and Zopounidis, 2002, p.3)

3.2.1 Multi-objective decision making (MODM)

MODM models generally deal with continuous problems in which the number of variables is infinite and variables used to define the decision problem tend to be continuous. Most of MODM methods are based on mathematical programming in which there are more than one objective to be optimized and try to obtain an appropriate compromise solution form a set of efficient solution (also called as non-dominated or pareto optimal solutions). Generally a multi-objective mathematical programming (MOMP) model can be formulated as follows:

$$\left.\begin{array}{l} Max(or\,Min)\ \{f_1(x), f_2(x), ..., f_k(x)\} \\ Subject\ to: g_j(x) \le b_j \end{array}\right\} \qquad (3.1)$$

Where x is the vector of the decision variables, $\{f_1(x), f_2(x), ..., f_k(x)\}$ are the objective functions to be maximized (or minimized), $g_j(x) \le b_j$ is a set of constraints. If the objective functions and constraints are formulated linearly, then MOMP model becomes a multi-objective linear programming (MOLP). Most of the MOMP models in the literature are formulated as a MOLP and several methodologies have been developed to solve these models such as STEM (Benayoun et al., 2001) and Zionts and Wallenious (1976)'s interactive approach. GP is the one of the most powerful and well known MOMP solution methodology. Up to date several variants of GP have been proposed to address MODM problems.

3.2.2 Multi-attribute decision making (MADM)

In MADM, each alternative is described by using multiple attributes. For a given set of alternatives, MADM models try to choose the best alternative among them, rank the alternatives from the best to the worst or classify them into classes. Although the MADM methods are generally used to solve discrete problems, some of them can also be used within the context of continuous decision problems (Doumpos and Zopounidis, 2002).

3.3 Multi-attribute decision making methods

Among the MADM methods developed in the literature, analytical hierarchy process (AHP), multi-attribute utility theory (MAUT) and outranking methods are more frequently applied to discrete decision problems than all other methods. The following sub-sections give a brief introduction to the main concept and features of them.

3.3.1 Analytic hierarchy process (AHP)

AHP was proposed by Saaty (1980) to solve the MADM problems which can be structured using a hierarchy (attributes, criteria, alternatives, etc.). AHP is one of the most commonly used MADM methods because of easily understandable algorithm of it. AHP involves several steps in solving the decision problem. In the first step, hierarchical structure of the problem is defined by decision maker. In the top level of the hierarchy, the main goal is defined, while the last level of the hierarchy includes the alternatives to be evaluated. The levels between the top and the bottom involve the evaluation criteria and sub-criteria used to define the upper level criteria. In the second step, the relative priorities of the elements in each level of the hierarchy are determined by pairwise comparisons using 1-9 scale. In this step, performing the pairwise comparison requires the answering of such questions: "How much more is criterion *A* contributing to the goal than criterion *B*?" or "How much more is alternative *A* performing better with respect to the relevant criterion than alternative *B*?". After a sequence of such pairwise comparisons, the relative significances (weights) of elements in the hierarchy are determined using the eigenvector method. In the final step, determination of the relative priorities of the alternatives is performed by combining the relative weights (Macharis et al., 2004). A detailed description of the methodological framework underlying AHP can be obtained form the book of Saaty (1980).

3.3.2 Multi-attribute utility theory (MAUT)

MAUT is an extension of utility theory that allows the preferences to be represented in terms of value functions $U(g)$, where g is the vector of the evaluation criteria $g=(g_1, g_2,..,g_n)$. The MAUT based models integrate multiple marginal value functions into an aggregated utility function to be maximized. Commonly, marginal utility functions are aggregated into an additive fashion (Doumpos and Zopounidis, 2002):

$$U(g) = w_1 u_1(g_1) + w_2 u_2(g_2) + ... + w_n u_n(g_n) \tag{3.2}$$

Each marginal utility function $u_i(g_i)$ defines the utility of the alternatives for each individual criterion g_i. Weights w_i reflects the relative importance of criterion i. The utility function can be defined as linear or non-linear. Simple multi-attribute rating technique (SMART) is the simplest version of MAUT in which marginal utility functions are defined linearly and utility of an alternative is simply obtained as weighted average of marginal utility values. We refer the interested reader the book of Keeney and Raiffa (1993) for a detailed explanation.

3.3.3 Outranking methods

Outranking methods try to find a binary relation between alternatives to show an alternative is preferred ("outranks") to another one. The basic principle of outranking is that alternative *a* will be preferred over *b* if *a* performs better than *b* on a majority of criteria and there is no criterion such that *b* is strongly better than *a*. (Le Teno&Mareschal,1998).

The partial compensation and incomparability are the distinctive features of outranking methods. In contrast to traditional linear weighting techniques, outranking methods are only partially compensatory (De Boer et al., 1998; Dulmin and Mininno, 2003). If the decision maker cannot declare alternative *a* is better than alternative *b* or vice versa, the outranking methods allow explicitly for incomparability (Geldermann et al., 2000).

The more commonly used outranking methods are ELECTRE and PROMETHEE. There are several variants of both methods. The methods and their variants will be explained in the following sub-sections.

3.3.3.1 ELECTRE methods

ELECTRE type methods are the most known outranking methods and they were successfully applied to a wide range of areas. Several versions of ELECTRE methods exist in literature, such as ELECTRE I, II, III, IV and TRI. Although all of them have same fundamental concepts, they were developed and used for different types of decision problems. ELECTRE I (Roy, 1968) was developed for selection purposes. ELECTRE II, III and IV (Roy 1991) were proposed to rank the alternatives from the best to the worst. Finally, ELECTRE TRI (Yu, 1992) was proposed based on the ELECTRE III framework to deal with the classification problems. Since this dissertation focuses on the sorting problematic, more pages will be devoted to in explaining ELECTRE TRI in the later sections. However, in this section, ELECTRE III, which is the base of ELECTRE TRI, will be briefly explained. A detailed description of ELECTRE methods and applications can be found in the works of Figueira J., Greco et al. (2004), Georgopoulou et al. (1997), Rogers and Bruen (2000) and Karagiannidis and Moussiopoulos (1997).

Thresholds and outranking relation are two important concepts in ELECTRE methods. Assume G represents a set of criteria, g_j, j=1,2,…,r and A a set of alternatives. If the performances of two alternatives a and b is defined by two functions according to the j^{th} criterion as $g_j(a)$ and $g_j(b)$, the preference relationships among alternatives can be defined by introducing the concepts of indifference (q) and preference (p) thresholds as follows (Roy, 1991):

$$\left.\begin{array}{lll} aPb \text{ (} a \text{ is strongly preferred to } b\text{)} & \text{if} & g_j(a)-g_j(b) \geq p_j \\ aQb \text{ (} a \text{ is weakly preferred to } b\text{)} & \text{if} & q_j < g_j(a)- g_j(b) < p_j \\ aIb \text{ (} a \text{ is indifferent to } b\text{)} & \text{if} & g_j(a) - g_j(b) \leq q_j \end{array}\right\} \quad (3.3)$$

The ELECTRE methods try to find an outranking relation aSb which means "a is at least as good as b". In ELECTRE III, two important principles called as concordance and discordance are used to accept the assertion aSb. The j^{th} criterion is in concordance with the claim aSb if $g_j(b) - g_j(a) \leq q_j$. On the other hand, the j^{th} criterion is in discordance with the claim aSb if $g_j(b) - g_j(a) \geq p_j$. To measure the strength of claim aSb, the concordance index $C(a,b)$ can be defined as in Equation 3.4 (Hokkanen and Salminen, 1997).

$$C(a,b) = \frac{1}{K}\sum_{j=1}^{m} k_j c_j(a,b) \quad where\ K = \sum_{j=1}^{m} k_j \quad (3.4)$$

where k_j is the weight of criterion j, and the concordance degree $c_j(a,b)$ states the degree of the claim alternative a is at least as good as alternative b in terms of criterion j. The concordance degree $c_j(a,b)$ can be calculated as follows:

$$\left.\begin{aligned} &c_j(a,b)=0 && if \;\; g_j(b)-g_j(a)>p_j \\ &c_j(a,b)=1 && if \;\; g_j(b)-g_j(a)\le q_j \\ &c_j(a,b)=\theta && if \;\; in \;\; between \;\; and \;\; \theta=\frac{p_j+g_j(a)-g_j(b)}{p_j-q_j} \end{aligned}\right\} \quad (3.5)$$

Calculation of the discordance index requires an additional threshold value called 'veto'. The veto threshold, *v*, allows to discard claim *aSb* if $g_j(b)\ge g_j(a)+v_j$. The discordance index for each criterion *j*, $d_j(a,b)$ can be determined as shown in Equation 3.6.

$$\left.\begin{aligned} &d_j(a,b)=0 && if \;\; g_j(b)-g_j(a)\le p_j \\ &d_j(a,b)=1 && if \;\; g_j(b)-g_j(a)>v_j \\ &d_j(a,b)=\gamma && if \;\; in \;\; between \;\; and \;\; \gamma=\frac{g_j(b)-g_j(a)-p_j}{v_j-p_j} \end{aligned}\right\} \quad (3.6)$$

A discordance matrix is produced for each criterion. Different from concordance, one discordant criterion is sufficient to reject outranking relation. Finally, the degree of outranking is defined by $S(a,b)$ and can be calculated by Equation 3.7 (Hokkanen and Salminen, 1997).

$$\left.\begin{aligned} &S(a,b)=c(a,b) && \text{if } d_j(a,b)\le c(a,b) \;\; \forall j\in J, \\ &S(a,b)=c(a,b)*\prod_{j\in J(a,b)}\frac{1-d_j(a,b)}{1-c(a,b)} && \text{otherwise,} \\ &\text{where J (a,b) is the set of criteria for which } d_j(a,b)\succ c(a,b). \end{aligned}\right\} \quad (3.7)$$

In order to obtain the final ranking, a distillation process is employed. It provides two preorders, descending and ascending. In the first one, the rank order is performed starting from the best-rated alternative, while, in the second one, the rank order starts from the worst-rated alternative. The final partial order of the alternatives can be obtained based on these two preorders (Hokkanen and Salminen, 1997).

3.3.3.2 PROMETHEE methods

PROMETHEE (Brans and Vincke, 1985; Brans et al., 1986) is a ranking method quite simple in conception and application compared to other methods for multi-criteria analysis (Goumas and Lygreou, 2003).

Let A be a set of alternatives and $g_j(a)$ represent the value of criterion g_j (j=1,2,...,J) of alternative $a \in A$. For each pair of actions, a preference function $F_j(a,b)$ that represents preference level of a to b on criterion j can be defined as follows,

$$\left.\begin{array}{ll} F_j(a,b)=0 & \mathit{iff}\;\; g_j(a)-g_j(b)\le q_j \\ F_j(a,b)=1 & \mathit{iff}\;\; g_j(a)-g_j(b)\ge p_j \\ 0<F_j(a,b)<1 & \mathit{iff}\;\; q_j<g_j(a)-g_j(b)<p_j \end{array}\right\} \tag{3.8}$$

$F_j(a,b)$ takes values in the range of [0,1] and is calculated using a predefined function and two important thresholds (indifference (q_j) and preference (p_j) thresholds). Six different types of preference functions have been suggested (Brans and Vincke, 1985). Aggregated preference indicator can be determined using the weights w_j assigned to each criterion as follows:

$$\Pi(a,b)=\sum w_j F_j(a,b) \tag{3.9}$$

In PROMETHEE I, ranking of the alternatives is performed using the following two outranking flows.

$$\phi^{+}(a)=\frac{1}{n-1}\sum_{x\in A}\Pi(a,x)\;\; \mathit{leaving\;\; flow} \tag{3.10}$$

$$\phi^{-}(a)=\frac{1}{n-1}\sum_{x\in A}\Pi(x,a)\;\; \mathit{entering\;\; flow} \tag{3.11}$$

The leaving flow shows the strength of the alternative $a \in$ A with respect to all the other alternatives $x \in$ A. On the other hand, the entering flow measures the weakness of the alternative *a*. In PROMETHEE I, alternative *a* is preferred to alternative *b*, *aPb*, if alternative *a* has a greater leaving flow than the leaving flow of alternative *b* and a smaller entering flow than the entering flow of alternative *b*.

$$a \text{ P } b \text{ if: } \phi^{+}(a) \geq \phi^{+}(b) \text{ and } \phi^{-}(a) \leq \phi^{-}(b). \tag{3.12}$$

PROMETHEE I evaluation allows indifference and incomparability situations. Therefore, sometimes partial rankings can be obtained. In the indifference situation (*a*I*b*), two alternatives *a* and *b* have the same leaving and entering flows.

$$a \text{ I } b \text{ if: } \phi^{+}(a) = \phi^{+}(b) \text{ and } \phi^{-}(a) = \phi^{-}(b). \tag{3.13}$$

Two alternatives are considered incomparable, *a*R*b*, if alternative *a* is better than alternative *b* in terms of leaving flow, while the entering flows indicate the reverse.

$$a \text{ R } b \text{ if: } \phi^{+}(a) > \phi^{+}(b) \text{ and } \phi^{-}(a) > \phi^{-}(b) \text{ or}$$
$$\phi^{+}(a) < \phi^{+}(b) \text{ and } \phi^{-}(a) < \phi^{-}(b). \tag{3.14}$$

For each alternative *a*, it can also be determined the net flow for each criterion separately. Let us define the single criterion net flow for criterion g_j as follows (Mareschal and Brans, 1988),

$$\phi_j(a) = \frac{1}{n-1} \sum_{x \in A} (F_j(a,x) - F_j(x,a)) \tag{3.15}$$

$\phi_j(a)$ measures the strength of alternative *a* over all the other alternatives on criterion *j*. The larger the single criterion net flow $\phi_j(a)$ the better alternative a on criterion g_j (Figueira et al., 2004). In PROMETHEE II, the complete ranking can be obtained by using the net flows. The higher net flow, the better alternative.

$$\phi(a) = \phi^{+}(a) - \phi^{-}(a) \text{ net flow} \tag{3.16}$$

Mareschal and Brans (1988) proposed also a geometrical representation of a decision problem. Using single criterion net flows, a geometrical representation can be obtained from a principal component analysis. Up to date, besides PROMETHEE I and II, several extensions of PROMETHEE have been developed to represent different problems such as PROMETHEE III, V, TRI and CLUSTER. PROMETHEE III is an extension of PROMETHEE II in which the net flow is enriched by a standard deviation. PROMETHEE V (Brans and Mareschal, 1992) proposes the use of integer linear programming (ILP) in order to select the subset of alternatives that maximizes the sum of net flows. Finally, Figueria et al. (2004) proposed TRI and CLUSTER versions of PROMETHEE to deal with the classification problems. Detailed explanation about these versions will be given in the following sections.

3.4 Multi-criteria classification

As already mentioned, a decision maker may formulate the MCDM problems in three different ways: choosing, ranking and classification/sorting problematic (Roy, 1996). Figure 3.2 shows these decision making problematics.

In many real world decision making situation, decision makers have to assign a set of alternatives evaluated on a set of criteria into homogenous classes (De Smet and Montona-Guzman, 2004). Such problems can be defined as classification or clustering problems. To better understand the classification problems in MCDM context, the term “sorting” should be explained in detail.

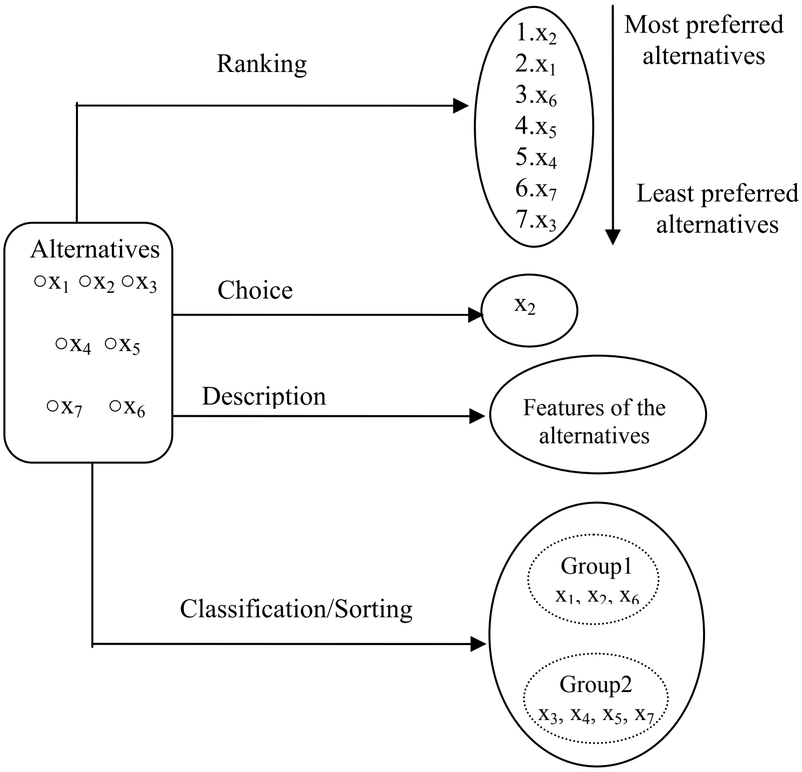


Figure 3.2 Decision making problematics (Doumpos and Zopounidis, 2002; p.5)

Although the classification and clustering terms are generally used interchangeably in the literature, they have different meaning in the MCDM literature. Classification algorithms perform the assignment of alternatives into predefined classes. On the other hand, clustering algorithms try to regroup the alternatives into classes in order to make the distances between the alternatives within a same class the shortest and the distances between the different classes the longest (Leger and Martel, 2002).

If the categories are defined in a nominal way, which means that the categories are not ordered from the best to the worst, the problem is called as *nominal* classification problem. On the contrary, the categories are defined in an ordinal way in *ordinal classification or sorting* problems. Within the MCDM context, MCC problems are generally studied as *sorting* problematic. In this thesis, we are focusing on the sorting problems. Figure 3.3 outlines the difference between the terms in a graphical way.

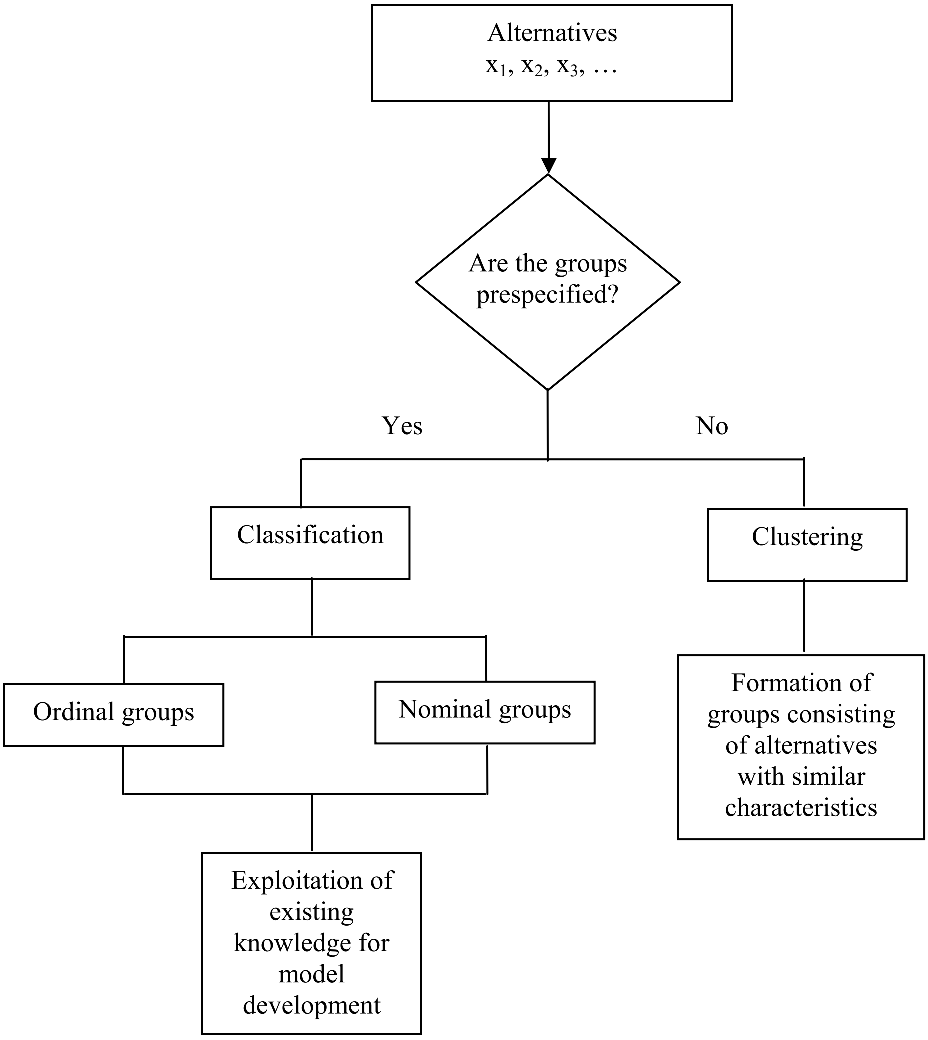


Figure 3.3 The classification vs Clustering problem (Doumpos and Zopounidis, 2002; p.5)

3.5 Multi-criteria classification problems and methodologies

MCC has received a lot of attention from operations research literature because of the significance of the real-world classification problems. Many researchers have developed decision models for both nominal and ordinal classification problems and utilized both kinds of classification algorithms to solve real-world problems. Doumpos and Zopounidis (2002) listed the some characteristic examples as follows:

- Medical diagnosis (Belacel, 2000): Patients are assigned to the diseases considering the symptoms observed,

- Pattern Recognition (Ripley, 1996; Nieddu and Patrizi, 2000): the physical objects or human characteristics are recognized and classified into predefined classes,
- Job evaluation and Human resource management (Gochet et al., 1997; Chen et al., 2006): Workers are assigned to the proper jobs according to their skills and job requirements,
- Production management (Catelani and Fort, 2000; Shen et al., 2000): Monitoring and control of production systems for fault diagnosis purposes,
- Marketing (Siskos et al., 1998): Marketing policies for penetration to new markets are categorized and selected, customers are categorized based on their characteristics etc.,
- Environmental management and energy policy (Diakoulaki et al., 1999): it involves the diagnosis of environmental impacts,
- Financial analysis (Zopounidis and Doumpos, 1999, 2000; Doumpos et al., 2001): Firms are categorized into several risks classes based on their financial performances to predict bankruptcy risks or countries are grouped into predefined classes to assess the risks etc.

To address these real-world classification problems, a number of methods have been proposed. A complete survey of all the methods that have been developed for Multi-criteria classification and sorting can be found in the work of Zopounidis and Doumpos (2002).

Doumpos and Zopounidis (2002) classified the MCC methods into two categories:

- Techniques based on the direct interrogation of the decision maker,
- Preference disaggregation classification methods.

Henceforth, all subsequent discussion made in this chapter adopts the classification presented by Doumpos and Zopounidis (2002).

Most known MCS methods that require the direct interrogation of the decision maker are ELECTRE TRI (Yu, 1992) and PROMETHEE TRI (Figueira et al., 2004). On the other hand, UTADIS (Doumpos et al., 2001), MHDIS (Zopounidis and Doumpos, 2000) and PAIRCLASS (Doumpos and Zopounidis, 2004) are the most known preference disaggregation methods. Besides these methods, various MCC methods have also been proposed in the literature such as N-TOMIC (Massaglia and Ostonella, 1991), PROAFTN (Belacel, 2000), PROCFTN (Belacel and Boulassel, 2004) and interactive approaches (Köksalan and Ulu, 2003).

The subsequent sections of this chapter discuss the model development aspects of the methods that require the direct interrogation of the decision maker, preference disaggregation methods and other methods proposed in the literature, respectively.

3.5.1 Techniques based on the direct interrogation of the decision maker

The techniques classified into this category require that the decision maker determines all the preferential parameters involved (i.e., weights, thresholds, profiles). When the construction of an adequate number of representative alternatives (or training samples) from each group is impossible, such techniques comes in handy. Most of the MCS procedures need a process of the aggregation of the criteria. Some researchers used outranking relations to aggregate multiple criteria. The extensions of two well-known outranking approaches, ELECTRE and PROMETHEE, will be discussed in detail.

3.5.1.1 ELECTRE TRI

ELECTRE TRI (Yu, 1992; Mousseau et al., 2000) is based on a well-known outranking technique ELECTRE III (Roy, 1991). ELECTRE TRI assigns a discrete set of alternatives $A=\{a_1, a_2,\dots, a_n\}$ evaluated on a set of criteria $G=\{g_1, g_2, \dots,g_j\}$ into k+1 ordered categories. In ELECTRE TRI, the assignment of an alternative a is caused by the comparison of a with the profiles defining the limits of categories (Mousseau et al., 2000). Let B be a set of the limit profiles distinguishing k+1 categories ($B=\{1,2,\ldots,k\}$). b_h represents the upper limit of category C_h and the lower limit of category C_{h+1}, h=1,2,…k. These fictitious alternatives are introduced as the boundaries among each pair of consecutive groups (Doumpos and Zopounidis, 2002). Since the groups are ordered from the best to the worst, each profile must satisfy the condition $g_j(b_{h+1}) \geq g_j(b_h)$ for all criteria.

ELECTRE TRI also requires the determination of some parameters such as weights, preference, indifference and veto thresholds. It starts by building an outranking relation S between each alternative and each limit profiles by using a credibility index $\sigma(a,b_h) \in [0,1]$ that represents the degree of credibility of the assertion aSb_h (Mousseau et al., 2000). ELECTRE TRI uses the framework of ELECTRE III method discussed in section 3.3.3.1 to determine the credibility index.

In order to define the relationship between an alternative and a profile, ELECTRE TRI requires the determination of an additional parameter λ, which is a cut-off point defined by the decision maker. After determining the cut-off point, the preference relation between alternative a and profile b_h can be obtained as follows (Doumpos and Zopounidis, 2002):

- a is indifferent to b_h: $(a\mathrm{I}b_h) \Leftrightarrow (aSb_h) \wedge (b_hSa)$
- a is preferred to b_h: $(a\mathrm{P}b_h) \Leftrightarrow (aSb_h) \wedge (\text{not}\, b_hSa)$
- a is incomparable with b_h : $(a\mathrm{R}b_h) \Leftrightarrow (\text{not }aSb_h) \wedge (\text{not}\, b_hSa)$

In ELECTRE TRI, two assignment procedures are available (Mousseau et al., 2000):

- Pessimistic procedure
  - Compare a successively to b_i, for $i=k, k-1,\ldots,0$,
  - b_h being the first profile such that aSb_h, assign a to category C_{h+1} ,
- Optimistic procedure
  - Compare a successively to b_i, *for* $i=1,2,\ldots,k+1$,
  - b_h being the first profile such that b_hPa, assign a to category C_h .

Pessimistic and optimistic assignment procedures of ELECTRE TRI highly depend on the value of cut-off point that ranges between 0.5 and 1. When the cut-off point decreases, the pessimistic and optimistic characters of the rules are weakened (Mousseau et al., 2000).

In the standard version of ELECTRE TRI, all parameters are set by decision maker. Some researchers have proposed several methodologies to infer some of this information using a set of training sample: (Mousseau and Slowinski, 1998; Mousseau et al., 2000; Mousseau et al., 2001).

More recently, Damart et al. (2006) extends the ELECTRE TRI method to address the problem where a group of decision makers wishes to cooperatively develop a common Multi-criteria evaluation model to sort alternatives into ordered categories. They suggested the use of a DSS called IRIS (Dias and Mousseau, 2003) to support the methodology proposed. In the proposed methodology, it is assumed that both the performances of the alternatives to be sorted and the limit profiles are known a priori. The IRIS DSS is used to infer the criteria weights and a cutting level.

3.5.1.2 PROMETHEE TRI

As mentioned before, PROMETHEE methods were developed to deal with ranking problems like ELECTRE. Contrarily to ranking problems, MCS and clustering algorithms based on PROMETHEE have not received much attention until recent years. Some researchers have developed clustering algorithms (De Smet and Montano-Guzman, 2004; De Smet and Gilbart, 2001). On the other hand, for the multi-criteria ordinal classification (sorting) problems focused in this research, Doumpos and Zopounidis (2004) and Figueira et al. (2004) have recently proposed two important methods from which our methodology is inspired: PAIRCLASS and PROMETHEE TRI, respectively. PAIRCLASS is a kind of preference disaggregation technique; therefore it will be discussed in the later sections.

PROMETHEE TRI (Figueira et al., 2004) is a member of the family of PROMETHEE methods, proposed for dealing with sorting problems. Differently from ELECTRE TRI, PROMETHEE TRI use central alternatives to assign an alternative a to a category. They defined a central alternative r_h as a typical element which can be used to characterize a category C_h. PROMETHEE TRI performs the classification into two steps. In the first step, the single criterion net flows are computed for each alternative and central alternative. As discussed in Section 3.3.3.2, single criterion net flows measure the strength of an alternative over all the other alternatives on each criterion and are between +1 (being the best) and -1 (being worst). These computed net flows represent the profiles of alternatives and reference alternatives. Figure 3.4 and 3.5 represent the profiles of alternative a and reference alternative r_h on each criterion, respectively.

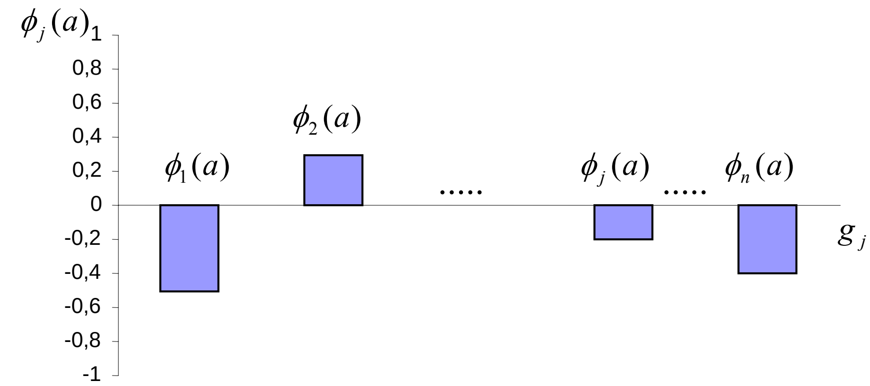


Figure 3.4 The profile of the alternative a

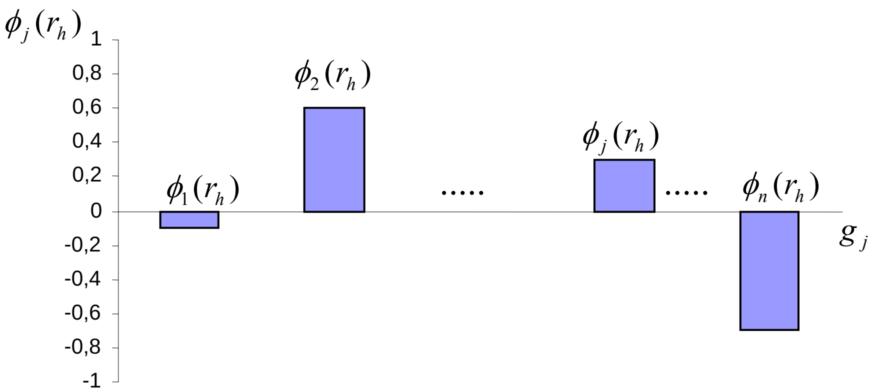


Figure 3.5 The profile of the reference alternative r_h

Then, in the second step, one can define the deviation between alternative a and r_h as follows (see Figure 3.6),

$$e(a,r_h) = \sum_{j \in J} \left| \phi_j(a) - \phi_j(r_h) \right| w_j \tag{3.17}$$

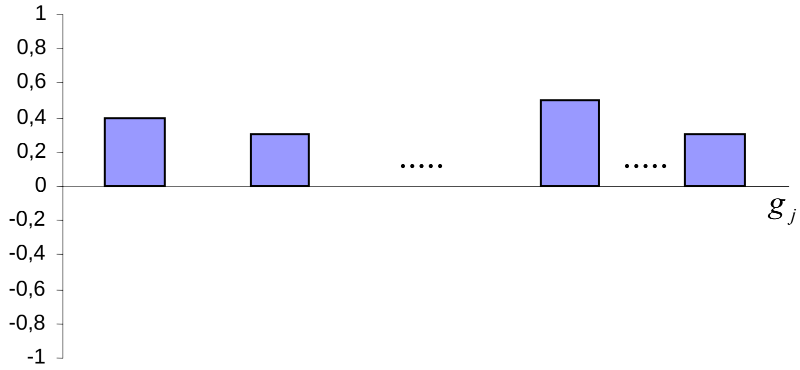


Figure 3.6 Absolute deviation between the reference r_h and alternative a

An alternative a is assigned to category l, if the deviation is minimum.

$$a_i \in C_l \;\; if \;\; e(a,r_l) = \min_{h=1,\ldots,k} \{ e(a,r_h) \} \tag{3.18}$$

Despite its distinctive features compared to ELECTRE TRI and UTADIS and its strong ability to differentiate the alternatives having different profiles, PROMETHEE TRI may assign an alternative a to a worse category than alternative b's, although the alternative a is preferred to b according to PROMETHEE results. Since PROMETHEE TRI does not use the outranking relation between two alternatives obtained by PROMETHEE, it uses only single criterion net flows as inputs. It is obvious that the use of single criterion net flow may not always give the ordered categories. Furthermore, it is important to note that it works with central reference alternatives such a nominal classification method. However, it may be hard to define the central alternatives a priori for some sorting problems such as supplier classification.

In their paper, Figueira et al. (2004) also proposed a nominal classification method named as PROMETHEE CLUSTER. They extended PROMETHEE TRI method for clustering problems. PROMETHEE CLUSTER discriminate a set of alternatives into *k* clusters after the following steps (Figueira et al., 2004):

- Decision maker define the number of cluster (*k*),
- *k* central reference alternatives are randomly selected from the set of alternatives,
- *k* clusters are obtained using PROMETHEE TRI method,
- Redefine more suitable reference alternatives according to the members of each clusters,
- Apply PROMETHEE TRI by considering the new reference alternatives.

The procedure stops when cluster membership no longer changes (Figueira et al., 2004).

In their paper (Figueira et al., 2004), they also mentioned some open problems and fruitful future research suggestions that inspired our proposed sorting methodology. Furthermore, we know at present that the authors revised their paper, but the revised version has not yet been published (Figueria, 2006).

3.5.2 Preference disaggregation classification methods

Every MCC method requires that the decision maker specifies some technical and preferential information which are necessary for the development of the classification model (Doumpos and Zopounidis, 2002). In the preference disaggregation classification methods, the estimation of the required parameters is performed using mathematical programming models so that the sum of all misclassifications in the training sample is minimized. Therefore, such methods assumed that the reference set is known a priori. Since this thesis proposes a MCS method that requires the direct interrogation of the decision maker, preference disaggregation analysis paradigm is beyond the scope of the research proposed in this thesis. A more detailed explanation about the preference disaggregation analysis paradigm and the contribution of it to MCC models can be found in Doumpos and Zopounidis (2002).

The most known MCC methods that uses preference disaggregation paradigm in the model development are UTADIS (UTilites Additives DIScriminates), MHDIS (Multi-group Hierarchical DIScrimination) and PAIRCLASS (PAIRwise CLASSification). UTADIS and MHDIS use utility functions as aggregation model while PAIRCLASS uses an outranking relation for classification purposes. The following sub-sections give a brief introduction about these important methods.

3.5.2.1 UTADIS

In UTADIS, marginal utility functions help to evaluate each alternative on each criterion in utility terms. The objective of the UTADIS method is to develop a criteria aggregation model used to assign the alternatives into *k* predefined ordered groups (i.e., C_1 is the best category, while C_k is the worst one) (Zopounidis and Doumpos, 2002). The criteria aggregation model developed has an additive form (Pasiouras et al., 2006):

$$U(g) = \sum_{i=1}^{n} w_i u_i(g_i) \tag{3.19}$$

The global utility of an alternative ranges between 0 and 1 and measures the overall performance of that alternative. The assignment of an alternative to a specific class is caused by the comparison of the global utility of the alternative to the utility thresholds that define the lower bound of each class (Zopounidis and Doumpos, 2002). If the alternatives are wanted to be classified into k categories, the classification of the alternatives is performed through the following classification rules (Doumpos and Zopounidis, 2002):

$$\left.\begin{array}{ll} U(a_j) \geq u_1 & \Rightarrow a_j \in C_1 \\ u_2 \leq U(a_j) < u_1 & \Rightarrow a_j \in C_2 \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots & \\ U(a_j) < u_{k-1} & \Rightarrow a_j \in C_k \end{array}\right\} \tag{3.20}$$

Where $u_1, u_2, \ldots, u_{k-1}$ denote the utility thresholds and distinguish two consecutive groups. The estimation of the additive value function and the cut-off threshold is performed using linear programming techniques so that the misclassification in the reference set is minimized (Pasiouras et al., 2006). Detailed descriptions and further explanation about the derivation of the mathematical programming formulation can be found in Doumpos and Zopounidis (2002).

3.5.2.2 MHDIS

Similar with UTADIS, MHDIS uses utility functions as aggregation model and mathematical programming models for preference disaggregation purposes. Different form UTADIS, MHDIS assigns the alternatives to the classes using a sequential process (Zopounidis and Doumpos, 2000). It starts by discriminating the first group from all the others, and then proceeds to the discrimination between the alternatives belonging into the other groups (Pasiouras et al., 2006). Assume that we have k groups and are in the q^{th} stage, therefore at stage q the sequential process must decide whether the alternative belongs into group C_q or it belongs at most in the group C_{q+1} (i.e., it belongs into one of the groups C_{q+1} to C_k) (Doumpos and Zopounidis, 2002).

Since at each stage there are two choices to be decided, MHDIS also has two additive utility functions in each one of the $k-1$ steps. The first function $U_q(a_j)$ measures the utility of the first decision (i.e., alternative a_j belongs to group C_q), while the second function $(U_{\sim q}(a_j))$ measures the utility of second choice (Zopounidis and Doumpos, 2000). The classification of the alternative a_j is performed according to these utilities (Doumpos and Zopounidis, 2002):

$$\left.\begin{array}{l} if\ U_q(a_j) > U_{\sim q}(a_j)\ then\ a_j \in C_q \\ if\ U_q(a_j) < U_{\sim q}(a_j)\ then\ a_j \in C_q^{>} \end{array}\right\} \quad (3.21)$$

Where $C_q^{>}$ denotes the groups C_{q+1} to C_k.

Although MHDIS uses mathematical programming models to estimate the parameters in the same manner with UTADIS, instead of only one linear program, MHDIS requires two linear programs and a mixed integer program (Pasiouras et al., 2006). A detailed explanation about the model development aspects can be obtained in Zopounidis and Doumpos (2002).

3.5.2.3 PAIRCLASS

Doumpos and Zopounidis (2004) suggested an extension of PROMETHEE for sorting problems, which employs pairwise comparisons. In PAIRCLASS, the concepts of PROMETHEE methods are used to perform the pairwise comparisons between the alternatives to be classified and a set of reference alternatives which represent each class.

As with UTADIS and MHDIS, PAIRCLASS requires that a set of reference alternatives (training samples) that characterize each group are known a priori. Assume that a set of alternatives a_k will be assigned two groups C_1 and C_2 (C_1 is better than C_2) and a set of reference alternatives $a_i \in C_1$ and $a_l \in C_2$ exist. A decision for a new alternative a_k can be made through its comparison to the reference alternatives $a_i \in C_1$ and $a_l \in C_2$. The outranking character of a_k over a reference alternative (a_l) that belongs the group C_2 can be defined as the weighted average of the preference of a_k over a_l on each criterion g_j follows (Doumpos and Zopounidis, 2004):

$$P_{kl} = \sum_{j=1}^{n} w_j F_j(a_k, a_l) \tag{3.22}$$

In the same manner, the outranked character of a_k by a reference alternatives that belong to group C_1 is defined as follows (Doumpos and Zopounidis, 2004):

$$P_{ik} = \sum_{j=1}^{n} w_j F_j(a_i, a_k) \tag{3.23}$$

where w_j denotes the weight of criterion j and F_j denotes the preference function that represents preference level of an alternative over another one on criterion j. Then the classification of a_k is performed by considering a so-called net flow f_k (Doumpos and Zopounidis, 2004):

$$f_k = \frac{1}{m_2} \sum_{a_l \in C_2} P_{kl} - \frac{1}{m_1} \sum_{a_i \in C_1} P_{ik} \tag{3.24}$$

where m_1 and m_2 denote the number of reference alternatives in group 1 and 2, respectively. After defining a cut-off point z, the classification rule becomes:

$$\left.\begin{array}{lll} If & f_k > z & a \in C_1 \\ If & f_k < z & a \in C_2 \end{array}\right\} \tag{3.25}$$

As it can be remembered in Section 3.3.3.2, the proposed procedure is based on the leaving flow, entering flow and net flow concepts of PROMETHEE methodology. Nevertheless, PAIRCLASS does not use the six forms of predefined preference functions which are the basic elements of the PROMETHEE method. They proposed a linear programming approach to obtain the preference functions and the weights from a set of reference alternatives. In PROMETHEE methods, $F_j(a_k, a_l)$ represents the strength of the preference of the decision maker for a_k over a_l on criterion j and is an increasing function of the difference $d_j^{kl} = g_j(a_k) - g_j(a_l)$, and there are six predefined forms of preference functions. In PAIRCLASS, each preference function F_j is modeled as a piece-wise linear function, which is divided into subintervals, as follows:

$$F_j(a_k, a_l) = \begin{Bmatrix} 0 & if\ d_j^{kl} < 0 \\ h_j(d_j^{kl}) & if\ d_j^{kl} \geq 0 \end{Bmatrix} \tag{3.26}$$

The estimation of both the criteria weights w_j and the preference functions F_j is performed by using a linear programming model so that the weighted sum of the misclassifications is minimized (Pasiouras et al., 2006). Further details about the piece-wise linear preference function, the linear programming model developed and the description of PAIRCLASS can be found in Doumpos and Zopounidis (2004) and Pasiouras et al., (2006)

3.5.3 Other methods

All the aforementioned MCS methods have received much attention from MCDM literature and used to solve different classification problems. Apart from these methods, some researchers have proposed several methods that have different methodological frameworks.

Besides ELECTRE TRI, PROMETHEE TRI and CLUSTER and PAIRCLASS, the use of outranking relation in the development of classification methods has also been considered by other researchers. Massaglia and Ostanello (1991) proposed an outranking classification method named as N-TOMIC to assign the alternatives into ordered classes following the three consecutive steps. N-TOMIC uses the limit profiles, concordance and discordance concepts like ELECTRE TRI to perform the assignments of alternatives into three groups (i.e., high performance, uncertain alternatives, low performance). N-TOMIC needs that decision maker determines all parameters (criteria weights, thresholds, profiles). PROAFTN (Belacel, 2000) is also another outranking based MCC method. In contrast to other methods, in PROAFTN, the groups are defined in nominal way which means that the groups are not ordered from the best to the worst. Each group is characterized by a reference profile as in PROMETHEE TRI, then a fuzzy indifference relation quantifying the strength of the claim "alternative a_j is indifferent to profile r_k" is developed based on the concordance and discordance concepts discussed for the ELECTRE TRI. The assignment of an alternative is performed by comparing it to all reference alternatives in terms of fuzzy indifference relation and assigning into the most similar group. More recently, Belacel et al. (2006) have extended PROAFTN by using the preference disaggregation analysis paradigm for inferring parameters of the method from a training sample. Belacel and Boulassel (2004) proposed PROCFTN method for nominal classification problems. This procedure uses a fuzzy scoring function for choosing a subset of prototypes, which represent the closest resemblance with an object to be assigned.

Archer and Wang (1993) and Östermark (1999) used neural networks (NNs) for Multi-criteria classification purposes. Köksalan and Ulu (2003) proposed an interactive approach for dealing with sorting problems. Valls and Torra (2000) proposed a method to obtain best set of alternatives. The proposed methodology allows the use of missing values and different types of data (e.g. numbers, linguistic labels or truth values). The method firstly obtains the clusters of alternatives then these clusters are ordered form the best to the worst. The use of rough set theory has also been proposed to deal with sorting problems (see Greco et al., 2001).

Chen et al. (2006) have recently proposed a nominal classification algorithm for dealing with constrained classification problems. The proposed algorithm allows to define different criteria for each category and to include additional constraints about the structure of categories (i.e., each alternative can be assigned at most one group, some alternatives are not assigned to any groups, each alternatives must be assigned to at least one group etc.). They proposed a SMART-based optimization model to solve the MCC problem.

3.6 Summary and the need for the proposed research

The main contribution of this chapter is to provide a discussion of the MCC problem, a brief description of the most known MCS methods and a review of existing MCC techniques. The literature review presented in this chapter leads to the determination of several research questions that related to the gaps in the literature.

Although several methodologies have been developed to deal with sorting problems, most of them assume that adequate number of reference alternatives have already been determined and use these reference alternatives as training samples to infer some of the model parameters. In the problems that can be solved using such methods, the determination of the reference alternatives is relatively easy. For instance, in the credit risk assessment problem of a bank, financial data of the past applicants and the information about whether these firms met the dept obligations or not can be derived from the database of bank (Zopounidis and Doumpos, 2001). However, in the supplier classification problem presented in this thesis, the determination of a set of training sample may not be possible, especially in the early product development phases. Furthermore, in the former instance, the bank is not concerned with identifying the best firms among not-failed ones or the worst firms among the failed ones. Their concern is to be able to identify the firms that will fail or not (Zopounidis and Doumpos, 2001). However, in the latter instance, relative evaluation of suppliers, benchmarking between groups and individual suppliers and identifying potential reasons for differences in supplier performance should be the major concern.

Among the methods that require direct interrogation of the decision maker, PROMETHEE TRI is one of the most suitable approaches that can provide available information for such comparisons because of PROMETHEE's strong ability in comparing the alternatives and identifying the relationships between criteria. However, as stated earlier, since it works like a nominal classification algorithm, PROMETHEE TRI does not guarantee the ordered categories. These facts raise the following research question:

1) How can we develop a PROMETHEE based MCS methodology that provide required information to the decision maker and ensures the ordered categories?

To the best of our knowledge, in most of the MCS methods, it is assumed that the performances of an alternative on a set of criteria are known exactly. However, as Kahraman et al. (2003) stated, in the supplier selection process, some criteria may be impractical to evaluate, information may be difficult to obtain, complex to analyze, or there may not be sufficient time to perform these issues. In such cases, decision making becomes difficult due to the incomplete or imprecise nature of available information. As stated earlier, when the performances of alternatives can be only approximately determined, fuzzy set theory (FST) comes in handy to model these uncertainties and imprecision. The MCDM literature involves numerous fuzzy approaches for the ranking problems but few studies, which apply FST, have been proposed to solve sorting problems (see Belacel and Boulassel, 2004). In the PROCFTN (Belacel and Boulassel, 2004) classification procedure, the assignment of alternatives is based on a scoring function from a fuzzy preference relation. However, they assumed that the objects are fully understood and are described by crisp values of attributes. Furthermore, up to date, the effects of incomplete or imprecise nature of available information on the sorting process have not been fully explored in the literature.

Considering this fact and the aforementioned gap in the existing literature, the second research question of interest is:

2) How can we extend the sorting methodology that is developed for research question 1 so that it can also deal with the fuzzy input data?

As discussed in the first and second chapters, although the main aim of this research is to propose novel methodologies for effective strategic sourcing decisions, this thesis also concern with sorting problematic. Chapter 5 of this thesis is devoted to explain proposed fuzzy and crisp sorting methodologies in great detail. Before providing explanations of the proposed methodologies, Chapter 4 presents a brief overview of fuzzy sets that are used to build the proposed methodologies in this research. A general overview of how fuzzy sets are used in solving MCDM problems and what makes them appropriate tools for solving these problems are given.

CHAPTER FOUR
FUZZY SETS IN MULTI-CRITERIA DECISION MAKING

4.1 Introduction

As stated in earlier chapters, supplier selection is a multi-criteria decision making (MCDM) problem that involve multiple and conflicting criteria. It was also pointed out that MCDM literature offers various multi-attribute decision making (MADM) and multi-objective decision making (MODM) methodologies to support supplier selection and order allocation decisions. In most of the related studies in the literature, it is assumed that the decision problem is fully understood and all information can be obtained exactly. However, in a real world supplier selection problem, many input information are not known precisely (Amid et al., 2006). Uncertainty in supplier selection problems may be associated with unquantifiable or unobtainable information of alternative suppliers or the target values of the objectives determined by the decision maker. In such cases, the supplier selection problems that can be tackled by MADM or MODM methods become fuzzy MADM and fuzzy MODM problems, respectively, and the classical models can not be used any longer. Therefore, the use of fuzzy MCDM methods should be the major concern (Tsai, 1999).

As emphasized in the first three chapters, this research proposes a MCS method to deal with supply base reduction problem by classifying the suppliers into the ordered groups. To solve supplier classification problem where the input values cannot be expressed precisely, we also propose a fuzzyfied extension of the multi-criteria sorting (MCS) method that we propose in Chapter 5. Additionally, an integrated supplier selection and order allocation methodology based on interactive fuzzy goal programming (IFGP) is proposed to overcome the vagueness of the goals. Hence the main objective of this chapter is to review the basic concepts of fuzzy set theory (FST) proposed by Zadeh (1965), which will be used in the proposed methodologies in this research. Therefore, in this chapter, a general overview of how fuzzy sets are used in solving MCDM problems and what makes them appropriate tools for solving these problems are given.

The remainder of this chapter is organized as follows: A brief overview of fuzzy sets is given first. Then decision making in fuzzy environment is examined. In section 3, fuzzy mathematical programming techniques, more specifically fuzzy linear programming (FLP), fuzzy goal programming (FGP) and IFGP techniques, are presented. Finally, fuzzy versions of standard MADM techniques are reviewed and one specific method, fuzzy PROMETHEE, is explained.

4.2 Fuzzy sets

Fuzzy sets are a generalization of conventional set theory that was introduced by Zadeh in 1965 as a mathematical way to represent vagueness in everyday life (Bezdek, 1993). Since then, a huge number of fuzzy methods have been developed by the researchers who study on operations researchers and artificial intelligence (AI), and numerous real-world problems have been successfully solved using fuzzy methods.

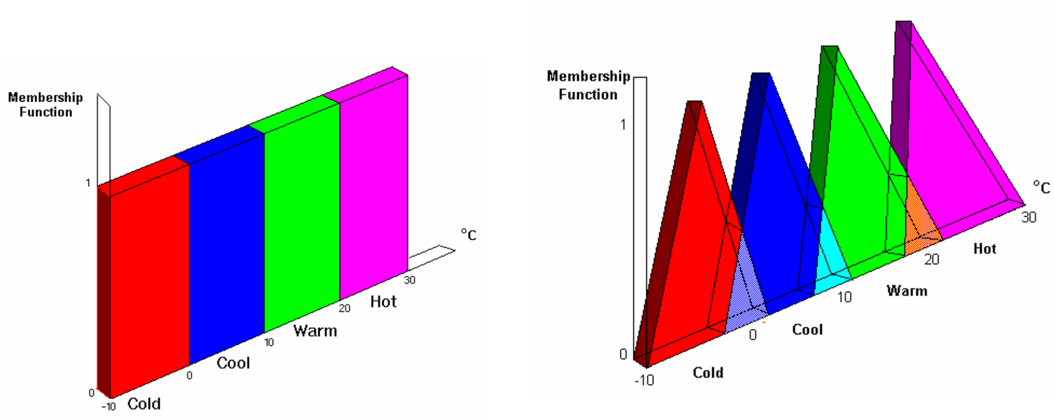
In real life, some information can only be approximately determined. For instance, "*The processing time is about 13 min*" shows that one value around 13 is true but not known exactly. This situation can be defined by an ordinary set in which the set of numbers L from 12 to 14 is crisp, and, can be written as; $L = \{r \in \Re \mid 12 \le r \le 14\}$. And also, the *characteristic function* of this set (Bezdek, 1993):

$$C_L(r) = \begin{Bmatrix} 1 & 12 \le r \le 14 \\ 0 & otherwise \end{Bmatrix} \text{ and } C_L : \Re \to \{0,1\} \tag{4.1}$$

The values of C_L is equal to 1, when r is in L; otherwise C_L is equal to zero. So ordinary sets correspond to two–valued logic: is or isn't, black or white, 1 or 0 (Bezdek, 1993).

Unlike the ordinary set, this situation can be defined by a fuzzy set using the membership function concept. The membership function of a fuzzy set has values between 0 and 1, which denote the degree of membership of a member in the given set.

The difference between ordinal (conventional) set theory and FST can be clearly seen from the “temperature of a room” example (Aziz and Parthiba, 1996). Figure 4.1 illustrates how ordinary sets and fuzzy sets characterize the temperature of a room.



a) Convetional sets

b) Fuzzy sets

Figure 4.1 Comparison with fuzzy sets to conventional sets (Aziz and Parthiba, 1996)

It is clear from the Figure 4.1 that the conventional set theory is not sufficient to define a transition from warm to hot by the increment of one degree of centigrade of heat. In the real world a smooth drift from warm to hot would occur. This natural phenomenon can be described more accurately by FST (Aziz and Parthiba, 1996).

In general, a fuzzy set is defined as follows (Sakawa, 1993, p.7):

“Let X denotes a universal set. Then a fuzzy set F in X is defined as a set of ordered pairs $F = \{(x, \mu_F(x)) \mid x \in X\}$, *where,* $\mu_F(x)$ *is called the membership function for the fuzzy set F. The* $\mu_F(x)$ *represents the grade of membership of x in F. Thus, the nearer the value of* $\mu_F(x)$ *is unity, the higher the grade of membership of x in F.”*

When X is a finite set whose elements are $x_1, x_2,..., x_n$, a fuzzy set F on X is expresses as (Sakawa, 1993):

$$F = \{(x_1, \mu_F(x_1)), (x_2, \mu_F(x_2),...., (x_n, \mu_F(x_n))\} \tag{4.2}$$

In the literature, a lot of ways were presented to represent a fuzzy set. For instance, Zadeh (1965) writes this fuzzy set as:

$$F = \mu_F(x_1)/x_1 + \mu_F(x_2)/x_2 +,....,+ \mu_F(x_n)/x_n = \sum_{i=1}^{n} \mu_F(x_i)/x_i \tag{4.3}$$

In the same manner, when X is infinite,

$$F = \int_X \mu_F(x)/x \tag{4.4}$$

Where "$\int$ " and " $\sum$ "denote the set-theoretic "or". Before defining the basic operations in FST, basic definitions about fuzzy sets should be given as follows (Zimmerman, 1996; Terano et al., 1992):

- *"The support of a fuzzy set F, S(F), is the crisp set of all $x \in X$ such that* $\mu_F(x) > 0$.
- *A fuzzy set with a membership function that has a grade of 1 is called normal. In other words, A is called "normal"* $\leftrightarrow \max_{x \in X} \mu_F(x) = 1$.
- *A fuzzy set F is convex if* $\mu_F(\lambda x_1 + (1-\lambda)x_2) \geq \min\{\mu_F(x_1), \mu_F(x_2)\}, x_1, x_2 \in X, \lambda \in [0,1]$
- *The crisp set of elements that belong to the fuzzy set F at least to the degree α is called the α-level set:* $F_\alpha = \{x \in X \mid \mu_F(x) \geq \alpha\}$

$F_{\alpha} = \{x \in X \mid \mu_F(x) > \alpha\}$ *is called strong α-level set or strong α-cut".* Examples of α - level set are illustrated in Figure 4.2.

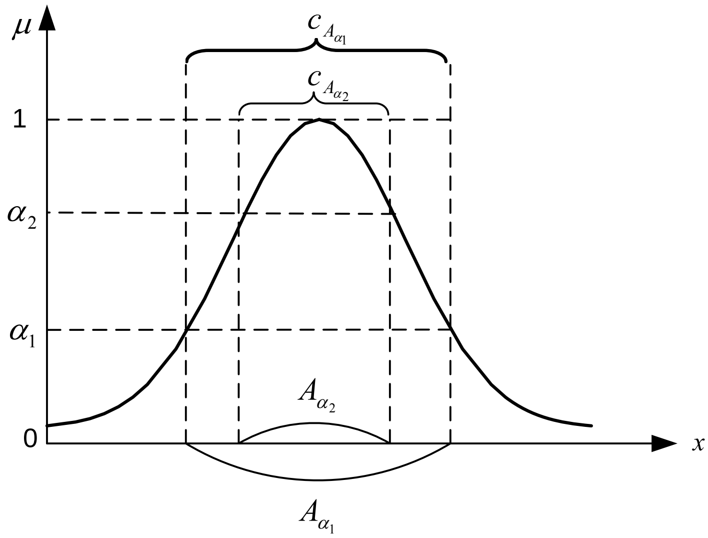


Figure 4.2 Examples of α - level sets (Sakawa, 1993, p. 15)

4.2.1 Basic operations in fuzzy set theory

Union, intersection, and complement are the basic operations in classical set theory. Fuzzy sets have also similar operations; however these operations are defined using the membership functions as follows (Sakawa, 1993; Zimmerman, 1996):

- *Intersection*: The intersection of two fuzzy sets A and B is defined by the membership function $\mu_C(x)$ of the intersection $C = A \cap B$ as follows:

  $\mu_C(x) = \min\{\mu_A(x), \mu_B(x)\}, \quad x \in X$,

- *Union*: The union of two fuzzy sets *A* and *B* is defined by the membership function $\mu_D(x)$ of the union $D = A \cup B$ as follows:

  $\mu_D(x) = \max\{\mu_A(x), \mu_B(x)\}, \; x \in X$,

- *Complementation*: The membership function of the complement of a normalized fuzzy set *A*, denoted by $\overline{A}$, is defined as follows:

  $\mu_{\overline{A}}(x) = 1 - \mu_A(x), \qquad x \in X$.

4.2.2 Fuzzy numbers

For a normal and convex fuzzy set, if a weak α-cut (α level-set) is a closed interval, it is called a fuzzy number (Terano et al., 1992). Fuzzy numbers are used to characterize imprecise numerical information such as "about 5" or "approximately less than 5". A fuzzy number can be expressed in some membership function forms. Two important and widely used membership functions are linear triangular and linear trapezoidal. Figure 4.4 and 4.5 illustrate these membership functions, respectively.

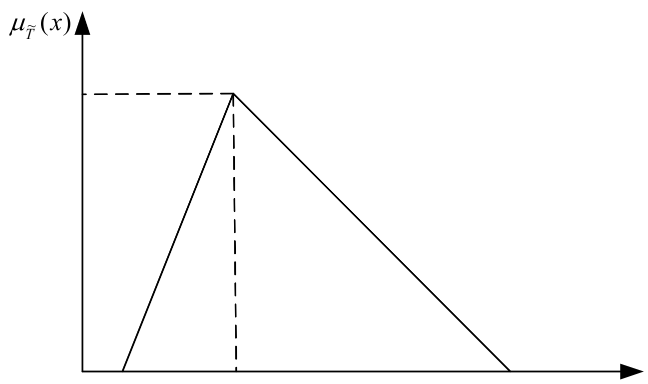


Figure 4.4 Triangular fuzzy number

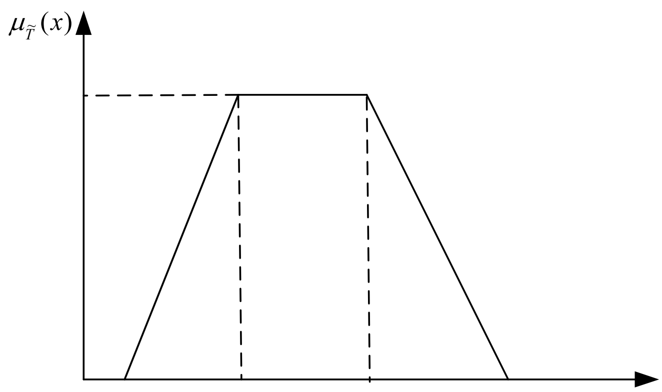


Figure 4.5 Trapezoidal fuzzy number

4.2.3 Algebraic operations with fuzzy numbers

To perform the algebraic operations with fuzzy numbers, the algebraic operations "+", "-", "x", and "/" in ordinary numbers are extended to fuzzy numbers via the extension principle (see Sakawa, 1993). The algebraic operations of fuzzy numbers are much more difficult compared with the algebraic operations of crisp numbers. To increase the computational efficiency of fuzzy numbers, *L-R* type fuzzy numbers are introduced by Dubois and Prade (1978) as follows (Sakawa, 1993, p.26):

"A fuzzy number M is said to be an L-R fuzzy number if

$$\mu_M(x) = \begin{cases} L\left(\dfrac{m-x}{\alpha}\right) & x \le m,\ \alpha > 0 \\ R\left(\dfrac{x-m}{\beta}\right) & x \ge m,\ \beta > 0 \end{cases} \tag{4.5}$$

where m is the mean value of M and α and β are left and right spreads, respectively, and a function L(.) is a left shape function satisfying

(1) L(x)=L(-x)

(2) L(0)=1

(3) L(x) is nonincreasing on [0,∞)."

Symbolically, *M* is denoted by $(m,\alpha,\beta)_{LR}$. It is obvious that the different functions can be chosen for *L(x)*, however the linear function, which is already illustrated in Figure 4.4, is the most widely used one.

For two *L-R* fuzzy numbers M=$(m,\alpha,\beta)_{LR}$ and N=$(n,\gamma,\delta)_{LR}$, the basic operations are as follows (Zimmerman, 1996):

- $(m,\alpha,\beta)_{LR} \oplus (n,\gamma,\delta)_{LR} = (m+n,\ \alpha+\gamma,\ \beta+\delta)_{LR}$ (4.6)
- $-(m,\alpha,\beta)_{LR}=(-m,\beta,\alpha)_{LR}$ (4.7)
- $(m,\alpha,\beta)_{LR} \Theta (n,\gamma,\delta)_{LR} = (m-n,\ \alpha+\delta,\ \beta+\gamma)_{LR}$ (4.8)
- If M<0 and N>0, then

$(m,\alpha,\beta)_{LR} \otimes (n,\gamma,\delta)_{LR} \cong (mn,\ m\gamma+n\alpha,\ m\delta+n\beta)_{LR}$ (4.9)

If M<0 and N>0, then

$(m,\alpha,\beta)_{LR} \otimes (n,\gamma,\delta)_{LR} \cong (mn,\ n\alpha\text{-}m\delta+,\ n\beta\text{-}\ m\gamma)_{RL}$ (4.10)

If M<0 and N<0, then

$(m,\alpha,\beta)_{LR} \otimes (n,\gamma,\delta)_{LR} \cong (mn,\text{-}\ n\beta\text{-}\ m\delta,\ \text{-}n\alpha\text{-}\ m\gamma)_{RL}$ (4.11)

4.3 Fuzzy sets in multi-criteria decision making

As stated earlier chapters, almost every real-world decision making problem involve multiple criteria. However, generally these problems occur in a somehow uncertain environment. The performance of alternatives, constraints of the problem and goals of decision makers may not be known precisely. In such cases, different tools are needed to deal with uncertainty that exists in the problem. Before FST was proposed, generally the methods based on the probability theory had been offered to deal with this problem.

Belman and Zadeh (1970) indicated that much of the decision making in the real world takes place in an environment in which the goals, the constraints, and the consequences of possible actions are not known precisely. Additionally they criticized the use of the techniques of probability theory for every decision making problem ignoring the nature of the problem with following words (Sakawa, 1993):

"...In doing so, we are tacitly accepting the premise that imprecision – whatever its nature – can be equated with randomness. This, in our view, is questionable assumption".

Considering these facts, Belman and Zadeh (1970) introduced fuzzy goal, fuzzy constraints and fuzzy decision concepts (Sakawa, 1993). Assume in a decision making problem that there are *k* fuzzy goals $G_1,..,G_k$ represented by their membership functions $\mu_{G_1}(x),...,\mu_{G_k}(x)$ and *m* fuzzy constraints $C_1,..,C_m$ represented by their membership functions $\mu_{C_1}(x),...,\mu_{C_m}(x)$. Belman and Zadeh (1970) defined fuzzy decision D and its membership function as follows:

$$\left.\begin{aligned} &D = G_1 \cap ... \cap G_k \cap C_1 \cap ... \cap C_m \\ &\mu_D(x) = \min(\mu_{G_1}(x),...,\mu_{G_k}(x),\mu_{C_1}(x),...,\mu_{C_m}(x)) \end{aligned}\right\} \tag{4.12}$$

The maximizing decision is then defined as (Sakawa, 1993):

$$\underset{x \in X}{\text{maximize}}\, \mu_D(x) = \underset{x \in X}{\text{maximize}}\ \ \min(\mu_{G_1}(x),...,\mu_{G_k}(x),\mu_{C_1}(x),...,\mu_{C_m}(x)) \tag{4.13}$$

The concepts of fuzzy goal, fuzzy constraint and fuzzy decision are firstly used in MODM models by Zimmerman (1976) introducing FST into conventional linear programming problems (Zimmerman, 1996). Then numerous extensions of conventional mathematical programming models have been proposed based on FST. Fuzzy mathematical programming models will be discussed in detail in the next section.

Besides MODM problems, FST also successfully applied to a variety of MADM problems. As stated in the previous chapter, every MADM model needs a decision matrix which characterizes the performance of alternatives in terms of criteria involved. In real-world decision problems, the performance of alternatives may not be determined precisely due to unquantifiable information, incomplete information, and non-obtainable information (Bozdag et al., 2003). In such cases, FST should be introduced into the MADM models to be utilized.

In the related literature, a lot of fuzzy MADM methods have been proposed. Some of them extend the well-known MADM methods so that they can deal with the fuzzy input data and use basic fuzzy operations to solve the problem. Some of them are: Fuzzy AHP (Kahraman et al., 2003), Fuzzy TOPSIS (Chen et al., 2006), Fuzzy Simple Additive Weighting (SAW) (Triantaphyllou and Lin, 1996), Fuzzy PROMETHEE (Gelderman et al., 2000; Goumas and Lygreou, 2000) etc. As discussed in previous chapters, in this research, we propose a PROMETHEE based MCS procedure that can deal with both of fuzzy and crisp data. Therefore we will provide a brief explanation about Fuzzy PROMETHEE in the section 4.5.

4.4 Fuzzy mathematical programming

When modeling a MODM problem, estimating exact values of the coefficients, the right hand side values of constraints, the target values of goals are difficult tasks. Even if all information can be provided by a decision maker, the uncertainty still exists in the problem. Therefore, in order to reflect this uncertainty, it is needed to construct a model with inexact parameters, constraints and goals. Many researchers considered this problem as a FLP with fuzzy coefficients of which a membership function was defined for each fuzzy coefficient (Wang & Wang, 1997).

Inuiguchi & Ramik (2000) stated that two major different kinds of uncertainties, ambiguity and vagueness exist in the real life. While ambiguity is associated with such situations in which the choice between two or more alternatives is left unspecified (e.g., "processing time of a job takes *about 8 min*" phrase shows that one value around 8 is true but not known exactly), vagueness is associated with the difficulty of making sharp or precise distinctions in the world (e.g., "decision maker wants to make profit substantially larger than $ 3400" phrase does not define a sharp boundary of a set of satisfactory values but shows that values around 3400 and larger than 3400 are to some extent and completely satisfactory, respectively) (Inuiguchi & Ramik, 2000).

Inuiguchi & Ramik (2000) also classified the fuzzy mathematical programming methods into three categories considering the kinds of uncertainties treated in the method:

- Fuzzy mathematical programming with vagueness: it treats decision making problem under fuzzy goals and constraints,

- Fuzzy mathematical programming with ambiguity: it treats ambiguous coefficients of objective functions and constraints but does not treat fuzzy goal and constraints,
- Fuzzy mathematical programming with vagueness and ambiguity: it treats ambiguous coefficients as well as vague decision maker's preference.

There are a lot of fuzzy mathematical programming types. It would take a lot of space and time to introduce all those types of fuzzy mathematical programming. As discussed in the first chapter, in this dissertation, we use IFGP in order to tackle supplier selection and order allocation problem. Thus, we will restrict ourselves to describe only three types of fuzzy mathematical programming. These are FLP, FGP and IFGP.

4.4.1 Fuzzy linear programming

Consider a LP model,

$$\begin{array}{ll} \min imize & z = cx \\ subject\ to & Ax \leq b \\ & x \geq 0 \end{array} \tag{4.14}$$

where c= (c_1, c_2, ..., c_n) is the *n* dimensional row vector of coefficients of objective function, *x* is an *n*-dimensional column vector of the decision variables, *A* is an *m x n* matrix of constants, and *b* is an *m*-dimensional column vector of right-hand side constants. According to Zimmermann (1978), fuzzy version of the model (4.14), which express the imprecision and uncertainty naturally exist in the problem, can be adopted as follows;

$$\left.\begin{array}{l} cx \prec z_0 \\ Ax \prec b \\ x \geq 0 \end{array}\right\} \tag{4.15}$$

Where the symbols "$\prec$ and $\succ$" denote the fuzzified versions of "$\leq$ and $\geq$" and can be read as "essentially less (greater) than or equal to", respectively (Mohamed, 1997).

Zimmermann (1978) defined a linear membership function, $\mu_1(cx)$ for the goal as follows:

$$\mu_1(cx) = \begin{cases} 1 & if \quad cx \leq z_0, \\ 1-(cx-z_0)/d_1 & if \quad z_0 \leq cx \leq z_0 + d_1, \\ 0 & if \quad cx \geq z_0 + d_1 \end{cases} \tag{4.16}$$

He also proposed a linear membership function $\mu_{2i}(a_i X)$ to treat the i^{th} fuzzy constraint as follows:

$$\mu_{2i}((Ax)_i) = \begin{cases} 1 & if \quad a_i x \leq b_i \\ 1-(a_i x - b_i)/d_{2i} & if \quad b_i \leq a_i x \leq b_i + d_{2i} \\ 0 & if \quad a_i x \geq b_i + d_{2i}, \end{cases} \tag{4.17}$$

Where d_1 and d_{2i} ($i=1,2,...,m$) are chosen constants of admissible violations of the goal and the set of constraints, respectively (Mohamed, 1997). $\mu_1(cx)$ and $\mu_{2i}((Ax)_i)$ denote the degree of the membership of goals and constraints. It is assumed that the i^{th} membership function should be 1 if the i^{th} constraint is very well satisfied, 0 if the i^{th} constraint is strongly violated its limit d_{2i}, and linear from 0 to1 (Sakawa, 1993). Figure 4.6 illustrates the "essentially less than or equal to" type linear membership function.

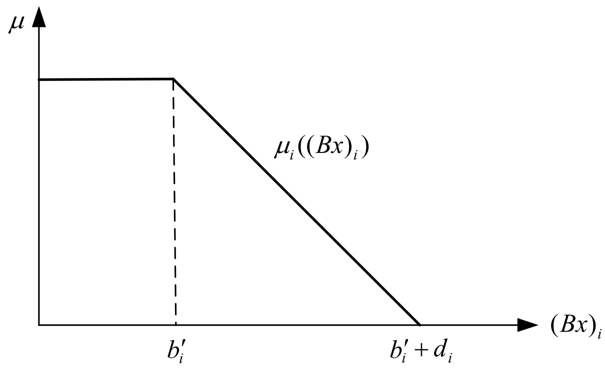


Figure 4.6 "$\prec$" type linear membership function

The degree of the membership of goals and constraints express the satisfaction of the decision maker with the solution, so membership functions value must be maximized (Mohamed, 1997). In FLP models, the conventional distinction between objectives and constraints no longer applies (Chang & Wang, 1997).

After defining the linear membership functions, the maximizing decision is then defined by using the fuzzy decision theorem of Bellman and Zadeh (1970):

$$\max_x \min(\mu_1(cx),...,\mu_{21}(a_1x),...,\mu_{2m}(a_mx)) \tag{4.18}$$

Introducing one new variable λ, this problem can be transformed as:

$$\begin{array}{ll} \max & \lambda \\ \textit{subject to} & \mu_1(cx) \geq \lambda \\ & \mu_{2i}(a_ix) \geq \lambda \quad i = 1,2,...,m \\ & x \geq 0 \end{array} \tag{4.19}$$

According to above membership functions, FLP for (4.15) can be rewritten as following (Mohamed, 1997):

$$\begin{array}{ll} \max & \lambda \\ \textit{subject to} & \lambda \leq 1 - (cx - z_0)/d_1 \\ & \lambda \leq 1 - (a_ix - b_i)/d_{2i} \quad i = 1,2,...m \\ & \lambda \geq 0, x \geq 0. \end{array} \tag{4.20}$$

It is obvious that FLP model can be easily extended to fuzzy multi-objective linear programming (FMOLP) by defining a membership function for each of objective functions. Assume that there are k linear objective functions to be minimized; the corresponding FMOLP model can be defined as

$$\begin{array}{lll} \max & \lambda & \\ \textit{subject to} & \lambda \le 1-(c_k x - z_{0k})/d_{1k} & k=1,2,\dots,k \\ & \lambda \le 1-(a_i x - b_i)/d_{2i} & i=1,2,\dots,m \\ & \lambda \ge 0, x \ge 0. & \end{array} \tag{4.21}$$

The construction of the linear membership functions is a difficult task. To tackle this problem, Zimmerman (1978) proposed the use of pay-off table. According to the Zimmerman (1978), once the MOLP model is developed, it is solved with each of the objective functions by themselves. In other words first objective function is set as the objective and the model is solved. Then second, third and other objectives are all set as objective one by one and solved. For each solution the value of the objective and the other objective function values are recorded. By this way the payoff table is constructed which is given in Table 4.1 below.

Table 4.1 The payoff table

	The objective function			
Value	Z_1	Z_2	$\dots$	Z_M
Z_1	Z_{11}	Z_{12}	$\dots$	Z_{1M}
Z_2	Z_{21}	Z_{22}	$\dots$	Z_{2M}
$\vdots$	$\dots$	$\dots$	$\dots$	$\dots$
Z_M	Z_{M1}	Z_{M2}	$\dots$	Z_{MM}

Looking at the figures in Table 4.1, the best lower bound (l_k) and the worst upper bound (u_k) are determined. Then the membership functions of each objective can be defined as follows:

$$\mu_{z_k}(x) = \begin{cases} 1 & ; \quad Z_k(x) \le l_k \\ \dfrac{u_k - Z_k(x)}{u_k - l_k} & ; \quad l_k < Z_k(x) \le u_k \\ 0 & ; \quad Z_k(x) > u_k . \end{cases} \tag{4.22}$$

Various types of membership functions can be used to support the fuzzy analytical framework although the fuzzy description is hypothetical and membership values are subjective (Chang & Wang, 1997).

4.4.2 Fuzzy goal programming

Goal programming (GP) is one of the most powerful MODM approaches. A standard GP formulation requires that the target values of the goals and the parameters of the constraints are precisely known a priori. However, one of the major drawbacks for a decision maker in using GP is to determine precisely the goal value of each objective function (Arikan and Güngör, 2001).

The main idea behind GP is to minimize the distance between Z_k and an aspiration level (target value of the objective function) $\overline{Z}_k$, which is expressed by the deviational variables. In FGP, membership function values of the each objective replace by the deviational variables (Mohamed, 1997).

FST in GP was first considered by Narasimhan (1980). Narasimhan & Rubin (1984), Hannan (1981), Ignizio (1982) and Tiwari et al. (1986, 1987) extended the FST to the field of GP. Ramik (2000), Rao et al. (1988), Wang & Fu (1997), Mohamed (1997), Ohta & Yamaguchi (1996), Abd El-Wahed & Abo-sinna (2001) and Mohammed (2000) have investigated various aspects of decision problems using FGP theoretically.

A typical FGP problem formulation can be stated as follows:

Find x_i $\quad i = 1,2,...,n$

to satisfy

$$\begin{aligned}
&Z_m(x_i) \prec \overline{Z}_m && m = 1,2,...,M, \\
&Z_k(x_i) \succ \overline{Z}_k && k = M+1, M+2,...,K, \\
&g_j(x_i) \le b_j && j = 1,2,...,J, \\
&x_i \ge 0 && i = 1,2,...,n.
\end{aligned} \tag{4.23}$$

where

$Z_m(x_i)$ = the mth goal constraint,

$Z_k(x_i)$ = the kth goal constraint,

$\overline{Z}_m(x_i)$ = the target value of the mth goal,

$\overline{Z}_k(x_i)$ = the target value of the kth goal,

$g_j(x_i)$ = the jth inequality constraint,

b_j = the available resource of inequality constraint j.

In formulation (4.23), the symbols "$\prec$" and "$\succ$" denote the fuzzified versions of "$\le$" and "$\ge$" and can be read as "approximately less (greater) than or equal to". These two types of linguistic terms have different meanings. Under "approximately less than or equal to" situation, the goal m is allowed to be spread to the right-hand-side of $\overline{Z}_m$ ($\overline{Z}_m = l_m$ where l_m denote the lower bound for the m^{th} objective) with a certain range of r_m ($\overline{Z}_m + r_m = u_m$, where u_m denote the upper bound for the m^{th} objective). Similarly, with "approximately greater than or equal to", p_k is the allowed left side of $\overline{Z}_k$ ($\overline{Z}_k$ - $p_k = l_k$, and $\overline{Z}_k = u_k$) (Wang and Fu, 1997).

As can be seen, GP and FGP have some similarities. Both of them need an aspiration level for each objective, which is determined by the decision maker. In addition to the aspiration levels of the goals, FGP needs max-min limits (u_k, l_k) for each goal (Mohamed, 1997).

After constructing fuzzified aspiration levels with respect to the linguistic terms of "approximately less than or equal to", and "approximately greater than or equal to", appropriate fuzzy membership function can be developed for each goal as follows:

For "approximately less than or equal to";

$$\mu_{z_m}(x) = \begin{cases} 1 & if \quad Z_m(x) \le l_m, \\ 1 - \dfrac{Z_m(x) - l_m}{u_m - l_m} & if \quad l_m \le Z_m(x) \le u_m, \\ 0 & if \quad Z_m(x) \ge u_m. \end{cases} \tag{4.24}$$

For "approximately greater than or equal to";

$$\mu_{z_k}(x) = \begin{cases} 1 & if \quad Z_k(x) \ge u_k, \\ 1 - \dfrac{u_k - Z_k(x)}{u_k - l_k} & if \quad l_k \le Z_k(x) \le u_k, \\ 0 & if \quad Z_k(x) \le l_k. \end{cases} \tag{4.25}$$

Figure 4.7 illustrates both types of membership functions.

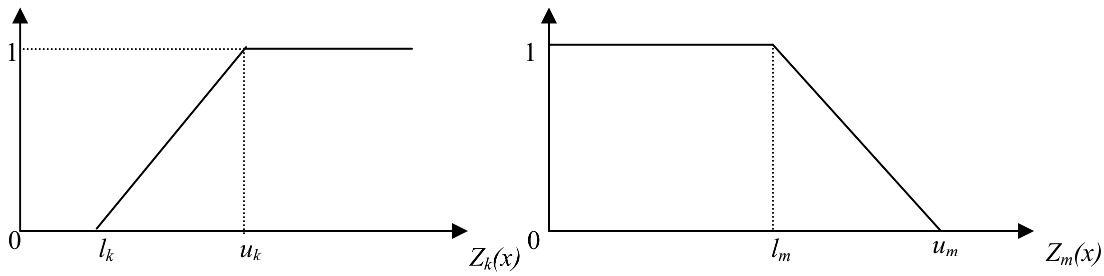


Figure 4.7 Membership functions of fuzzy goals

Using Belman and Zadeh (1970)'s fuzzy decision theorem, the fuzzy solution is obtained by the intersection of the all the membership functions representing the fuzzy goals. The membership function $\mu_F(x)$ which characterizes the fuzzy solution can be defined as follows (Sakawa, 1993):

$$\mu_F(x) = \mu_{Z_1}(x) \cap \mu_{Z_2}(x) .... \cap \mu_{Z_k}(x) = \min[\mu_{Z_1}(x), \mu_{Z_2}(x), ..., \mu_{Z_k}(x)] \tag{4.26}$$

Then the optimum decision is one that maximizes the minimum membership function values (Sakawa, 1993):

$$\max_{x \in F} \mu_F(x) = \max_{x \in F} \min[\mu_{Z_1}(x), \mu_{Z_2}(x), ..., \mu_{Z_k}(x)] \tag{4.27}$$

By introducing the auxiliary variable λ, which is the overall satisfactory level of compromise, formulation (4.23) can be transformed as:

$$\left.\begin{array}{lll} \text{maximize} & \lambda & \\ \text{subject to} & & \\ & \lambda \le \mu_{Z_k} & k = 1, ..., K \\ & g_j(x_i) \le b_j & i = 1, ..., n, \quad j = 1, ..., J \\ & x_i \ge 0 & i = 1, ..., n \\ & \lambda \in [0,1]. & \end{array}\right\} \tag{4.28}$$

Consideration of different relative importance and priority of the goals in the FGP problem is important because some goals are more important than others (Chen & Tsai, 2001). The preemptive structure in fuzzy environment and the different relative importance of the goals have been investigated by some researchers. In order to reflect the relative importance of the goals, the weighted average of membership function values was used by Hannan (Hannan, 1981). Tiwari et al. (Tiwari et al., 1987) proposed a weighted model that incorporates each goal's weight into the objective function in an additive fashion. Using Tiwari et al. (1987)'s approach, the model (4.23) can written as follows:

$$\left.\begin{array}{lll} \text{Maximize} & \sum_{k=1}^{K} w_k \mu_{Z_k} & \\ & & \\ \text{subject to} & & \\ & g_j(x_i) \le b_j & i = 1,\ldots, n, \quad j = 1,\ldots, J \\ & \mu_{Z_k} \in [0,1] & k = 1,\ldots, K \\ & x_i \ge 0 & i = 1,\ldots, n. \end{array}\right\} \quad (4.29)$$

Where w_k denotes the weight of the *k*th fuzzy goal, and $\sum w_k = 1$. Weights in the model show the relative importance of the fuzzy goals.

To deal with the same problem, Chen and Tsai (Chen & Tsai, 2001) proposed an additive formulation, however, one single problem is necessary to be solved, no matter how many priority levels are decided. They incorporate the preemptive priority structure into this formulation to find a set of solutions that maximize the sum of each fuzzy goal's achievement degree.

To illustrate the formulation, an example as follows can be useful (Chen & Tsai, 2001): there are four fuzzy goals, which have priority levels as follows:

- Priority level 1: Goal 1 and 4;
- Priority level 2: Goal 3;
- Priority level 3: Goal 2;

According to the above preemptive priority structure, the following relationship for the respective achievement degrees for the goals can be written:

$\lambda_1 \ge \lambda_3$
$\lambda_4 \ge \lambda_3$ and
$\lambda_3 \ge \lambda_2$

After addicting the above relationship to the model (4.23), the FGP can be formulated as(Chen & Tsai, 2001):

$$
\left.\begin{array}{lll}
\text{Maximize} & \sum_{k=1}^{K} \mu_{Z_k} & \\
\text{subject to} & & \\
& g_j(x_i) \le b_j & i = 1,\ldots, n, \quad j = 1,\ldots, J \\
& \mu_{Z_1} \ge \mu_{Z_3} & \\
& \mu_{Z_4} \ge \mu_{Z_3} & \\
& \mu_{Z_3} \ge \mu_{Z_2} & \\
& \mu_{Z_k} \in [0,1] & k = 1,\ldots, K \\
& x_i \ge 0 & i = 1,\ldots, n.
\end{array}\right\} \tag{4.30}
$$

Lin's (2004) proposed a weighted max–min model to reflect the relative weights for fuzzy goals to the solutions.

$$
\left.\begin{array}{lll}
\text{Maximize} & \lambda & \\
\text{subject to} & & \\
& \mu_{Z_k} \ge w_k \lambda, & k = 1, 2, \ldots, K, \\
& \mu_{Z_k} \in [0,1], &
\end{array}\right\} \tag{4.31}
$$

In the same manner as Tiwari et al. (1987)'s weighted additive approach, Lin's (2004) weighted max–min approach aims to obtain better achievement degrees for a higher priority goal. Differently, it includes also "min operator" that prevents obtaining too low achievement levels for lower priority goals.

In order to treating relative importance of goals in FGP models, Aköz and Petrovic (2006) proposed an approach that allows the decision maker to use the linguistic terms such as 'slightly more important than', 'moderately more important than' or 'significantly more important than' when expressing the fuzzy importance relation between objectives. The objective function is defined as the sum of achievement degrees of all the goals and degrees of satisfaction of the fuzzy relative importance relations among the goals. In the case of the preemptive goal priority, Aköz and Petrovic (2006) suggested new constraints to be added to the FGP model for each pair of fuzzy goals Z_{k1} and Z_{k2}, where the relative importance relations among the goals exist. To express the fuzzy importance relations, following constraints are added (Aköz and Petrovic, 2006):

When Z_{k1} is slightly more important than Z_{k2}:

$$\mu_{z_{k1}} - \mu_{z_{k2}} + 1 \geq \mu_{R1} \tag{4.32}$$

When Z_{k1} is moderately more important than Z_{k2}:

$$\frac{\mu_{z_{k1}} - \mu_{z_{k2}} + 1}{2} \geq \mu_{R2} \tag{4.33}$$

When Z_{k1} is significantly more important than Z_{k2}:

$$\mu_{z_{k1}} - \mu_{z_{k2}} \geq \mu_{R3} \tag{4.34}$$

Where μ_{R1}, μ_{R2} and μ_{R3} represents degrees of satisfaction of the above fuzzy relations, respectively. Let's assume that there are four fuzzy goals, which have 'slightly more important than', 'moderately more important than' and 'significantly more important than' fuzzy importance relation among them, respectively. After addicting the above relationship to the model (4.23), the FGP can be formulated as;

$$\left.\begin{array}{ll}
\text{Maximize} & \lambda(\sum_{k=1}^{4} \mu_{Z_k}) + (1-\lambda)(\mu_{R1} + \mu_{R2} + \mu_{R3} + \mu_{R4}) \\
\text{subject to} & \\
& g_j(x_i) \leq b_j \qquad i = 1,\ldots, n, \quad j = 1,\ldots, J \\
& \mu_{z_1} - \mu_{z_2} + 1 \geq \mu_{R1} \\
& \dfrac{\mu_{z_2} - \mu_{z_3} + 1}{2} \geq \mu_{R2} \\
& \mu_{z_3} - \mu_{z_4} \geq \mu_{R3} \\
& \mu_{Z_k}, \mu_{R1}, \mu_{R2}, \mu_{R3}, \lambda \in [0,1] \qquad k = 1,\ldots, K \\
& x_i \geq 0 \qquad i = 1,\ldots, n.
\end{array}\right\} \tag{4.35}$$

As it can be seen from the above formula, Aköz and Petrovic's (2006) approach requires the determination of an additional parameter λ. As the value of parameter λ decreases, the sum of the achievement degrees decreases. However, in this case the importance relations are weighted more (Aköz and Petrovic, 2006).

4.4.3 Interactive fuzzy goal programming

In the FLP and FGP approaches discussed in the above sections, the fuzzy decision of Belman and Zadeh (1970) is used to present the fuzzy preferences of the decision maker. Sakawa (1993) stated that the use of the fuzzy decision may not be appropriate in practice and consequently it becomes evident that an interaction with the decision maker is necessary. Sakawa (1993) also pointed out that fuzzy mathematical programming approaches can be strengthen by incorporating the desirable features of the interactive approaches into fuzzy approaches.

As stated in the first and second chapters, we assert in this dissertation that IFGP approaches provide more effective solutions for supplier selection and order allocation problem than the fuzzy approaches used in the supplier selection literature. If the decision maker is not satisfied with the current optimal solution, interactive FGP approaches allows the decision maker to act on this solution by updating the membership functions (Abd El-Wahed & Lee, 2006).

Abd El-Wahed and Lee (2006) stated that the main advantage of interactive approaches is that the decision maker controls the search directions during the solution procedure until a preferred compromise solution is obtained. Several researchers have paid considerable attention to develop interactive fuzzy approaches, such as Baptistella and Ollero (1980) and Werners (1987).

More recently, El-Wahed and Lee (2006) proposed an IFGP approach to determine the preferred compromise solution for the multi-objective transportation problem. The approach focuses on minimizing the worst upper bound to obtain an efficient solution which is close to the best lower bound of each objective function.

The solution procedure controls the search direction via updating both the membership values and the aspiration levels with the interaction of decision maker until the decision maker accepts the solution.

The solution procedure of IFGP can be summarized in the following steps (Abd El-Wahed & Lee, 2006 p.161):

"Step 1: Develop a multi-objective linear programming model.

Step 2: Solve the first objective function as a single objective problem. Continue this process K times for the K objective functions. If all the solutions are the same, select one of them as an optimal compromise solution and go to Step 8. Otherwise, go to Step 3.

Step 3: Evaluate the objective function at the K^{th} solution and determine the best lower bound (l_k) and the worst upper bound (u_k).

Step 4: Define the membership function of each objective function and also the initial aspiration level.

Step 5: Use model formula that is given in (4.28) and solve it as a linear programming problem.

Step 6: Present the solution to the decision maker. If the decision maker accepts it, go to Step 8. Otherwise, go to Step 7.

Step 7: Evaluate each objective function of the solution. Compare the upper bound of each objective with the new value of the objective function. If the new value is lower than the upper bound, consider this as a new upper bound. Otherwise, keep the old one as is. Repeat this process K times and go to Step 4.

Step 8: Stop."

As stated earlier, in this dissertation, the use of IFGP approach is suggested for supplier selection and order allocation problem. The IFGP procedure used in the proposed approach is slightly different from El-Wahed and Lee (2006)'s IFGP approach. In their approach, at each iteration El-Wahed and Lee (2006) changes all membership functions of the goals simultaneously and the procedure stops when the decision maker is satisfied or an infeasible solution is obtained. In order to avoid finding an infeasible solution, at each iteration the decision maker is allowed to change only one of the membership functions. In other words, in this thesis, we suggest to use Abd El-Wahed and Lee (2006)'s IFGP approach to solve supplier selection problem. The IFGP procedure used in the proposed approach will be discussed in great detail in the chapter 7.

4.5 Fuzzy PROMETHEE

When the performance of alternatives cannot be determined crisply, the incorporating FST into MADM methods comes in handy. Since, a PROMETHEE based sorting algorithm, which can deal with both fuzzy and crisp data, is proposed in this dissertation, one specific fuzzy MADM method, fuzzy PROMETHEE, is discussed in detail.

As discussed in the previous chapter, PROMETHEE method can handle data that are known exactly and have fixed numerical values, on the contrary, the fuzzy methods F-PROMETHEE I and II (Geldermann et al., 2000; Goumas and Lygreou, 2000; Martin et al., 2003) use the concept of fuzzy sets to treat the uncertainty exist in the problem. In the F-PROMETHEE methods, the performances of alternative solutions can be defined as fuzzy numbers, as well as crisp ones.

F-PROMETHEE method follows the procedure of PROMETHEE method described in the previous chapter step by step (Martin et al., 2003). Differently, F-PROMETHEE is based on the arithmetic operations of fuzzy numbers, which are presented by Dubois and Prade (1978). In a *L-R* type fuzzy number $x=(m,\alpha,\beta)$. The parameters m, m-α and m+β denote the most promising value, the smallest possible value, and the largest possible value that describe a fuzzy event, respectively. Since the performances of alternatives are fuzzy numbers, the results of the calculations are in the form of fuzzy numbers (see Geldermann et al., 2000). Other parameters, expressing the opinion of the decision maker, such as the weighting factors and preferences are considered as regular information with precise numerical values and not as fuzzy numbers (Martin et al., 2003).

Due to the fuzzy nature of performances, the results of the preference functions will be fuzzy. Goumas and Lygreou (2000) state that when the fuzzy preference function, say $\widetilde{F}(a,b)=(m,\alpha,\beta)$, takes values outside the interval 0-1, it should be adjusted accordingly so that m-α ≥ 0 and m+β ≤ 1, since it is assumed that $F_j(a,b) \in [0,1]$ and has no meaning outside this interval. After adjusting the preference function, the fuzzy outranking relation ($\widetilde{\Pi}$) is calculated as follows (Geldermann et al., 2000):

$$\widetilde{\Pi}(a,b)=\sum_{j=1}^{J} w_j \otimes \widetilde{F}_j(a,b) \tag{4.36}$$

Now, leaving and entering flows, which can be defined as measures of strengths and weaknesses of the alternatives, respectively, can be calculated using fuzzy outranking relations.

$$\widetilde{\Phi}^{+}(a)=\frac{1}{n-1}\sum_{x\in A}\widetilde{\Pi}(a,x) \qquad \textit{fuzzy leaving flow} \tag{4.37}$$

$$\widetilde{\Phi}^{-}(a)=\frac{1}{n-1}\sum_{x\in A}\widetilde{\Pi}(x,a) \qquad \textit{fuzzy entering flow} \tag{4.38}$$

The rank ordering of the decision alternatives can be based on the defuzzification of the fuzzy leaving and entering flows. In the defuzzification phase, different approaches can be used. Geldermann et al. (2000) suggested the Centre of Area

(COA) method as a defuzzification method. The defuzzification of the leaving and entering flows can be performed using COA method as follows (Geldermann et al., 2000):

$$x_{defuzz} = \frac{\int x.\mu(x)dx}{\int \mu(x)dx} \tag{4.39}$$

Gelderman et al. (2000) stated that the COA approach gives reasonable results and allows a consistent evaluation of trapezoidal and triangular fuzzy data as well as of crisp data. A number of defuzzification methods have been proposed to compare and to rank fuzzy numbers. The reader is referred to Bortolan and Degani (1985) and Wang and Kerre (2001a,b) for a review of the literature.

After calculating the defuzzified leaving and entering flows, the approach is similar to the crisp one to obtain F-PROMETHEE I and II. The net flow can be obtained by taking difference between the defuzzified flows. Detailed explanations about Fuzzy PROMETHEE can be found in the works of Gelderman et al. (2000), Goumas & Lygreou (2000) and Martin et al. (2003).

4.6 Summary

In this chapter, we give a brief review of the fundamentals of FST. Decision making in a fuzzy environment is discussed in detail. Fuzzy MODM methods are reviewed and more specifically FLP, FGP and IFGP methods are explained. Lastly the necessity of fuzzy MADM methods is emphasized and Fuzzy PROMETHEE method, which will be used throughout the remainder of this thesis, is explained in detail.

In the next chapter, the proposed MCS method, PROMSORT, is discussed. An extension of the proposed methodology named as Fuzzy-PROMSORT is also introduced.

CHAPTER FIVE
THE PROPOSED MULTI-CRITERIA SORTING METHODS BASED ON PROMETHEE METHODOLOGY

5.1 Introduction

As emphasized in Chapter 2, with increasing importance of Just-in-Time (JIT) philosophy and effective purchasing decisions on the performance of whole supply chain, many firms are forcing to adopt the strategy of supply base reduction. The literature review presented in Chapter 2 reveals that there is a strong need for firms to reduce the number of suppliers and an emerging trend to classify supplier into two or more categories.

As mentioned earlier, in this research, we propose two different methodologies for strategic supplier evaluation and selection problem. The first methodology mainly deals with the prequalification of the suppliers, while the second one is proposed to tackle the order allocation problem. More specifically, in the first methodology, we focus on constructing supplier classes based on the overall performances, reducing the bad performers within the supply base, identifying the differences between supplier classes and providing the feedbacks to ineffective suppliers.

Although a number of methods have been proposed for supply base reduction, as discussed in Chapter 2, there are some limitations and disadvantages of them. The major shortcoming of the existing methods is that most of them are not based on the multicriteria evaluation of suppliers. Because of the multiple criteria nature of the supplier selection and evaluation problems, we believe that a multi-criteria sorting (MCS) method will be more efficient in order to reduce supply base. To the best of our knowledge, MCS methods have not yet been applied for supplier selection and evaluation problems. Therefore, the proposed methodology is centered on developing a new MCS method for supplier classification. This chapter is devoted to explain the proposed MCS methodology named as PROMSORT.

This chapter is further organized as follows. The second section presents the methodological framework of PROMSORT. Section 2 also discusses the difference of PROMSORT compared to other MCS methods and illustrates a financial classification example to show how the proposed method can be used to classify the alternatives into predefined classes. Section 3 demonstrates how PROMSORT can be extended so that it can also deal with the fuzzy input data. The main shortcomings of the proposed methodology are discussed in section 4. Finally, in section 5, a basic computer program based on the proposed methodology is presented.

5.2 PROMSORT

PROMSORT is a PROMETHEE based MCS method that assigns alternatives to predefined ordered categories. It should be remembered that the proposed method is inspired from the works of Figueira et al. (2004) and Doumpos and Zopounidis (2004). The assignment of an alternative *a* to a certain category is performed by using both of the profiles defining the limits of the categories and the reference alternatives in different steps. In PROMSORT, the categories are distinguished by using limit profiles just like as ELECTRE TRI.

Let G be a set of the criteria $g_1, g_2, \ldots, g_j$ (G={1,2,…,j}) and B be a set of the limit profiles distinguishing k+1 categories (B={1,2,…,k}). b_h represents the upper limit of category C_h and the lower limit of category C_{h+1}, h=1,2,…k (see Figure 5.1). Assume that C_2>C_1 means that category 2 outranks category 1, the set of profiles (B=$\{b_1,b_2,\ldots,b_k\}$) must have the following property:

$$[b_k\, P\, b_{k-1}],[b_{k-1} P\, b_{k-2}],......,[b_2\, P\, b_1] \tag{5.1}$$

This property means that the categories should be ordered and distinguishable. Assuming the more preferred to less, the following condition helps to obtain the ordered and distinguishable categories:

$$\forall j,\ \forall h=1..\text{k-1},\ g_j(b_{h+1}) \geq g_j(b_h) + p_j. \tag{5.2}$$

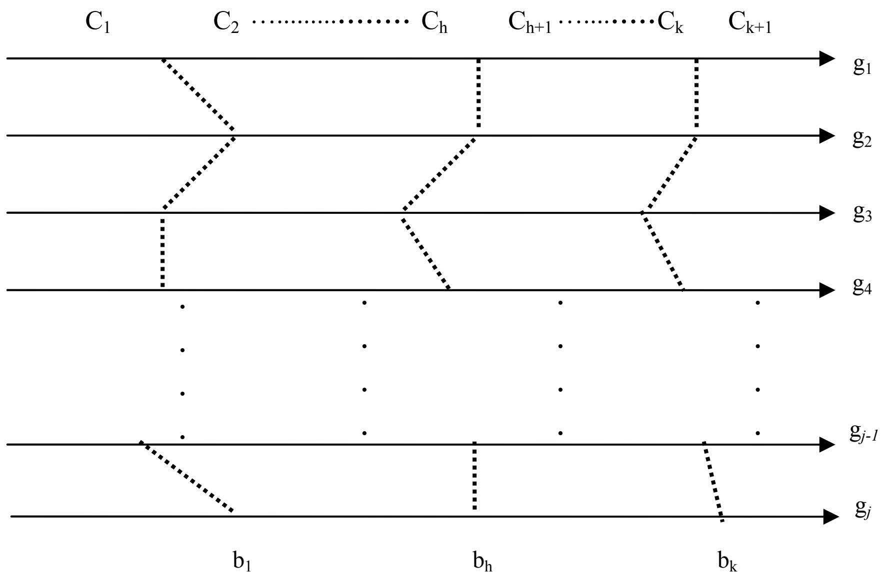


Figure 5.1 Definition of categories using limit profiles

If you recalled Section 3.3.3.2, PROMETHEE I provides two flows named as the leaving Φ^+ and entering flows Φ^- in order to obtain preference relation between alternatives. By using these flows, the comparison between two the limit profiles b_{h-1} and b_h, which distinguishes the categories C_{h-1}, C_h and C_{h+1}, is defined as follows:

b_h is preferred to b_{h-1} :

$$(b_h P b_{h-1}) \text{ if } \left.\begin{array}{c} \Phi^+(b_h) > \Phi^+(b_{h-1}) \, and \, \Phi^-(b_h) < \Phi^-(b_{h-1}), or \\ \Phi^+(b_h) = \Phi^+(b_{h-1}) \, and \, \Phi^-(b_h) < \Phi^-(b_{h-1}), or \\ \Phi^+(b_h) > \Phi^+(b_{h-1}) \, and \, \Phi^-(b_h) = \Phi^-(b_{h-1}) \end{array}\right\} \tag{5.3}$$

b_h is indifference to b_{h-1} :

$$(b_h I b_{h-1}) \text{ if } \Phi^+(b_h) = \Phi^+(b_{h-1}) \, and \, \Phi^-(b_h) = \Phi^-(b_{h-1}) \tag{5.4}$$

b_h is incomparable with b_{h-1} :

$$(b_h R b_{h-1}) \;\; if \;\; \left. \begin{array}{c} \Phi^+(b_h) > \Phi^+(b_{h-1})\, and\, \Phi^-(b_h) > \Phi^-(b_{h-1}), or \\ \Phi^+(b_h) < \Phi^+(b_{h-1})\, and\, \Phi^-(b_h) < \Phi^-(b_{h-1}) \end{array} \right\} \tag{5.5}$$

It should be noted that the entire set of alternatives including the limit profiles are considered to perform the PROMETHEE I calculations. In other words, PROMSORT assumes that the limit profiles that distinguish the ordered categories belong to the initial data set.

5.2.1 Sorting process

PROMSORT performs the assignment of alternatives to categories following the three steps:

- Construction of an outranking relation using PROMETHEE I,
- The use of the outranking relation in order to assign alternatives to categories except the incomparability and indifference situations,
- Final assignment of the alternatives based on pairwise comparison.

5.2.1.1 Construction of an outranking relation using PROMETHEE I

In PROMSORT, categories are defined by lower and upper limits like ELECTRE TRI and both limit profiles and reference alternatives are used to assign an alternative to a category. In order to determine the reference alternatives, firstly all alternatives are compared with the limit profiles using the outranking relation obtained by PROMETHEE. The comparison of an alternative a with a limit profile b_h is defined as follows:

a is preferred to b_h:

$$(aPb_h)\ \ iff \quad \begin{array}{c} \Phi^+(a) > \Phi^+(b_h)\, and\, \Phi^-(a) < \Phi^-(b_h), or \\ \Phi^+(a) = \Phi^+(b_h)\, and\, \Phi^-(a) < \Phi^-(b_h), or \\ \Phi^+(a) > \Phi^+(b_h)\, and\, \Phi^-(a) = \Phi^-(b_h) \end{array} \tag{5.6}$$

a is indifference to b_h :

$$(aIb_h)\ \ iff \qquad \Phi^+(a) = \Phi^+(b_h)\, and\, \Phi^-(a) = \Phi^-(b_h) \tag{5.7}$$

a is incomparable with b_h:

$$(aRb_h)\ \ iff \quad \begin{array}{c} \Phi^+(a) > \Phi^+(b_h)\, and\, \Phi^-(a) > \Phi^-(b_h), or \\ \Phi^+(a) < \Phi^+(b_h)\, and\, \Phi^-(a) < \Phi^-(b_h) \end{array} \tag{5.8}$$

5.2.1.2 Initial assignment of the alternatives

The assignment of alternatives to categories results directly from the outranking relation. (Assume that $C_2 > C_1$ means that category 2 outranks category 1).

- Compare alternative a successively to b_i, for i=k, k-1,…,1,
- b_h being the first profile such that aPb_h ,
- b_t being the first profile such that aRb_t or aIb_t ,
- If $h>t$, assign a to category C_{h+1} ,
- Otherwise do not assign alternative a to any category (it is not certain that alternative a should be assigned to category t or t+1).

After the second phase, it is possible that some alternatives could not have been assigned to a category, since outranking relation indicates that these alternatives are indifferent or incomparable to a limit profile and could not be assigned to a category directly. On the other hand, some alternatives could be assigned to the categories. In the third stage, we will use these alternatives as the reference actions of the categories to be able to assign the alternatives which have not yet been assigned. The reference alternatives have the following properties:

- each limit profile b_h outranks all reference alternatives in C_h,
- each reference alternative in C_h outranks all lower limit profiles (b_{h-1}, b_{h-2},…),
- each reference alternative in C_h outranks all reference alternatives in C_{h-1}, C_{h-2},.. ,
- there can be preference, indifference or incomparability relations between all alternatives in the same category.

5.2.1.3 Final assignment

In the second phase, some alternatives are assigned in h+1 ordered categories C_{h+1}>C_h>….C_1. Now, these alternatives are the reference alternatives for ordered categories.

Suppose;

- a reference set X_h consists of m of the alternatives for category h , i.e., $X=\{x_1, x_2, ..., x_m\}$.

For an alternative a which has not yet been assigned to a category,

- determine a distance (similar as Doumpos and Zapounidis (2004))

$$d_k = \frac{1}{n_t} d^+{}_k - \frac{1}{n_{t+1}} d^-{}_k \qquad (5.9)$$

Where d_k^+ measures the outranking character of a over all alternatives assigned to category C_t, d_k^- measures the outranked character of a by all alternatives assigned to category C_{t+1} and n_t is the number of reference alternatives of category C_t.

$$d^{+}{}_{k} = \sum_{x \in X_t} (\Phi(a) - \Phi(x)) \tag{5.10}$$

$$d^{-}{}_{k} = \sum_{x \in X_{t+1}} (\Phi(x) - \Phi(a)) \tag{5.11}$$

where $\Phi(a)$ is the net flow of alternative a.

- assign a cut-off point b. if the distance is greater than the cut-off point, assign alternative a to the category C_{t+1}, otherwise assign to C_t. Here, b can be specified by the decision maker and reflects the decision maker's point of view :pessimistic or optimistic. For example, b can be set to 0 or 1 for optimistic and pessimistic cases, respectively. If b is set equal to zero, unassigned alternatives will be assigned according to distance function. Contrarily, in the second instance (b=1), all unassigned alternatives will be assigned to worse class. Alternatively, one can set b to (-1, 0 ,1). In this case, (b=-1) means that all unassigned alternatives will be assigned to better class.

$$\begin{array}{lll} \textit{If} & d_k > b & a \in C_{t+1} \\ \textit{If} & d_k < b & a \in C_t \end{array} \tag{5.12}$$

In the last step, a distance function is calculated for all alternatives which have not yet been assigned. As it can be seen, it is similar with the distance function proposed by Doumpos and Zapounidis (2004). However, instead of preference indices, we used the sum of the difference between net flow values of alternatives in order to measure outranking character of a over reference alternatives that belong to category C_t (e.g. $\sum_{x \in X_t} (\Phi(a) - \Phi(x))$) and outranked character of a by all reference alternatives that belong to category C_{t+1} (e.g. $\sum_{x \in X_{t+1}} (\Phi(x) - \Phi(a))$). Thus, we take into account not only the effects of reference alternatives, but also the effects of all alternatives which have not yet been assigned to a category in order to decide on the classification of alternative *a*. It forces that assignments are consistent with the PROMETHEE rankings.

It is obvious that two identical alternatives cannot be classified into different classes since identical alternatives have the same net flow value in PROMETHEE. Additionally, it can be easily seen that given any two alternatives a_1 and a_2 such that $a_1 \; P \; a_2$, a_2 cannot be classified to a better category than a_1. Considering these facts, we assert that PROMSORT guarantees the ordered categories. In this research, we state that the categories are ordered, if the following conditions are hold:

- no alternative in C_{h-1} is strictly preferred to any alternative in C_h, C_{h+1},.., C_k
- no alternative in C_{h-1} is strictly preferred to any higher level limit profiles (b_{h-1}, b_h,…, b_k).

5.2.2 Comparison of PROMSORT with PROMETHEE TRI and ELECTRE TRI

PROMSORT operates in a similar way to PROMETHEE TRI and ELECTRE TRI which are the sorting methods that require the direct interrogation of the decision maker. As discussed in Chapter 3, PROMETHEE TRI performs the assignment of alternatives to the predefined categories using the concept of "*central alternative*". However, no specific guidelines are provided to build the reference alternatives that characterize the ordered categories. Furthermore, since it works like a nominal classification algorithm, PROMETHEE TRI does not guarantee the ordered categories. In comparison with PROMETHEE TRI, PROMSORT has some distinctive features such as;

- It uses both "limit profiles" and "reference alternatives" concepts,
- It gives decision maker the flexibility to define the point of view: pessimistic or optimistic,
- It guarantees the ordered categories.

On the other hand, although both of them use limit profiles to define categories, there are some differences between PROMSORT and ELECTRE TRI. Besides limit profiles, PROMSORT also uses reference alternatives in the assignment phase. Because of the distinctive features of PROMETHEE from ELECTRE (Brans et al., 1986), we believe that PROMSORT is more flexible and easier to understand than ELECTRE TRI. In addition, in PROMSORT, the use of the single criterion net flows helps the decision maker to identify the differences among categories and to see the shortcomings of individual actions as compared with limit profiles.

To better understand the similarities/differences between the methods, an illustrative case study will be given in the next section.

5.2.3 Illustrative case study: Business failure risk assessment

The main aim of this example is to understand the similarities/differences between the PROMSORT and other outranking sorting methods. In the next chapter, we will concentrate on how the proposed methodology can be effectively used for supplier management and analyze the robustness of the proposed methodology. We will also compare the PROMSORT with other outranking sorting methods again. However, in this section, we only focus on how PROMSORT ensures consistent results with PROMETHEE and what makes it different from other methods.

The PROMSORT method is applied to a real world classification problem concerning the evaluation of business failure risk presented in the study of Dimitras et al., (1995). This problem was also studied by Figueria et al. (2004) to test PROMETHEE TRI. Detailed descriptions and further explanation about the case studied can be found in Figueria et al. (2004) and Dimitras et al., (1995).

The application involves 40 firms that were classified in five predefined classes (instead of the three in the original paper, the number of categories is equal to five as in Figueira et al. (2004)):

- Class 1: Very high risk [worst category];
- Class 2: High risk;
- Class 3: Medium risk;
- Class 4: Low risk;
- Class 5: Very low risk [best category].

The firms were evaluated on the basis of a set of 7 criteria. The evaluation criteria included five quantitative criteria (financial ratios) and two qualitative criteria. Parameters, the weights and the indifference and preference thresholds of a linear preference function, and profile limits for PROMSORT were given in Table 5.1. The same set of parameters and profile limits were used for ELECTRE TRI. The λ-cutting level is set to 0.85. In order to use PROMETHEE TRI 5 additional central actions should be defined (see Table 5.2). The data used and all other required information is gathered from the work of Figueira et al. (2004).

Table 5.1 Parameters for PROMETHEE and Profile Limits for PROMSORT (Figueira et al., 2004)

Code	Evaluation criteria	Obj.	Weight	q	p	b_1	b_2	b_3	b_4
g_1	Earning before interest / Total assets	Max.	0.01	1	2	-10	0	8	25
g_2	Net income / Net worth	Max.	0.295	4	6	-60	-40	-20	30
g_3	Total liabilities / Total assets	Min.	0.225	1	3	90	75	60	35
g_4	Interest expenses / Sales	Min.	0.01	1	2	28	23	18	10
g_5	General and admin. expenses/Sales	Min.	0.225	3	4	40	32	22	14
g_6	Managers work experience	Max.	0.01	0	0	1	2	4	5
g_7	Market niche / Position	Max	0.225	0	0	0	2	3	4

Table 5.2 Reference actions for PROMETHEE TRI (Figueira et al., 2004)

	Evaluation criteria						
Reference Action	g_1	g_2	g_3	g_4	g_5	g_6	g_7
r_1	-12.0	-62.5	92.5	29.5	42.5	0.5	0.0
r_2	-5.0	-50	82.5	25.5	36.0	1.5	1.0
r_3	4.0	-10	67.5	20.5	27.0	3.0	2.5
r_4	16.5	25	47.5	14.0	18.0	4.5	3.5
r_5	30.5	48.5	27.0	5.0	7.0	5.0	4.5

Following the PROMSORT methodology, both pessimistic and optimistic were obtained and given in Table 5.3. PROMSORT assignments are compared with the assignments of ELECTRE TRI and PROMETHEE TRI given in Table 5.4.

Table 5.3 PROMSORT Assignments

Class	PROMSORT Optimistic (*b*=0)	PROMSORT Pessimistic (*b*=1)
C1	{}	{}
C2	$\{a_{35}\}$	$\{a_{35}\}$
C3	$\{a_{24},a_{31},a_{34},a_{36},a_{37},a_{38},a_{39}\}$	$\{a_{14},a_{19},a_{21},a_{24},a_{26},a_{31},a_{34},a_{36},a_{37}, a_{38},a_{39}\}$
C4	$\{a_1,a_3,a_4,a_5,a_8,a_9,a_{10},a_{11},a_{13},a_{14},a_{16},a_{18},a_{19},a_{20}, a_{21},a_{22},a_{23},a_{25},a_{26},a_{27},a_{28}, a_{30},a_{32},a_{33}\}$	$\{a_1,a_2,a_3,a_4,a_5,a_6,a_8,a_9,a_{10},a_{11},a_{12},a_{13},a_{15},a_{16}, a_{17},a_{18},a_{20},a_{22},a_{23},a_{25},a_{27},a_{28},a_{30},a_{32},a_{33}\}$
C5	$\{a_0,a_2,a_6,a_7,a_{12},a_{15},a_{17},a_{29}\}$	$\{a_0,a_7,a_{29}\}$

Table 5.4 PROMETHEE TRI and ELECTRE TRI Assignments

Class	PROMETHEE TRI	ELECTRE TRI Pessimistic	ELECTRE TRI Optimistic
C1	{}	$\{a_{28}\}$	{}
C2	$\{a_{14},a_{24},a_{35},a_{36},a_{38},a_{39}\}$	$\{a_{14},a_{24},a_{31},a_{34},a_{35},a_{36},a_{38},a_{39}\}$	{}
C3	$\{a_{13},a_{19},a_{20},a_{21},a_{23},a_{25}, a_{26},a_{27},a_{28},a_{31},a_{33},a_{34}, a_{37}\}$	$\{a_2,a_3,a_4,a_8,a_9,a_{10},a_{11},a_{12},a_{13}, a_{16},a_{18},a_{19},a_{20},a_{21},a_{23},a_{25},a_{26}, a_{27},a_{32},a_{33},a_{37}\}$	$\{ a_{35}\}$
C4	$\{a_1,a_4,a_5,a_6,a_{10},a_{22}, a_{32}\}$	$\{a_1,a_5,a_6,a_7,a_{15},a_{17},a_{22},a_{29},a_{30}\}$	$\{a_{22},a_{24},a_{36},a_{37},a_{38}\}$
C5	$\{a_0,a_2,a_3,a_7,a_8,a_9,a_{11}, a_{12},a_{15},a_{16},a_{17},a_{18},a_{29}, a_{30}\}$	$\{a_0\}$	$\{a_0,a_1,a_2,a_3,a_4,a_5,a_6,a_7,a_8,a_9,a_{10},a_{11}, a_{12},a_{13},a_{14},a_{15},a_{16},a_{17},a_{18},a_{19},a_{20},a_{21}, a_{23},a_{25},a_{26},a_{27},a_{28},a_{29},a_{30},a_{31},a_{32},a_{33}, a_{34},a_{39}\}$

According to the result, it should be noted that no assignment done by PROMETHEE TRI and PROMSORT is outside the range of ELECTRE TRI assignments. Both PROMETHEE TRI and PROMSORT are based on the methodological framework of PROMETHEE method. If you recall in Section 3.3.3.2, PROMETHEE I obtains the preference relations between alternatives using leaving and entering flows of alternatives and provides incomplete rankings using these preference relations. On the other hand, PROMETHEE II gives a complete ranking by using net flows of alternatives. Therefore it is expected that the assignments performed by a PROMETHEE based sorting algorithm should be consistent with PROMETHEE results. Since both PROMETHEE based sorting methods, PROMETHEE TRI and PROMSORT, assume that the reference alternatives and profile limits belong to the initial data, respectively, it is clear that PROMETHEE gives slightly different results for both cases. Therefore, we actually expect that PROMETHEE TRI should give the consistent classification according to PROMETHEE results that consider the reference actions in the initial data, while PROMSORT results should be harmony with PROMETHEE results which assume that the limit profiles belong to the initial data. If we use PROMETHEE II in order to rank alternatives from the best to the worst, we obtain following rank order including the reference alternatives:

$$a_0, r_5, a_7, a_{29}, a_{15}, a_6, a_{17}, a_2, a_{12}, a_9, a_5, a_{11}, a_{16}, r_4, a_{30}, a_3, a_1, a_{18}, a_4, a_8, a_{22}, a_{20}, a_{10},$$
$$a_{32}, a_{25}, a_{27}, a_{13}, a_{33}, a_{26}, a_{19}, a_{23}, a_{21}, a_{14}, a_{28}, a_{31}, a_{36}, a_{38}, r_3, a_{34}, a_{39}, a_{37}, a_{24}, a_{35}, r_2, r_1$$

In PROMETHEE TRI, the use of single criterion net flow does not guarantee the ordered categories. For instance, according to the PROMETHEE results it should be noted that a_6 is ranked better than a_2, a_3, a_8, a_9, a_{11}, a_{12}, a_{16}, a_{17}, a_{18}, a_{30}. However, in PROMETHEE TRI, the all actions are assigned to a better category than a_6. The outranking relations obtained from PROMETHEE I between a_6 and a_2, a_3, a_8, a_9, a_{11}, a_{12}, a_{16}, a_{17}, a_{18}, a_{30} can be seen as follows:

$$[a_6\ R\ a_2]\ ;\ [a_6\ P\ a_3]\ ;\ [a_6\ P\ a_8]\ ;\ [a_6\ R\ a_9]\ ;\ [a_6\ P\ a_{11}]\ ;\ [a_6\ R\ a_{12}]\ ;\ [a_6\ P\ a_{16}]\ ;$$
$$[a_6\ R\ a_{17}]\ ;\ [a_6\ P\ a_{18}]\ ;\ [a_6\ P\ a_{30}]$$

As it can be seen clearly, there are incomparability relations between a_6 and a_2, a_9, a_{12} and a_{17}. Therefore the assignment of these alternatives to a better category than a_6 can be acceptable. However, although a_6 is preferred to a_3, a_8, a_{11}, a_{16}, a_{18}, and a_{30} according to PROMETHEE I results, it is assigned to a worse category. Same conclusions can be derived for a_1, a_5, a_{14}, a_{36}, and a_{39}. It should be remembered again that all comparisons are based on the assumption that the reference actions belong to the initial data set. On the other hand, in the case of PROMSORT, PROMETHEE II gives the following rank order including the limit profiles:

$$a_0, a_7, a_{29}, b_4, a_{15}, a_6, a_{17}, a_2, a_{12}, a_9, a_5, a_{16}, a_{11}, a_{30}, a_1, a_3, a_{18}, a_4, a_8, a_{22}, a_{20}, a_{10},$$
$$a_{32}, a_{25}, a_{27}, a_{13}, a_{33}, a_{26}, a_{19}, a_{23}, a_{21}, a_{28}, a_{14}, b_3, a_{31}, a_{36}, a_{38}, a_{34}, a_{37}, a_{39}, b_2, a_{35}, b_1$$

PROMSORT optimistic assignments are fully consistent with PROMETHEE results. In pessimistic assignments, a_{23} and a_{28} are assigned to a better category than a_{19} and a_{26}, although they are ranked lower by PROMETHEE II. However, there are incomparability relations between these alternatives. So the assignments can be acceptable and the categories are still ordered. It should be remembered also for PROMSORT that all comparisons are based on the assumption that the limit profiles belong to the initial data set.

In the light of these results, we can say that PROMETHEE TRI may not assign the alternatives to the categories fully consistent with PROMETHEE results. On the other hand, assignments of PROMSORT are consistent with PROMETHEE results. Since PROMSORT uses preference relation to sort alternatives into ordered categories, whereas PROMETHEE TRI uses a kind of similarity based measurement. Therefore, PROMSORT seems to be a reliable tool to assign the firms to the ordered risk categories.

ELECTRE TRI optimistic and pessimistic procedures assign the firms to the risk classes in wide range. For instance, in pessimistic procedure, a_{28} is assigned to the worst (Class 1) class. Contrarily, ELECTRE TRI optimistic procedure assigned it to the best class (Class 5). In ELECTRE TRI optimistic procedure, 85 % of the firms were assigned to the best category although there are huge differences in performances between some of them. As discussed in Chapter 3, pessimistic and optimistic assignment procedures of ELECTRE TRI highly depend on the value of cut-off point that ranges between 0.5 and 1.

After assigning the firms to risk levels, PROMSORT methodology suggests using single criterion net flows of PROMETHEE in order to identify the differences among risk classes and to show the weak and strong features of the firms as compared with profile limits with regard to each criterion.

As discussed in section 3.3.3.2 of Chapter 3, $\phi_j(a)$ measures the strength of alternative *a* over all the other alternatives on criterion *j*. In order to compare the firm classes obtained from PROMSORT, we determined average single criterion net flows for each group. The average single criterion net flows of groups are given in Table 5.5.

Table 5.5 Average single criterion net flows for firm classes

Class	Evaluation criteria						
	g_1	g_2	g_3	g_4	g_5	g_6	g_7
C1	------------	------------	------------	------------	------------	------------	------------
C2	-1,0000	-0,8372	-0,2605	-0,8651	-0,8837	-0,6512	-0,8837
C3	-0,5538	-0,6226	-0,3360	-0,5196	-0,4405	-0,6246	-0,4485
C4	0,0585	0,0995	0,0127	0,1284	0,1707	0,0920	-0,0446
C5	0,6427	0,5888	0,4186	0,5474	0,3980	0,4302	0,6424

Figure 5.2 illustrates, for optimistic assignment, the comparison of the classes by means of average single criterion net flows, while Figure 5.3 illustrates the comparison of firm "a_{36}" and profile limits by means of single criterion net flows. If you recall Section 3.3.3.2, single criterion net flows are between +1 (being the best) and -1 (being worst). Therefore, Figure 5.2 illustrates the average performance of each class on each criterion, while Figure 5.3 shows the individual performances of limit profiles and firm "a_{36}".

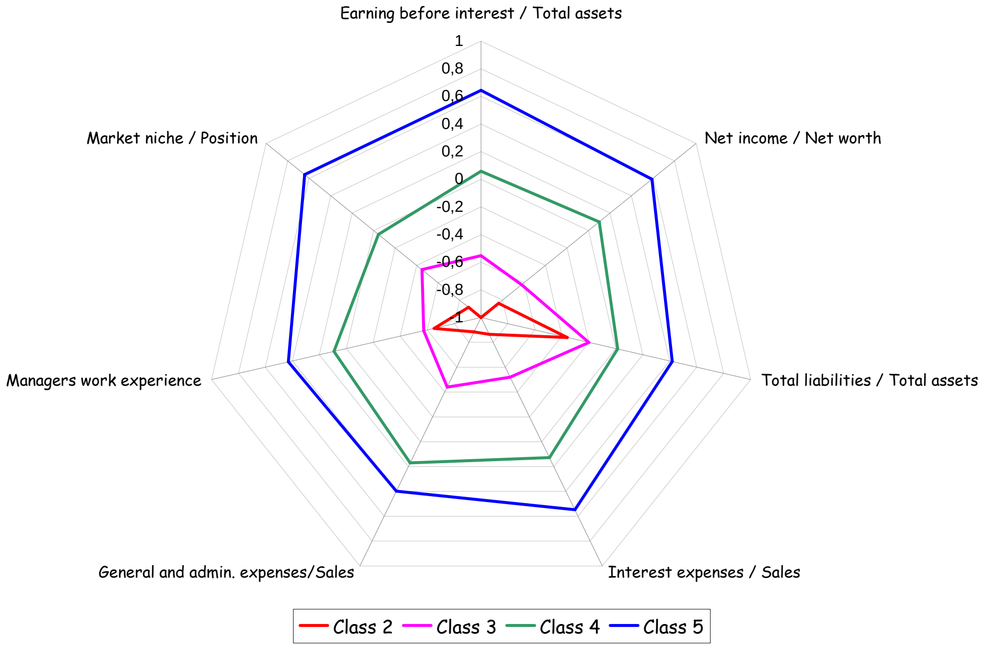


Figure 5.2 Comparisons by means of average single criterion net flow

Based on the results in Figure 5.2, for instance, one can conclude that the firms assigned to the fourth class, which represents the low risk category, have some weakness on “Market niche” and “Earning before interest / Total assets” criteria with respect to the firms assigned the fifth class. On the other hand, there are no significant differences between class 4 and 5 firms in terms of “General and admin. expenses/Sales”.

According to the results given in Figure 5.3, it can be concluded that firm “a_{36}” was assigned to the medium risk category due to its weaknesses on criterion 1, 2, 6, and 7 although it is a good performer on criterion 3, 4 and 5. By the help of this analysis, PROMSORT can provide effective information in order to measure, monitor, manage and control financial risks.

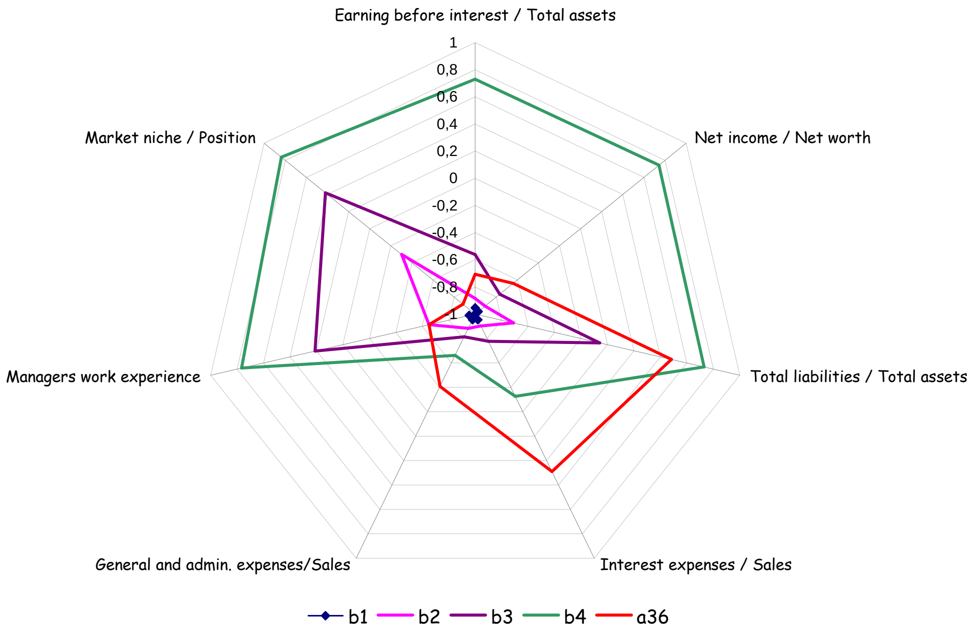


Figure 5.3 Comparisons by means of single criterion net flow

In the light of the above discussions, we can say that PROMSORT is an effective tool to assign the alternatives to the ordered categories. It provides reliable classification in terms of the preference relation between alternatives and valuable information to the decision maker about the weaknesses and strength of the alternatives and features of the categories. Additionally, PROMSORT allows ranking the alternatives within categories. Besides these advantages, PROMSORT has some disadvantages and open problems compared to other methods. All disadvantages and open problems will be discussed in detail in section 5.4 for the future research.

5.3 An extension of the proposed method: Fuzzy-PROMSORT

As discussed earlier, in most of the MCS methods, it is assumed that the performances of an alternative on a set of criteria are known exactly. However, as Kahraman et al. (2003) stated, in the supplier selection process, some criteria may be impractical to evaluate, information may be difficult to obtain, complex to analyze, or there may not be sufficient time to perform these issues. In such cases, decision making becomes difficult due to the incomplete or imprecise nature of available information. When the performances of alternatives can be only approximately determined, fuzzy set theory (FST) comes in handy to model these uncertainties and imprecision. Multi-criteria decision making (MCDM) literature is abound with numerous fuzzy approaches to the ranking problem but few studies, which apply FST, have been used to solve sorting problems (see Belacel and Boulasses, 2004). Hence, F-PROMSORT was developed to solve fuzzy ordinal classification problems.

Belacel and Boulassel (2004) have introduced a classification procedure, which is based on a scoring function from a fuzzy preference relation for solving classification problems. However, they assumed that the objects are fully understood and are described by crisp values of attributes. Furthermore, up to date, the effects of incomplete or imprecise nature of available information on the sorting process have not been fully explored in the literature.

In this chapter, we propose a new fuzzy MCS method, which is an extension of PROMSORT. In F-PROMSORT, the performance of alternatives, the profiles that distinguish the categories are defined as fuzzy numbers. To the best of our knowledge, it is the first time that a method, which can handle fuzzy performances of the alternatives, has been suggested as a tool for solving fuzzy sorting problems.

5.3.1 Fuzzy sorting process

F-PROMSORT is an extension of PROMSORT (Araz and Ozkarahan, 2005) method, i.e. a method that assigns alternatives to predefined ordered categories when the performances can be only approximately determined. Differently from PROMSORT, in F-PROMSORT, it is assumed that both of the performance of alternatives and profiles are defined as triangular fuzzy numbers $x=(m,L,R)$. The parameters m, L and R denote the most promising value, the smallest possible value, and the largest possible value that describe a fuzzy event, respectively.

Let B the set of fuzzy profiles defining k+1 categories ($B = \{\widetilde{b}_1, \widetilde{b}_2, .., \widetilde{b}_k\}$, $\widetilde{b}_h$ being the fuzzy upper limit of category C_h and the fuzzy lower limit of category C_{h+1}, *h=1,2,...k*. Also we have the fuzzy performance of alternative *a*: $\tilde{g}(a) = (\tilde{g}_1(a), \tilde{g}_2(a), \ldots, \tilde{g}_j(a))$.

F-PROMSORT assigns alternatives to categories following the three consecutive steps:

- Construction of an outranking relation using F-PROMETHEE I,
- First assignment decision except the incomparability and indifference situations,
- Final assignment of the alternatives based on pairwise comparison.

5.3.1.1 Construction of an outranking relation using Fuzzy-PROMETHEE I

In the first step, each alternative and profile is evaluated by the F-PROMETHEE I discussed in Chapter 3, since both performances of alternatives and profiles are fuzzy numbers. Then the comparison of an alternative $\tilde{a}$ with a fuzzy profile $\tilde{b}_h$ is defined by using the fuzzy entering and leaving flows in the following way:

$$\left.\begin{array}{lll}
\tilde{a}P\tilde{b}_h & iff & \left\{\begin{array}{c}
\tilde{\Phi}^+(a) > \tilde{\Phi}^+(b_h)\, and\, \tilde{\Phi}^-(a) < \tilde{\Phi}^-(b_h), or \\
\tilde{\Phi}^+(a) = \tilde{\Phi}^+(b_h)\, and\, \tilde{\Phi}^-(a) < \tilde{\Phi}^-(b_h), or \\
\tilde{\Phi}^+(a) > \tilde{\Phi}^+(b_h)\, and\, \tilde{\Phi}^-(a) = \tilde{\Phi}^-(b_h)
\end{array}\right\} \\
\tilde{a}I\tilde{b}_h & iff & \tilde{\Phi}^+(a) = \tilde{\Phi}^+(b_h)\, and\, \tilde{\Phi}^-(a) = \tilde{\Phi}^-(b_h) \\
\tilde{a}R\tilde{b}_h & iff & \left\{\begin{array}{c}
\tilde{\Phi}^+(a) > \tilde{\Phi}^+(b_h)\, and\, \tilde{\Phi}^-(a) > \tilde{\Phi}^-(b_h), or \\
\tilde{\Phi}^+(a) < \tilde{\Phi}^+(b_h)\, and\, \tilde{\Phi}^-(a) < \tilde{\Phi}^-(b_h)
\end{array}\right\}
\end{array}\right\} \tag{5.13}$$

The proposed evaluation is based on the defuzzification of the fuzzy entering and leaving flows. In the defuzzification phase, different approaches can be used. As discussed in the previous chapter, in the fuzzy PROMETHEE methods, the defuzzification of the leaving and entering flows is performed using Centre of Area (COA) method:

$$x_{defuzz} = \frac{\int x.\mu(x)dx}{\int \mu(x)dx} \tag{5.14}$$

5.3.1.2 First Assignment of the Alternatives:

This step is the same as with PROMSORT's. Differently, the assignment of alternatives to categories results directly from the outranking relation obtained by F-PROMETHEE I.

5.3.1.3 Final Assignment:

In the second phase, differently from PROMSORT, a fuzzy distance function is required.

$$\left.\begin{aligned} \tilde{d}_k &= \frac{1}{n_t}\tilde{d}^+{}_k - \frac{1}{n_{t+1}}\tilde{d}^-{}_k \\ \tilde{d}^+{}_k &= \sum_{x\in X_t}(\tilde{\Phi}(a) - \tilde{\Phi}(x)) \\ \tilde{d}^-{}_k &= \sum_{x\in X_{t+1}}(\tilde{\Phi}(x) - \tilde{\Phi}(a)) \end{aligned}\right\} \tag{5.15}$$

Where $\tilde{d}^+{}_k$ represents the fuzzy outranking character of a over all alternatives assigned to category C_t, $\tilde{d}^-{}_k$ represents the fuzzy outranked character of a by all alternatives belong to category C_{t+1} and $\tilde{\Phi}(a)$ is the fuzzy net flow of alternative a.

In fuzzy version, the assignment is performed by comparing defuzzified distance function with cut-off.

$$\left.\begin{aligned} &If \quad \tilde{d}_k \geq s \quad\quad a \in C_{t+1} \\ &If \quad \tilde{d}_k < s \quad\quad a \in C_t \end{aligned}\right\} \tag{5.16}$$

It should also be noted that the proposed methodology can handle the precise performances of alternatives and profiles as well as fuzzy numbers. In F-PROMSORT, the performances of some alternatives can be defined as fuzzy number, while the others as crisp. If all the performances are described as crisp numbers, outranking relation between alternatives and profiles can be constructed by crisp PROMETHEE method. Therefore, in such cases, the proposed methodology will be the same as PROMSORT.

In the next section, the example of supplier classification will be treated to illustrate the applicability of this method and to show how the fuzzy performances affect the classification of alternative suppliers.

5.3.2 Illustrative case study: Supplier classification in a fuzzy environment

In this section, we consider a hypothetic supplier classification problem to show the applicability of the proposed method for the case in which the performances of alternative suppliers can only be obtained as fuzzy numbers and to investigate the effects of the fuzzy performances on the classification. A manufacturer is in the new product development phase and wants to improve the delivery performance, reduce the costs of purchased product, and develope the strategic and long-term relationships with suppliers that have high capability in co-design activities in the development stages.

The company, firstly, wants to answer following questions: Which suppliers to consider for strategic partnerships?, Which suppliers must be a part of supplier development programs?, Which suppliers to consider for competitive partnerships for some product?, Which supplier must be pruned from the supply base?. Each supplier is evaluated on the basis of a set of five criteria:

g_1 : Delivery performance (0-100)

g_2 : Processing time (in days) (Dulmin and Mininno, 2003):Time needed to develop product structural design

g_3 : Design revision time (in days) (Dulmin and Mininno, 2003): Time needed to perform project revisions.

g_4 : Prototyping time (in days) (Dulmin and Mininno, 2003): Time needed to construct prototypes

g_5 : Cost reduction performance (0-100).

Three criteria have to be minimized (g_2, g_3, g_4) and two to maximize (g_1, g_5). The example involves 17 suppliers that were classified into four predefined classes:

- Class 1: suppliers to be pruned [worst category];
- Class 2: suppliers for competitive partnerships;
- Class 3: promising suppliers;
- Class 4: suppliers for strategic partnerships [best category].

Due to the early stages of a new product development, the input data about the evaluation of effectiveness of co-design activities carried out by suppliers may not be well defined. Therefore, it is assumed that the performance of alternative suppliers and limit profiles can only be obtained as triangular fuzzy numbers. The fuzzy performances are given in Table 5.6.

Table 5.6 Fuzzy performances of alternatives

	g_1			g_2			g_3			g_4			g_5		
Supplier	*m*	*L*	*R*	*m*	*L*	*R*	*m*	*L*	*R*	*m*	*L*	*R*	*m*	*L*	*R*
A1	65	50	70	45	43	55	22	20	30	20	18	28	60	45	60
A2	89	85	100	10	6	10	10	6	10	8	4	8	75	70	100
A3	54	52	56	46	42	50	20	16	23	20	19	24	55	50	60
A4	77	70	84	28	26	30	10	8	11	6	6	7	100	90	100
A5	77	74	92	49	37	51	13	11	14	12	9	12	94	90	100
A6	55	50	57	44	40	54	20	18	28	20	18	26	60	48	64
A7	70	63	77	35	30	38	19	17	20	9	9	9	84	76	92
A8	90	81	99	16	15	18	16	15	18	4	4	4	81	73	89
A9	65	62	68	34	29	37	11	9	13	9	7	9	50	40	60
A10	85	81	89	15	14	16	5	5	5	5	5	5	60	48	72
A11	90	86	99	14	14	15	8	8	9	4	4	4	85	68	102
A12	86	82	90	39	36	42	14	13	16	13	13	14	100	90	100
A13	90	86	94	40	36	44	15	13	16	10	9	11	60	50	70
A14	68	65	83	34	26	37	12	9	13	8	6	8	65	60	85
A15	86	76	86	12	12	20	10	8	18	16	14	26	50	40	52
A16	55	47	57	40	36	44	22	20	25	22	21	24	45	41	49
A17	100	95	100	18	13	18	10	9	11	7	5	7	85	77	100

Table 5.7 Fuzzy Limit Profiles

	g_1			g_2			g_3			g_4			g_5		
	m	*L*	*R*	*m*	*L*	*R*	*m*	*L*	*R*	*m*	*L*	*R*	*m*	*L*	*R*
Profile b_1	60	55	65	40	38	42	22	21	23	16	15	17	55	50	60
Profile b_2	75	70	80	30	28	32	18	17	19	9	8	10	75	70	80
Profile b_3	95	90	100	18	16	20	12	11	13	5	4	6	95	90	100
Weights	0.20			0.23			0.17			0.15			0.25		
q	2			1			0			0			0		
p	10			8			5			3			15		

Table 5.7 shows the fuzzy limit profiles for F-PROMSORT, the parameters, the weights and the indifference and preference thresholds of a linear preference function. Following the methodology described above, strategic supplier selection problem was solved for both the fuzzy and crisp performances of suppliers. It is

assumed that crisp performances are equal to the core *m* of the triangular fuzzy number $x=(m,L,R)$.

F-PROMSORT assignments for fuzzy data are given in Table 5.9. It is assumed that decision maker is optimistic, since the cut-off point was taken as zero.

Table 5.9 Assignments of the suppliers

	PROMSORT	
Class	**Crisp**	**Fuzzy**
C1	$\{a_1,a_3,a_6,a_{16}\}$	$\{a_1,a_3,a_6,a_{16}\}$
C2	$\{a_5,a_7,a_9,a_{13},a_{14}\}$	$\{a_7,a_9,a_{13},a_{15}\}$
C3	$\{a_2,a_4,a_8,a_{10},a_{12},a_{15},a_{17}\}$	$\{a_2,a_4,a_5,a_8,a_{10},a_{12},a_{14}\}$
C4	$\{a_{11}\}$	$\{a_{11},a_{17}\}$

In both PROMSORT (with crisp values) and F-PROMSORT (with fuzzy values) assignments, suppliers a_1,a_3,a_6, and a_{16} are assigned to the worst category as possible candidates for pruning. Although suppliers a_5,a_7,a_9,a_{13}, and a_{14} are the competitive suppliers that management should not consider as promising suppliers in PROMSORT assignment, a_5 and a_{14} are assigned to the promising suppliers' class when the fuzzy input data are considered. F-PROMSORT assigned supplier a_{15} to the second category while it is assigned to the third category by PROMSORT. In the same manner, PROMSORT only suggests a_{11} to the management as potential candidates for strategic sourcing. Besides a_{11}, F-PROMSORT states that the company should try to increase the scope of partnership with a_{17} also.

The reason of changing the classification is that membership functions of the fuzzy numbers describing the performance of the suppliers are not distributed symmetrically about the maximum membership grade (about the core *m*) (See Goumas and Lygreou, 2000). When the fuzzy numbers are used, the aggregated preference indices caused an improvement on overall performance of some suppliers such as, a_5, a_{14}, and a_{17}, or deteriorated overall performance of some other suppliers, such as a_{15}. These results show that when the performance of alternatives can only be approximately determined, the mean values (the core *m*) may result in an improper ranking and classification. Since the mean values do not reflect the uncertainties on the performances.

Additionally, in the crisp case, the determination of the profiles that represent what is required to become a strategic partner or a candidate in terms of each criterion is a problematic task. On the other hand, in the F-PROMSORT, it is easier to define the profiles alternatives with fuzzy numbers. In the light of these discussion, it can be seen that fuzzy versions is an effective decision making tool when the uncertainty and imprecision exist in sorting process.

In summary, it is easily seen that the only difference between PROMSORT and F-PROMSORT is that the former can only solve the fully constructed problems while the later allows the decision maker to use fuzzy numbers in evaluating the alternatives. Therefore, F-PROMSORT inherits all advantages and disadvantages of PROMSORT, which are discussed in the next section.

5.4 Open problems and possible future research directions

So far, we have introduced the characteristics, features, advantages, differences compared to other outranking MCS methods and the fuzzy extension of the proposed MCS method. Obviously, there are some limitations, disadvantages and open problems need to be considered in the future research. Since, in this dissertation, we mainly focus on strategic sourcing problems, further researches on the proposed sorting methodologies are not within the objectives of this research. Some of these open problems and disadvantages lead to several avenues for future research. In this section, these issues will be discussed below:

- The major drawback of PROMSORT, like other MCS methods, is that the decision maker must specify the considerable amount of information. The decision maker should assign values to profiles, weights and thresholds. Actually, in PROMETHEE, thresholds have a clear economical significance (Brans et al., 1986). In addition, in PROMSORT, a limit profile b_h is a virtual alternative representing required standards for an ordered category. Even if these parameters can be interpreted easily, it is difficult to fix directly their values. Therefore the findings of the methodology should be subjected to sensitivity analysis. As discussed in Chapter 3, some researchers have paid considerable attention to solve the same problem of ELECTRE TRI since it was initially proposed. By motivating them, one of the further research studies should be to develop an indirect estimation procedure for the parameters specified by the decision maker using a set of training samples.

- Since PROMSORT is based on PROMETHEE methodology, it inherits all advantages and disadvantages of it. As reported in the literature (see Wang and Triantaphyllou, 2006), one of the major disadvantages of PROMETHEE and similar methods (ELECTRE, TOPSIS, AHP, etc.) is the rank-reversal problem. The rank-reversal problem can be defined as that the ranking of alternatives may be alerted by the addition (or deletion) of non-optimal alternatives (Wang and Triantaphyllou, 2006). Wang and Triantaphyllou (2006) state that such these problems tend to occur when the alternatives appear to be very close to each other. Contrarily, if the alternatives are very distinctive from each other, then it is less likely that these problems will take place. In the present version of PROMSORT, it is assumed that the limit profiles belong to the initial data set. Obviously, these limit profiles, which are not actually contained in the initial data set, have an influence in the PROMETHEE computations and can change the preference relation between the alternatives actually involved the initial data set. Such a situation may result in a classification irregularity. This problem can be better explained by an example. Assume that a_1 and a_2 are two alternatives actually involved in the initial data set and PROMETHEE results say that a_1 is preferred to a_2 (i.e. $a_1 \; P \; a_2$) when the limit profiles are not taken into consideration. Then suppose that a set of limit profiles are defined in order to assign all alternatives to the ordered categories and, in this case, PROMETHEE results indicate that a_2 is preferred to a_1 because of the rank reversal problem of PROMETHEE. In such cases, we can say that a classification irregularity exists, if a_2 is assigned to a better category than a_1. Obviously, it is not necessary that every rank reversal problem causes a classification irregularity problem. However, it should be remembered that PROMSORT provides the ordered categories under the assumption of the limit profiles belong to the initial data set.

Summarily, in the present version of PROMSORT, addition of a new alternative, which are not actually contained in the initial data set, requires the re-computation of the PROMETHEE scores. The similar problem was also reported by Figueira et al. (2004) for PROMETHEE TRI. It is clear that PROMETHEE based sorting methods may have this kind of problems. It should be a further research to solve this problem.

- In some cases, a decision maker may not want to assign an alternative having superior performances in almost all criteria to a good category because of the too low performances of this alternative in a specific criterion. ELECTRE TRI method deals with such situations using *veto thresholds*. Since, in contrary to ELECTRE methods, PROMETHEE does not use the concept of "*veto*", this version of PROMSORT is unable to respond to such requests. The extension of the proposed method which can handle veto situation may give more realistic results for some real-life sorting problems such as supplier classification.

- Consider an alternative such that it has superior performances in some criteria while it performs too badly in some others. In such cases, incomparability relations can rarely be obtained with more than one limit profile. In such a case, the current version of PROMSORT method considers the best limit profile among them. Although it does not cause any inconsistency in the results, the following options are still possible: Do not assign this alternative to any category or change the limit profiles.

- As discussed in the earlier sections, F-PROMSORT uses COA method in the defuzzification phase because the known fuzzy versions of PROMETHEE method also use COA method. If all of the membership functions of the fuzzy numbers describing the performance of the alternatives and limit profiles are distributed symmetrically about the maximum membership grade (about the core *m*), F-PROMSORT gives the same results with PROMSORT that uses the core *m* describing the performance of alternative. This problem can be solved by proposing a new fuzzy PROMETHEE method that uses a different type defuzzification method.

5.5 Computer program for PROMSORT

In this research, a basic computer program named as **PromSort 1.0** has been written in the Visual Basic 6.0 programming language using the Microsoft Windows interface. The sample code of the program is presented in Appendix A. The program can also be obtained through the authors. **PromSort 1.0** allows the decision maker to sort alternatives to the predefined ordered classes by using PROMSORT methodology. Since PROMSORT is based on PROMETHEE methodology, it is assumed that Decision Lab 2000 software (Dec Lab, 2000), which is a multicriteria analysis and decision support software based on PROMETHEE methods, has already been installed into the computer. The following figure shows the startup window of the program.

Figure 5.4 Startup page

The structure of the options available in the software is described in Figure 5.5.

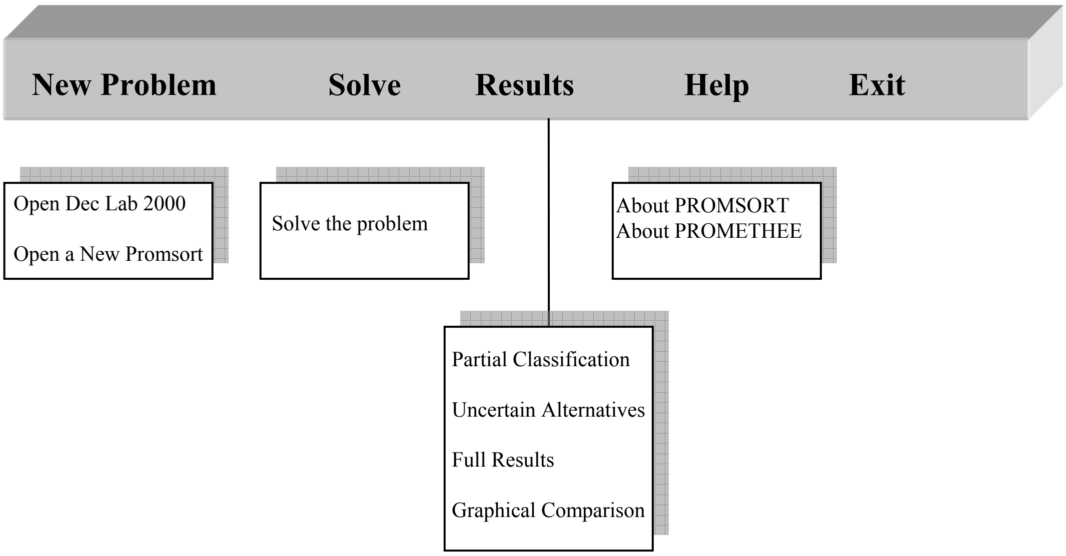


Figure 5.5 Descriptions of the main options of the software

The contents of the different options are the following:

- ***New Problem***: This option allows the decision analyst to create a new problem. **PromSort 1.0** needs the results files of Decision Lab 2000 software in order to solve a problem. To create a new problem in Decision Lab, the user can click the "*Open Dec Lab 2000*" button located on the main toolbar. This button automatically runs the Decision Lab 2000 software. If it is not installed on your computer, the program will show an error message. When the whole data set is input, the user can obtain two report files from Decision Lab software: Rankings and Scores. Ranking file is a HTML file that involves only PROMETHEE I results (Leaving, Entering and Net flows). On other hand, Scores file, which is also in HTML format, involves only the single criterion net flows of alternative including limit profiles. Both report files should be generated using Decision Lab software and saved in any directory into the computer, so that the user can recall them when using **PromSort 1.0** software. This can be done by choosing "*Open a New Promsort*" window (see Figure 5.6) from the menu through *New Problem* option located on the main toolbar.

In this window, the user must give a number of information such as the number of alternatives, the number of classes, the number of criteria etc.. The user can also select the HTML source files (rankings and scores) from anywhere in the computer using common dialog box. After selecting the source files, the user can solve the problem through the Solve option.

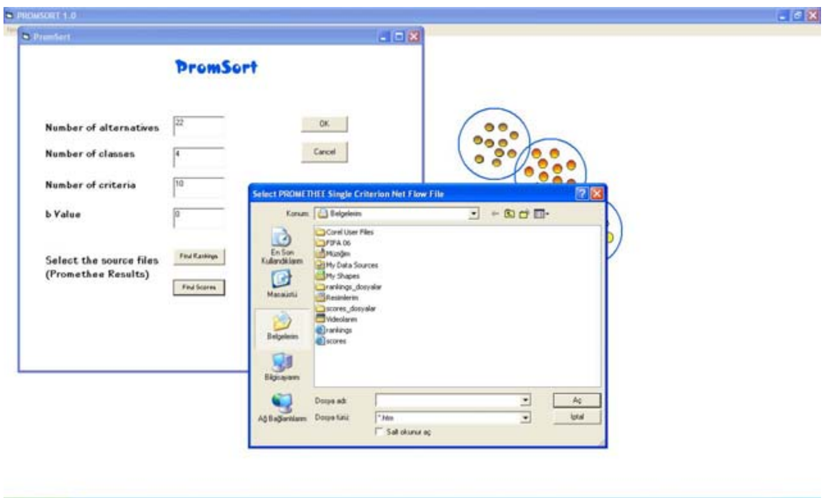


Figure 5.6 Open a new PROMSORT window

- ***Solve***: This option allows the user to solve the problem step by step through the *Solve the Problem* window. It also enables the user to obtain the full solution report. This window is presented in Figure 5.7

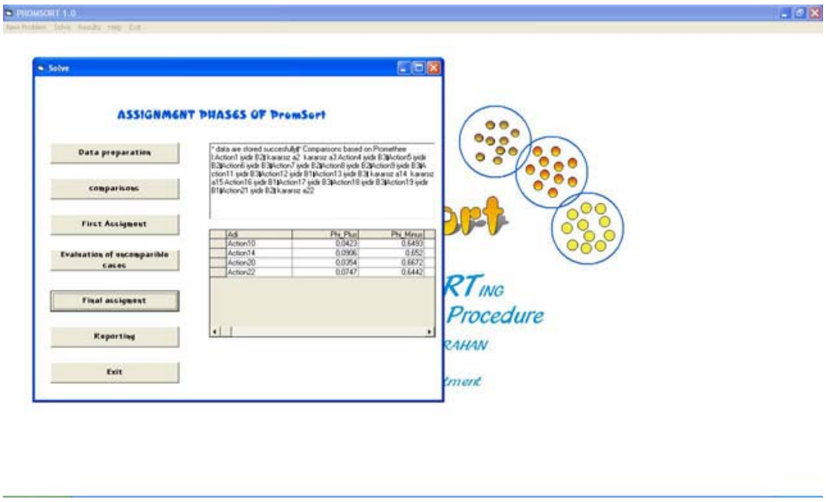


Figure 5.7 Solve the problem window

- ***Results***: After solving the problem, the user can obtain the results through *Results* option:
    - Partial classification of alternatives: It shows the first assignment of the alternatives such as the reference alternatives of each class and unassigned alternatives to any class (i.e., uncertain alternatives) (See Figure 5.8).
    - uncertain alternatives: It shows uncertain alternatives and the assignment of these alternatives for both optimistic and pessimistic procedures (see Figure 5.9).
    - full report: it shows the final assignment of the alternatives and the values of single criterion net flow of each alternative and limit profile (see Figure 5.10).
    - graphical comparison: it provides a visual representation of average performance of categories in terms of each criterion (see Figure 5.11).

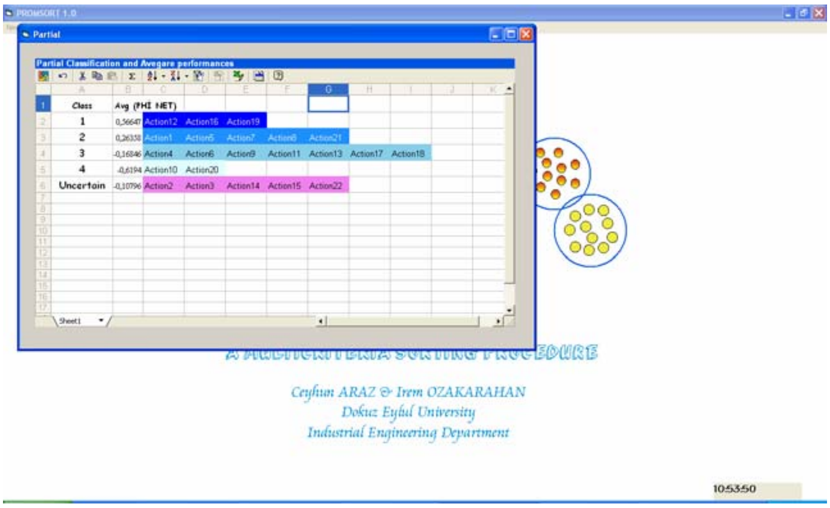


Figure 5.8 Partial classification of alternatives

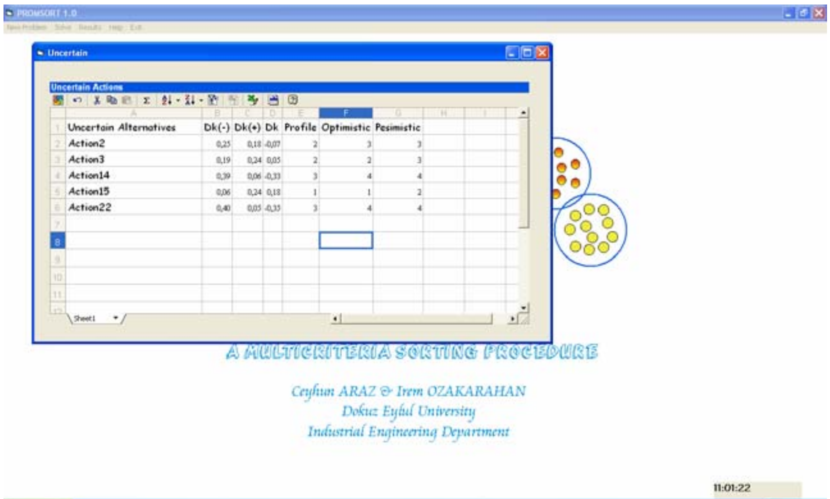


Figure 5.9 Uncertain alternatives

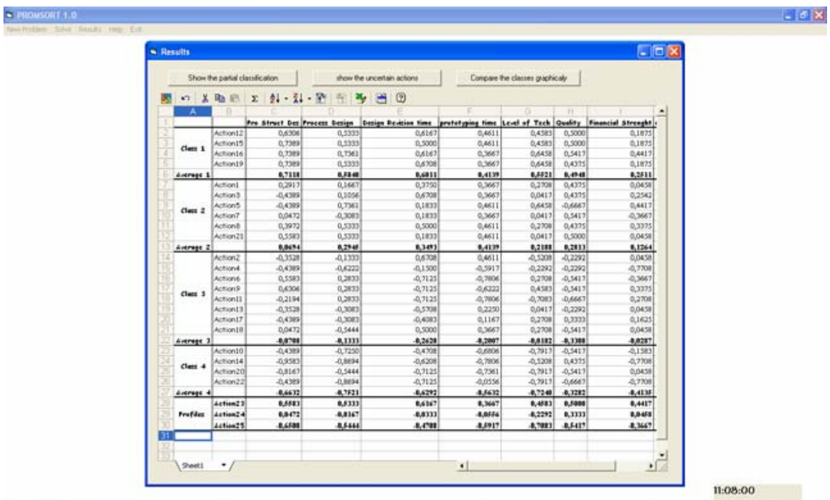


Figure 5.10 Full report

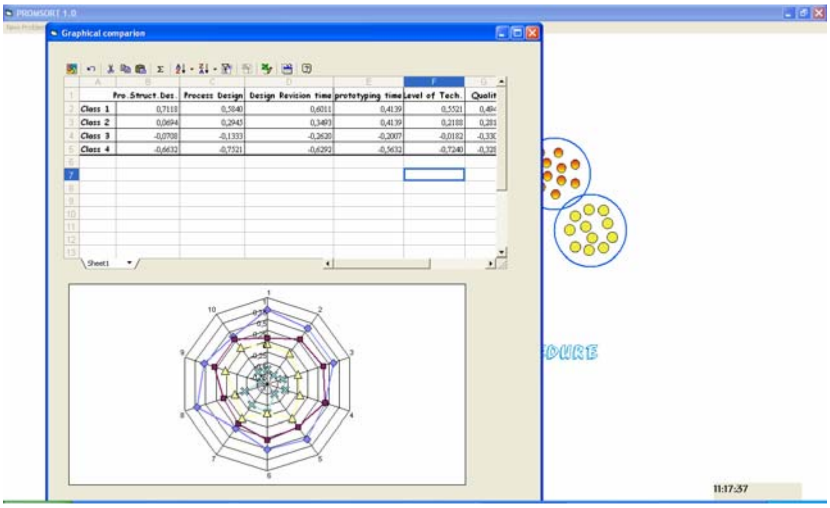


Figure 5.11 Graphical comparison

- ***Help***: It provides the user an online help about the methodological framework of PROMETHEE and PROMSORT methods and the use of Decision Lab 2000 and **PromSort 1.0** softwares.

- ***Exit*****:** it terminates the visual basic application.

5.6 Summary

In this chapter, the proposed MCS methodology, PROMSORT, is explained in detail. By means of a financial classification example, characteristics and features of the methodology are illustrated and the results of the methodology are compared with the results of other similar MCS methodologies. The development of an extended version of proposed methodology based on fuzzy sets is also presented. The limitations, disadvantages and open problems about the proposed method are discussed and some avenues of future research are emphasized. Additionally, in this Chapter, a basic software coded in Visual Basic 6.0 that allows decision maker to sort alternatives to the predefined ordered classes by using PROMSORT methodology is presented.

In the next chapter, the proposed supplier evaluation and management system that uses PROMSORT in assessing, classifying and monitoring suppliers is presented. By means of a strategic sourcing example, the robustness of PROMSORT methodology is also investigated.

CHAPTER SIX
STRATEGIC SUPPLIER EVALUATION AND MANAGEMENT SYSTEM

6.1 Introduction

Suppliers have strong impact on the performance of the whole supply chain as much as other members of the chain. Poor performance of a supplier could be enough to deteriorate the position of the supply chain in the market. For instance, a supplier has a negative impact on delivery performance of the supply chain if it delays their activities. Furthermore, the suppliers that do not have enough capabilities about product development may have little practical influence on the project success and even a negative impact on project development time (Primo and Amundson, 2002). Therefore, many firms, which are facing increased global competition, are looking for ways to find a set of capable suppliers (Andersen and Rask, 2006).

As stated in Chapter 2, today many manufacturers, which are operating under Just-in-Time (JIT) management philosophy, are adopting some strategies that include long-term relationships with a reduced number of capable suppliers (Andersen and Rask, 2003). Some researchers state that, nowadays, it is necessary to reduce the number of suppliers to a manageable number (i.e., Dowlatshahi et al., 2000; De Boer et al., 2001; Sarkar and Mohapatra, 2006). De Boer et al. (2001) express that supply base reduction is performed in the prequalification step and define the prequalification step as “sorting” process rather than “ranking” process. Despite of its increasing importance, the decision models that deal with reducing the set of all suppliers to a smaller set of acceptable suppliers are rare (Sarkar and Mohapatra, 2006). As discussed in Chapter 2, some methods have been used for prequalification models in the literature such as cluster analysis (CA), case based reasoning (CBR) and data envelopment analysis (DEA). Sarkar and Mohapatra (2006) pointed out that all of these methods have some limitations such as

- *“requirement of an exhaustive database of historical information (CBR)*
- *inability to predefine the number of elements in a cluster (CA)*
- *inability to identify suppliers who are both highly capable as well as high performers (DEA)”.*

Furthermore, despite of the multiple criteria nature of the supplier selection and evaluation problems, another shortcoming is that most of them are not based on the multicriteria evaluation of the suppliers. Therefore, in this research, we emphasize the importance of using multi-criteria sorting (MCS) methods in prequalification of suppliers.

Whereas supply base reduction is the first step in effective purchasing and supply chain management (SCM), it is not adequate by itself to improve the performance of purchasing function, and even to retain it in the current level. As mentioned in Chapter 2, besides supply base reduction, companies should adopt more comprehensive strategies that involve the decisions of the long-term strategic relationship with suppliers and suppliers’ involvement in product development and design.

As more companies become interested in developing and implementing strategic partnership with their key suppliers during product development, an effective tool is required to help concurrent design teams in classifying their suppliers based on their performances with the ability of continually monitoring and evaluating the suppliers’ performance. In this dissertation, we propose a methodology for effective strategic sourcing and evaluating supplier involvement during product development. The methodology utilizes PROMETHEE to evaluate the performance of alternative suppliers by simultaneously considering supplier capabilities and performance metrics and to provide a preference relation between suppliers. The proposed MCS method, PROMSORT, is utilized in sorting the suppliers based on their preference relations. If you recall Section 5.2.3, we showed that PROMSORT is a useful tool to assign the alternatives to the predefined ordered categories and to identify the differences in performances across the categories by means of a financial classification problem.

The proposed strategic supplier evaluation and management system can assist concurrent design teams in classifying suppliers into different categories (e.g., strategic partners, the promising suppliers which are possible candidates for supplier development programs, competitive suppliers and the suppliers to be pruned). It also identifies the differences in performances across supplier classes and helps concurrent design teams in monitoring the suppliers' performances and making decisions about necessary development programs.

This chapter is devoted to explain the proposed methodology for strategic sourcing. The second section presents the methodological framework. Section 2 also discusses the determination of the parameters used in the proposed methodology. Section 3 demonstrates how the proposed methodology can be applied to strategic supplier selection problem by means of a hypothetical example. In section 3, the robustness of PROMSORT methodology is also analyzed and the comparison with other MCS methods is also performed.

6.2 Proposed strategic supplier evaluation and management system

Strategic supplier evaluation and management system (SSEMS) of this research is based on the multicriteria evaluation of the suppliers. As shown in Figure 6.1, the methodology integrates three elements to evaluate and manage supply base and to select strategic partners in product development. These are:

- Supplier Evaluation System
- Supplier Sorting System
- Supplier Management System

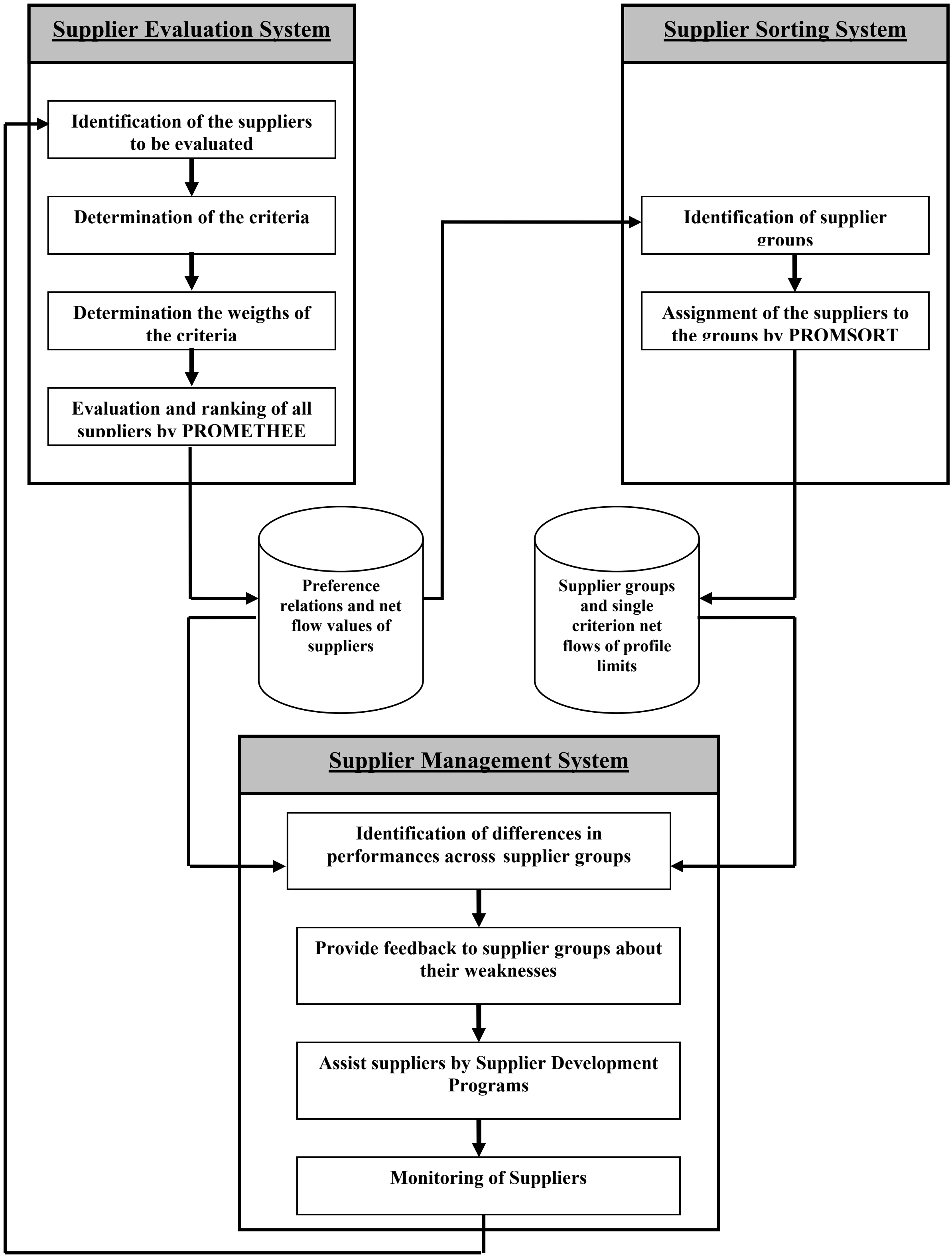


Figure 6.1. Procedure of SSEMS

6.2.1 Supplier evaluation system

Supplier evaluation system involves the identification of the alternative suppliers, the determination of the criteria to be considered and the weight of each criterion, evaluation of all suppliers and ranking these suppliers considering their performances.

In supplier evaluation phase, as discussed in Chapter 2, the criteria to be selected for evaluation of suppliers should emphasize long-term relationship and concurrent product development such as quality management practices, long-term management practices, financial strength, technology and innovativeness level, suppliers' cooperative attitude, supplier's co-design capabilities, and cost reduction capabilities, information coordination capabilities and supplier viability. Selected criteria should be clearly delineated to the suppliers (Dowlatshahi, 2000).

The evaluation and ranking of suppliers are performed by the PROMETHEE methods. PROMETHEE requires determination of some parameters, such as preference and indifference thresholds and weights of the criteria selected. The values of parameters should be determined by interacting with the concurrent design team whose members come from different departments. Additionally, the limit profiles, which distinguish categories of suppliers, should be determined in this phase because PROMSORT assumes that they belong to the initial data set.

The limit profiles should have a clear meaning as to what is required to become a strategic partner or a candidate. Additionally, suppliers should be informed a priori about these requirements.

No specific guidelines are provided to determine the weights of the criteria with PROMETHEE. The determination of the weights of criteria requires input of expert opinion (Merad et al., 2004). With interaction of the decision maker, different weighting methods such as AHP (Saaty, 1980), weighted least square method (Chu et al., 1979), linear rating scale (Nutt, 1980) and the entropy method (1948) etc. can be used to determine the weights.

6.2.2 Supplier sorting system

The role of the supplier sorting system is to categorize suppliers into predefined ordered groups based on their preference relations. In this step, the proposed MC sorting procedure, PROMSORT, is used. Suppliers are categorized as strategic partners (“perfect” suppliers), candidates for supplier development program (“good” suppliers), competitive suppliers (“moderate” suppliers) and pruning suppliers (“bad” suppliers) based on the results of the PROMETHEE methods.

Supplier sorting system provides all necessary information for supplier management system such as supplier groups, average single criterion net flow values of each group and single criterion net flow values of limit profiles. Average single criterion net flow values of each group in terms of each criterion measure the average strength of the alternatives that belong to this group over all the other groups on each criterion j. Single criterion net flow values provide valuable information to the team members to determine the weakness and strength of a group or an individual supplier.

6.2.3 Supplier management system

The supplier management system of the methodology addresses the managerial decisions about supplier classes and individual suppliers. The tasks of the supplier management system are to identify the distinctions in performances between supplier classes, to give feedback information to the member of classes about their weaknesses, to assist suppliers by providing knowledge, skills and experience via various supplier development programs, and to monitor suppliers’ performance in time. To perform these tasks, single criterion net flow values obtained from sorting system are used.

After providing necessary developmental programs, firms again assess suppliers' performance by PROMSORT to see whether the promising suppliers have improved their capabilities and reached the desired level regarding the aggregated performance or not. If so, firm will implement the strategic long-term relationship with the promising suppliers. If not, they will reduce the scope of the partnership with them or prune them from the supply base.

To better understand how the proposed methodology can be effectively used for supplier management, a case study is illustrated in the next section. Through this case, the robustness of the proposed methodology is also analyzed. We also re-compare the PROMSORT with other outranking sorting methods.

6.3 An illustrative case study: Strategic supplier selection

In this section, to be able to demonstrate the applicability of the proposed methodology to strategic sourcing, we consider a hypothetical problem. We assume that CI Inc. is a manufacturer working in the field of electronic industry. The manufacturer is subject to a global competition where the demands of frequent innovations and higher quality lead to competitive leverages for the new product development. They must be extremely responsive to meet the changing requirements of market.

The firm believes that significant improvements in product development can be achieved by developing strategic partnership with a set of innovative suppliers. Integration of right suppliers in concurrent engineering team, whose members come from different departments, is an important factor for success since they have strong influence on quality and cost of products, innovation capability and the time to market. Given these requirements, the firm has some vital objectives in supply management. These are:

- Reducing product development duration

- Improving the delivery, quality and cost performance of the product
- Developing the strategic relationships with innovative suppliers

Company managers believe that these objectives can be achieved by the help of an effective supplier management system. Therefore, concurrent design team of the company needs a tool to evaluate supplier's performance, select key suppliers for strategic partnership, develop promising suppliers for strategic partnership, monitor the supplier's overall performance, co-design contribution, and the support of supplier in concurrent engineering activities, and provide feedback to suppliers about their weaknesses. The proposed methodology can help concurrent design team to effectively deal with these problems.

Firstly, the company wants to answer following questions:

- Which suppliers should be selected as strategic partners? (perfect suppliers)
- Which suppliers must be supported via supplier development programs? (promising suppliers)
- Which suppliers to consider for competitive partnerships for some products?(moderate suppliers)
- Which suppliers no longer should be considered for the partnership in any level? (bad suppliers)

These supplier groups are identified by PROMSORT method. The company implements several concurrent engineering practices; therefore they want to evaluate the support of suppliers in development phases, such as support in Product Structural Design phase and Support in Process Design and Engineering phase). In addition, concurrent design team determines a set of ten criteria to evaluate each supplier with the aim of developing long-term strategic partnership and supplier involvement in product development:

g_1 : Support in Product Structural Design (De Toni and Nassimbeni, 2001)

g_2 : Support in Process Design and Engineering (De Toni and Nassimbeni, 2001)

g_3 : Design Revision time (Dulmin and Minnino, 2003) (in days)

g_4 : Prototyping time (Dulmin and Minnino, 2003) (in days)

g_5 : Level of Technology (Dulmin and Minnino, 2003)

g_6 : Quality Performance (Choy et al., 2005)

g_7 : Financial Strength (Dowlatshahi, 2000)

g_8 : Cost Reduction Performance (Lee et al, 2001)

g_9 : Delivery Performance (Talluri and Narasimhan, 2004)

g_{10} : Ease of communication (Choy et al., 2005)

Supplier's support in product structural design is assessed according to suppliers' contributions to the product simplification, modularization, component selection, standardization, and failure mode effect analysis (FMEA) activities etc. In addition, Supplier's effort within the design team about Design for Manufacturing/Design for Assembly (DFM/DFA) activities is evaluated with "Support in Process Design and Engineering" criterion. Furthermore, supplier's quality performance is assessed considering presence or absence of quality certification, their ability to use acceptable quality techniques and quality management practices.

Two criteria have to be minimized (g_3, g_4) and eight to be maximized (g_1, g_2, g_5, g_6, g_7, g_8, g_9, g_{10}). The number of categories is equal to four:

- C_1: suppliers to be pruned [*worst category*]
- C_2: suppliers for competitive partnerships
- C_3: promising suppliers
- C_4: suppliers for strategic partnerships [*best category*]

Table 6.1 shows the data for 22 suppliers and three limit profiles. PROMETHEE parameters, such as the weights of criteria and the preference and indifference thresholds on each criterion, are given in Table 6.2. Figure 6.2, which is constructed considering all the criteria to be maximized, illustrates the definition of categories for PROMSORT.

The values of parameters are determined by the interaction with the concurrent design team. Team members defined the limit profiles, which distinguish the categories, to represent what is required to become a strategic partner or a candidate in terms of each criterion. Additionally, uncertainties of the team members on criteria values were taken into account through the indifference and preference thresholds. We assume that the weights of criteria are determined after a meeting of the concurrent design team and discussing the weight of each criterion until a consensus on the weight structure is reached.

Table 6.1 Evaluation Matrix

	Criteria									
	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9	g_{10}
Supplier 1	84	83	12	7	85	85	80	85	95	90
Supplier 2	72	78	7	5	70	70	80	75	95	95
Supplier 3	70	82	7	7	80	85	89	65	90	95
Supplier 4	70	68	20	25	75	70	60	90	70	90
Supplier 5	70	95	15	5	95	50	95	95	80	95
Supplier 6	90	85	30	32	85	60	70	77	80	85
Supplier 7	80	75	15	7	80	95	70	84	90	80
Supplier 8	86	90	10	5	85	85	92	75	99	90
Supplier 9	92	85	30	26	90	60	92	75	90	90
Supplier 10	70	65	25	28	60	60	75	70	60	60
Supplier 11	75	85	30	32	65	50	90	80	89	60
Supplier 12	92	90	8	5	90	90	85	92	99	90
Supplier 13	72	75	27	10	80	70	80	70	89	80
Supplier 14	55	60	28	32	70	85	60	65	70	60
Supplier 15	95	90	8	5	90	90	85	85	98	90
Supplier 16	95	95	8	7	95	95	95	92	95	90
Supplier 17	70	75	24	12	85	80	84	70	86	80
Supplier 18	80	70	10	7	85	60	80	60	95	90
Supplier 19	95	90	7	7	95	85	85	95	97	95
Supplier 20	60	70	30	30	60	60	80	70	60	80
Supplier 21	90	90	15	5	80	90	80	75	99	90
Supplier 22	70	60	30	15	60	50	60	75	70	65
1. Limit Profile b1	65	70	25	25	65	60	70	70	70	65
2. Limit Profile b2	80	80	18	15	75	80	80	80	85	80
3. Limit Profile b3	90	90	8	7	90	90	95	90	95	90

Table 6.2 Parameters for PROMETHEE calculations

	Criteria									
Parameters	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9	g_{10}
q_j *(indifference threshold)*	--	--	--	--	5	5	5	--	5	5
p_j *(preference threshold)*	10	10	7	8	10	10	10	10	10	10
W_j *(weights)*	0.15	0.1	0.1	0.1	0.08	0.15	0.05	0.12	0.1	0.05

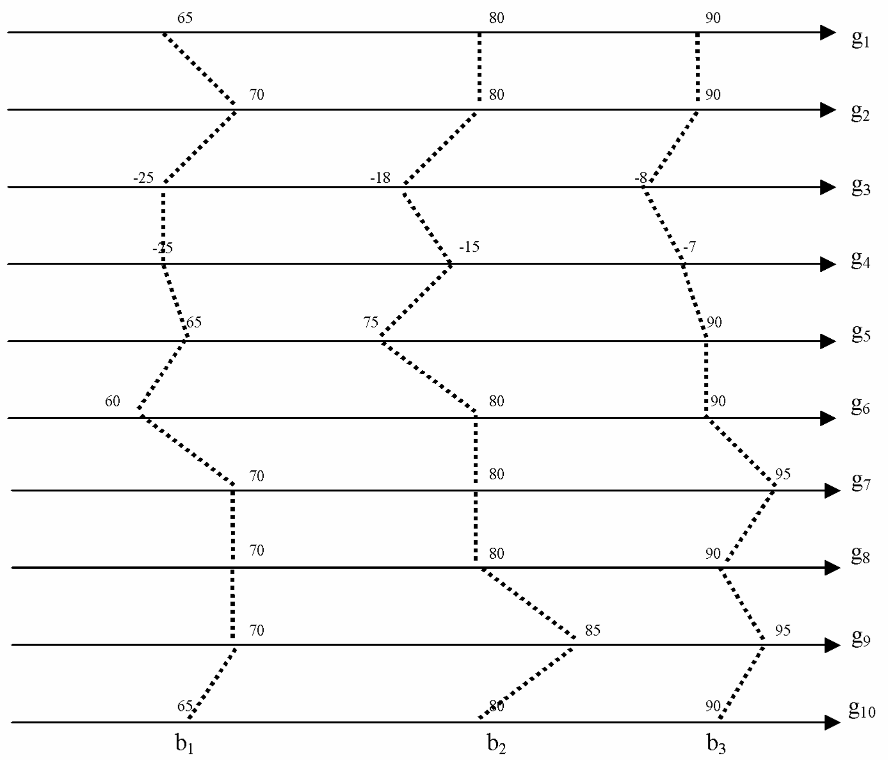


Figure 6.2 Defining categories for PROMSORT and ELECTRE TRI

6.3.1 Analysis of the PROMSORT results

Following the methodology described in Chapter 5, PROMSORT assignments both pessimistic and optimistic are given in Table 6.3.

Table 6.3 PROMSORT Assignments

Class	*PROMSORT Optimistic (b=0)*	*PROMSORT Pessimistic (b=1)*
C1	$\{a_{10},a_{14},a_{20},a_{22}\}$	$\{a_{10},a_{14},a_{20},a_{22}\}$
C2	$\{a_4,a_6,a_9,a_{11},a_{13},a_{17},a_{18}\}$	$\{a_2,a_3,a_4,a_6,a_9,a_{11},a_{13},a_{17},a_{18}\}$
C3	$\{a_1,a_2,a_3,a_5,a_7,a_8,a_{21}\}$	$\{a_1,a_5,a_7,a_8,a_{15},a_{21}\}$
C4	$\{a_{12},a_{15},a_{16},a_{19}\}$	$\{a_{12},a_{16},a_{19}\}$

PROMSORT results, for optimistic decision maker, reports that suppliers 12, 15, 16, and 19 are categorized in the best class. These suppliers should be ensured to participate in the concurrent engineering team and considered as potential candidates for strategic partnership. The company should mainly provide to improve integration with these suppliers and try to increase the scope of partnership.

Suppliers 1, 2, 3, 5, 7, 8, and 21 are the promising suppliers and management should carefully monitor the performances of these suppliers. Additionally, these are the prospective suppliers for supply development programs.

Suppliers 4, 6, 9, 11, 13, 17 and 18 are in the second category. Management should not consider them as potential or promising suppliers, however for some parts or products these suppliers may be counted as competitive suppliers. At last, suppliers 10, 14, 20, 22 should be pruned from the supply base.

Different from optimistic assignment, pessimistic procedure assigned the supplier 15 to the class 3 as a promising supplier. On the other hand, Suppliers 2 and 3 are removed from class 3 to class 2. This decision means that the firm should reduce the scope of partnership with these suppliers and not to invite these suppliers to the supplier development programs.

6.3.2 Identifying differences in performances across supplier groups

As discussed in the previous section, in order to identify the differences among supplier groups and alternative suppliers and show the shortcomings of suppliers as compared with limit profiles or alternative suppliers with regard to each criterion, single criterion net flows of PROMETHEE can be used.

The single criterion net flows for each alternative *(a_1, a_2, ...,a_{22})* and limit profiles *(b_1, b_2, b_3)* are presented in Table 6.4 and 6.5, respectively.

Table 6.4 Single Criterion Net Flows for alternative suppliers

	Criteria									
	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9	g_{10}
Supplier 1	0.271	0.146	0.339	0.396	0.250	0.417	-0.033	0.438	0.425	0.417
Supplier 2	-0.367	-0.163	0.714	0.552	-0.542	-0.167	-0.033	-0.192	0.425	0.458
Supplier 3	-0.475	0.079	0.714	0.396	0.000	0.417	0.500	-0.792	0.192	0.458
Supplier 4	-0.475	-0.658	-0.143	-0.552	-0.292	-0.167	-0.917	0.675	-0.708	0.417
Supplier 5	-0.475	0.833	0.095	0.552	0.750	-0.917	0.758	0.858	-0.367	0.458
Supplier 6	0.588	0.279	-0.750	-0.844	0.250	-0.542	-0.625	-0.058	-0.367	0.042
Supplier 7	0.088	-0.338	0.095	0.396	0.000	0.792	-0.625	0.375	0.192	-0.375
Supplier 8	0.371	0.583	0.500	0.552	0.250	0.417	0.658	-0.192	0.600	0.417
Supplier 9	0.671	0.279	-0.750	-0.594	0.542	-0.542	0.658	-0.192	0.192	0.417
Supplier 10	-0.475	-0.783	-0.441	-0.677	-0.833	-0.542	-0.325	-0.508	-0.958	-0.833
Supplier 11	-0.200	0.279	-0.750	-0.844	-0.750	-0.917	0.592	0.142	0.092	-0.833
Supplier 12	0.671	0.583	0.655	0.552	0.542	0.583	0.133	0.750	0.600	0.417
Supplier 13	-0.367	-0.338	-0.571	0.130	0.000	-0.167	-0.033	-0.508	0.092	-0.375
Supplier 14	-0.979	-0.929	-0.631	-0.844	-0.542	0.417	-0.917	-0.792	-0.708	-0.833
Supplier 15	0.792	0.583	0.655	0.552	0.542	0.583	0.133	0.438	0.558	0.417
Supplier 16	0.792	0.833	0.655	0.396	0.750	0.792	0.758	0.750	0.425	0.417
Supplier 17	-0.475	-0.338	-0.369	-0.047	0.250	0.250	0.100	-0.508	-0.108	-0.375
Supplier 18	0.088	-0.567	0.500	0.396	0.250	-0.542	-0.033	-0.958	0.425	0.417
Supplier 19	0.792	0.583	0.714	0.396	0.750	0.417	0.133	0.858	0.517	0.458
Supplier 20	-0.917	-0.567	-0.750	-0.760	-0.833	-0.542	-0.033	-0.508	-0.958	-0.375
Supplier 21	0.588	0.583	0.095	0.552	0.000	0.583	-0.033	-0.192	0.600	0.417
Supplier 22	-0.475	-0.929	-0.750	-0.250	-0.833	-0.917	-0.917	-0.192	-0.708	-0.833

Table 6.5 Single Criterion Net Flows for limit profiles

	Criteria									
	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9	g_{10}
Profile b1	-0.704	-0.567	-0.441	-0.552	-0.750	-0.542	-0.625	-0.508	-0.708	-0.833
Profile b2	0.088	-0.054	-0.042	-0.250	-0.292	0.250	-0.033	0.142	-0.167	-0.375
Profile b3	0.588	0.583	0.655	0.396	0.542	0.583	0.758	0.675	0.425	0.417

In order to compare the supplier groups obtained from PROMSORT, we determine average single criterion net flows for each group. The average single criterion net flows of groups are given in Table 6.6. Figure 6.3 illustrates the comparison of the groups by means of average single criterion net flows.

Table 6.6 Average Single Criterion Net Flows for supplier classes

	Criteria									
	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9	g_{10}
Class 1	-0,663	-0,752	-0,629	-0,563	-0,724	-0,328	-0,414	-0,450	-0,833	-0,667
Class 2	-0,071	-0,133	-0,262	-0,201	-0,018	-0,331	-0,029	-0,215	0,005	0,042
Class 3	0,069	0,294	0,349	0,414	0,219	0,281	0,126	0,072	0,274	0,274
Class 4	0,712	0,584	0,601	0,414	0,552	0,495	0,251	0,699	0,525	0,344

According to the results given in Figure 6.3, one can conclude that the suppliers assigned to the fourth category, which represents the candidate strategic partners, are superior on “Support in Product Structural Design” “Support in Process Design and Engineering”, “Level of Technology”, “Quality Performance” and “Cost Reduction Performance” compared to other suppliers.

Group 3 suppliers who are the primary candidates of supplier development programs have some weaknesses on these five criteria, especially on “Support in Product Structural Design”, “Level of Technology” and “Cost Reduction Performance”. The company could assist these suppliers by providing knowledge, skills and experiences on these issues. The performances of these suppliers on weak criteria can be improved by implementing supplier development programs.

On the other hand, there are no significant differences between group 3 and 4 in terms of “Prototyping Time”, “Financial Strength”, “Delivery Performance” and “Ease of Communication”. In summary, promising suppliers must improve their performances with respect to concurrent engineering practices, cost reduction, and quality, and make some investments on technology. In the same manner, group 1 and 2 suppliers must benchmark themselves against group 3 and 4 suppliers in order to increase their capabilities.

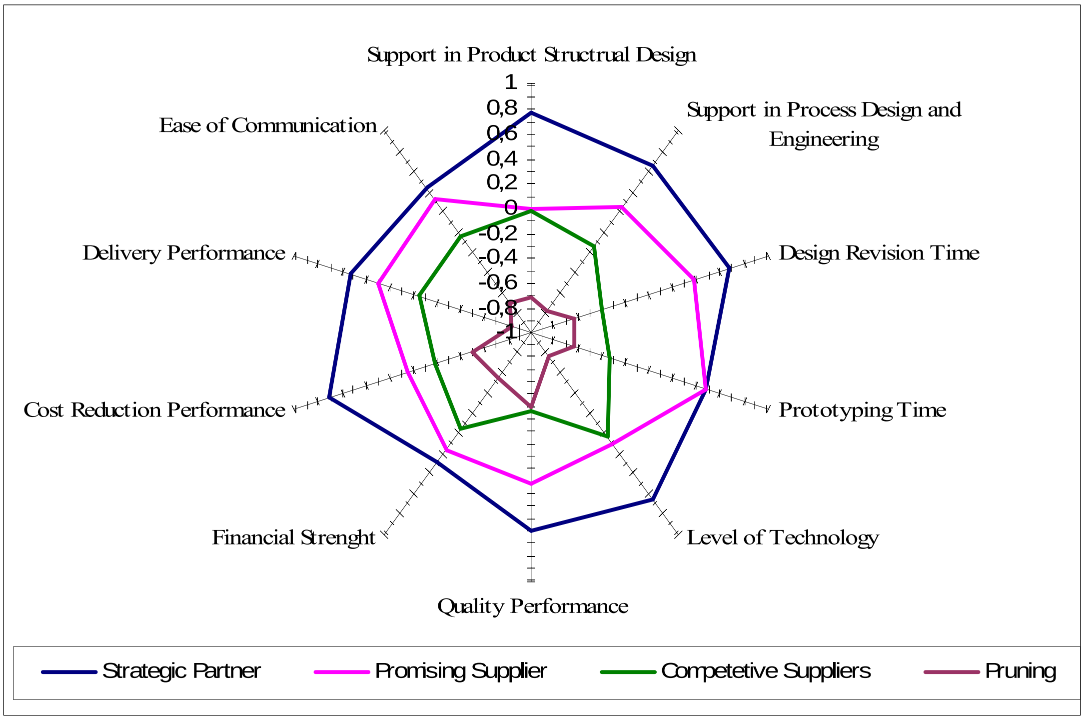


Figure 6.3 The comparison of the supplier groups by means of average single criterion net flows.

In the same manner, each alternative supplier can be compared with limit profiles b_1, b_2, and b_3 in terms of single criterion net flows. For instance, Figures 6.4, 6.5, 6.6 and 6.7 show the comparison of supplier 2, 5, 8 and 21, which are assigned to category 3 and candidates for supplier development programs, to limit profiles, respectively.

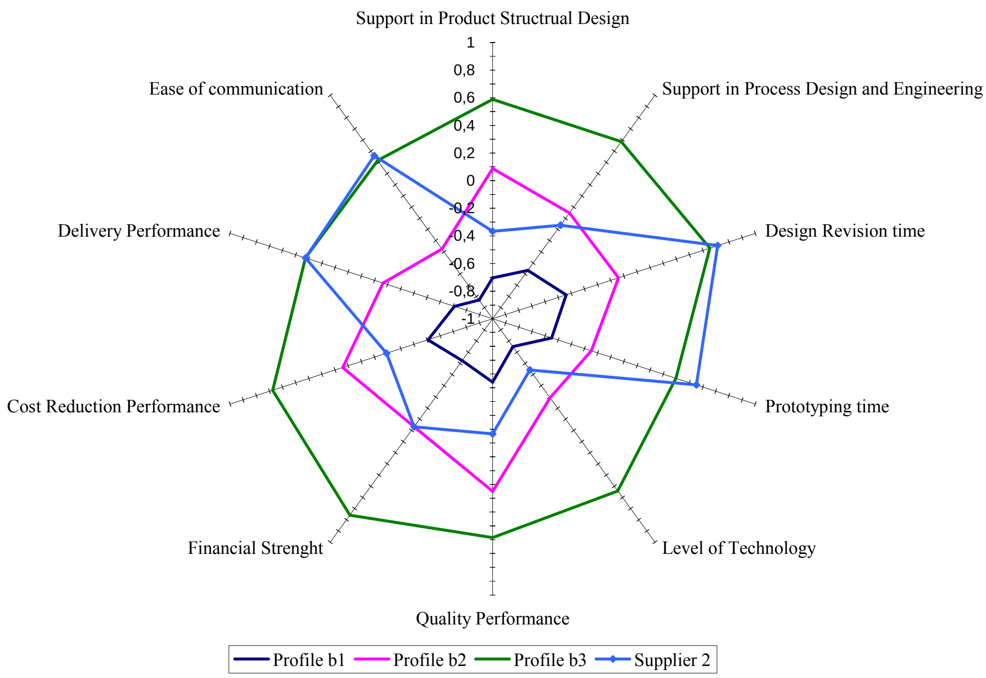


Figure 6.4 The comparison of supplier 2 with profiles by means of single criterion net flows

It can be seen from Figure 6.4 that supplier 2 is superior on “Design Revision Time”, “Prototyping Time”, “Delivery Performance” and “Ease of communication”. However, it is quite weak in the “Financial strength” and “Support in Process Design and Engineering”. However, the main shortcoming of supplier 2 is “Support in Product Structural Design”, “Level of Technology”, and “Cost Reduction Performance”. Supplier 2 must identify ways to improve the performance on these criteria. Manufacturer must assist supplier 2 by implementing supplier development programs on cost reduction and product structural design practices such as product simplification, modularization, and standardization and FMEA techniques etc. On the other hand, Supplier 2 should initiate its own training and development programs designed to improve performance on weak criteria.

When supplier 5 is considered, it is seen from Figure 6.5 that the supplier’s performance is too low on “Support in Product Structural Design”, “Quality Performance” and “Cost Reduction Performance”. However, if the supplier improves its performance on these criteria, it may become the strongest supplier in the base. The exact supplier development and training programs may be helpful for supplier 5.

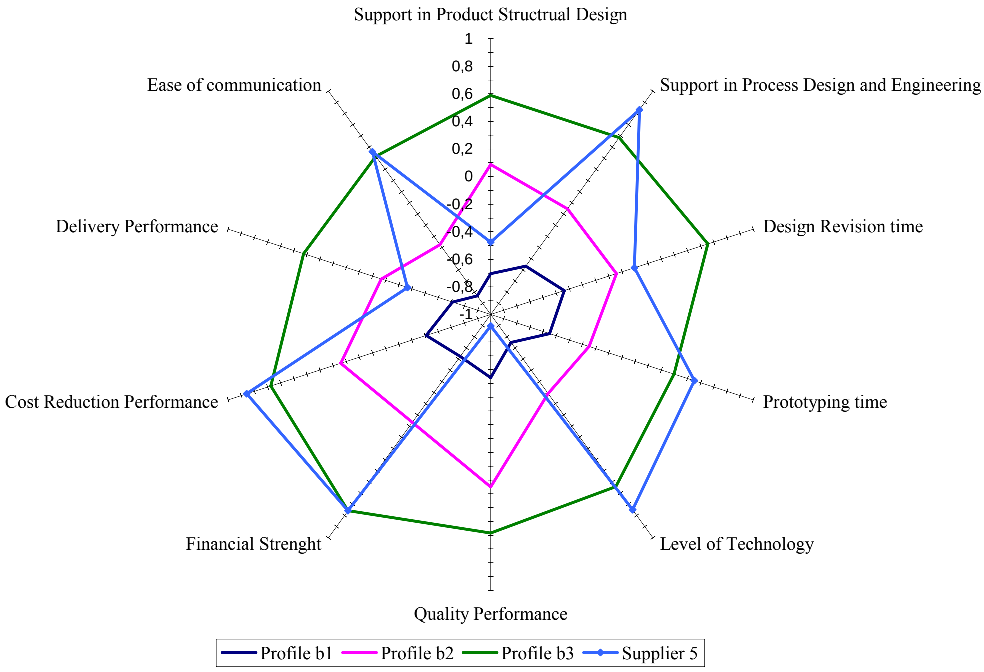


Figure 6.5 The comparison of supplier 5 with profiles by means of single criterion net flows

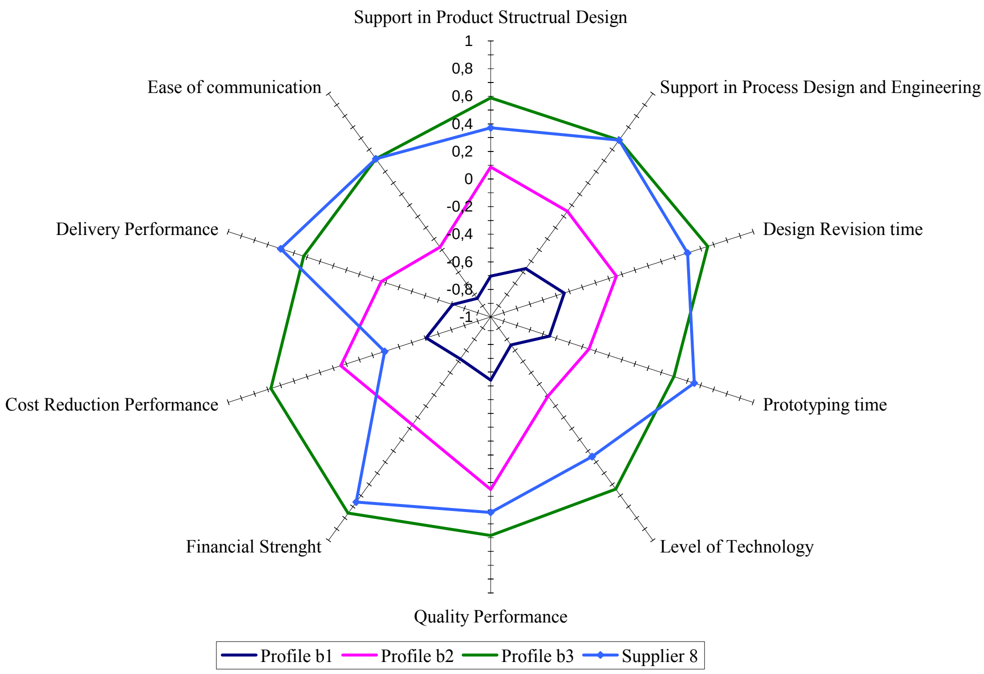


Figure 6.6 The comparison of supplier 8 with profiles by means of single criterion net flows

Other than these two suppliers, it is seen from Figure 6.6 that supplier 8 is a good performer on all criteria, except cost reduction performance, also has good co-design capabilities and a satisfactory effort in meeting the design changes. However, the cost reduction performance of supplier 8 needs careful inspection. Supplier 8 could learn from category 4 suppliers on how to reduce costs via cost reduction programs. If it can improve its performance in these criteria a little more, then it may be set as strategic partners of the company.

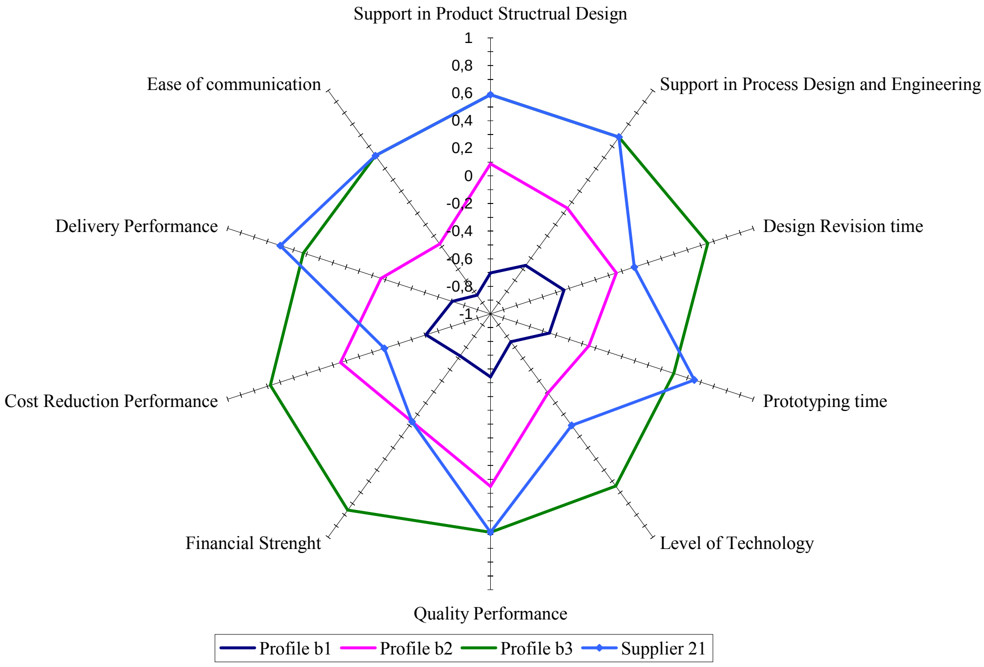


Figure 6.7 The comparison of supplier 21 with profiles by means of single criterion net flows

On the other hand, supplier 21 should be informed to take precautions for its financial positions, cost reduction performance and technology level. In addition, it should spend more effort to meet design revisions on time, although it helps design teams in FMEA studies and has valuable contributions on product design simplification and modularization, DFM and DFA activities and prototype development. All suppliers can be compared with limit profiles in order to show the shortcomings in the same manner.

6.3.3 Monitoring of the suppliers

In our methodology, the strategic supplier is defined as the potential supplier that might have achieved the limit profile values of the best class with regard to each criterion. After a sufficient period of support and time, the performances of all suppliers should again be evaluated by PROMSORT to see whether the suppliers have improved their performances and achieved the level of the strategic supplier regarding aggregated performance or not.

For instance, manufacturer will assist supplier 5 by implementing supplier development programs on product structural design practices, quality management and cost reduction. If supplier 5 has achieved the desired level with regard to overall performance (net flows), company will add supplier 5 to supplier base as strategic partner, otherwise company will make the decision whether supplier development programs will continue or not according to improvement on performances of supplier 5. Similar comments can be done for each supplier in the same manner.

6.3.4 Comparison of the results

In this section, PROMSORT assignments are compared with ELECTRE TRI and PROMETHEE TRI. The same set of parameters and limit profiles were used in ELECTRE TRI. However, contrary to PROMSORT and ELECTRE TRI, categories were characterized from fictitious reference alternatives in PROMETHEE TRI. The reference alternatives were defined as the central alternative of each category (see Table 6.7). PROMETHEE TRI and ELECTRE TRI assignments are given in Table 6.8 and Table 6.9, respectively.

Table 6.7 Reference alternatives for PROMETHEE TRI

Reference Action	*Evaluation Criteria* g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9	g_{10}
r_1	55	60	30	30	55	50	60	60	60	55
r_2	73	75	21	20	70	70	75	75	78	77
r_3	85	85	13	11	82	85	88	85	90	85
r_4	95	95	5	4	95	95	98	95	98	95

Table 6.8 PROMETHEE TRI Assignments

Class	*PROMETHEE TRI*
C1	$\{a_{10},a_{14},a_{20},a_{22}\}$
C2	$\{a_2,a_4,a_6,a_{11},a_{13},a_{17}\}$
C3	$\{a_1,a_3,a_7,a_8,a_9,a_{18},a_{21}\}$
C4	$\{a_5,a_{12},a_{15},a_{16},a_{19}\}$

Table 6.9 ELECTRE TRI Assignments

Class	*ELECTRE TRI Optimistic*	*ELECTRE TRI Pessimistic*
C1	$\{a_{10},a_{14},a_{20}\}$	$\{a_6,a_{10},a_{11},a_{14},a_{20},a_{22}\}$
C2	$\{a_{11},a_{13},a_{17},a_{22}\}$	$\{a_2,a_3,a_4,a_5,a_9,a_{13},a_{17},a_{18}\}$
C3	$\{a_1,a_2,a_3,a_4,a_5,a_6,a_7,a_8,a_9,a_{18},a_{21}\}$	$\{a_1,a_7,a_8,a_{21}\}$
C4	$\{a_{12},a_{15},a_{16},a_{19}\}$	$\{a_{12},a_{15},a_{16},a_{19}\}$

As discussed in the business failure risk assessment problem presented in Chapter 5, we expect that the assignments of PROMSORT and PROMETHEE TRI should be consistent with PROMETHEE results, since PROMETHEE TRI and PROMSORT are based on the methodological framework of PROMETHEE method. If we use PROMETHEE I method in order to rank alternatives from the best to the worst, we obtain the partial ranking that can be seen in Figure 6.8. On the other hand, PROMETHEE II provides the complete ranking of alternatives (actions in Figures) which is given in Figure 6.9.

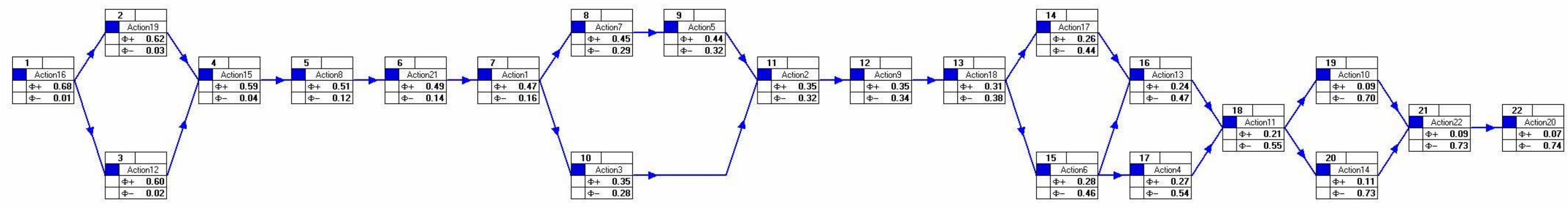


Figure 6.8 Partial ranking of alternatives using PROMETHEE I

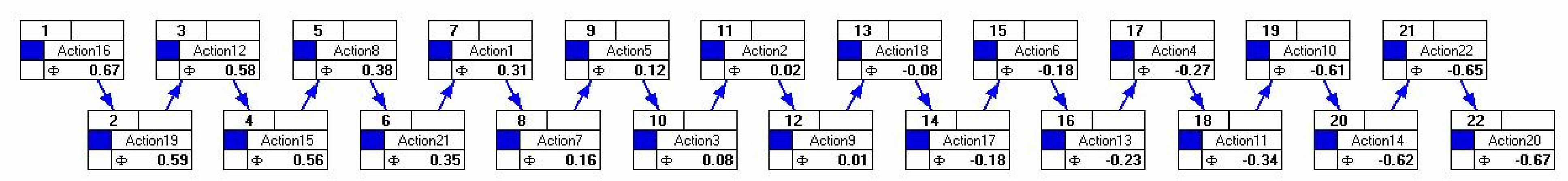


Figure 6.9 Complete ranking of alternatives using PROMETHEE II

As discussed earlier, in PROMETHEE TRI, the use of single criterion net flow didn't guarantee the ordered categories. As can be seen from Figure 6.8 and 6.9, PROMETHEE TRI has not provided ordered categories for the supplier selection case as well. For instance, according to the PROMETHEE results it should be noted that a_1, a_7, a_8, and a_{21} are ranked better than a_5. However, in PROMETHEE TRI, a_5 is assigned to the better category than the all actions a_1, a_7, a_8 and a_{21}. The outranking relations obtained from PROMETHEE I between a_5 and a_1, a_7, a_8 and a_{21} can be seen as follows:

$$[a_1\ P\ a_5]\ ;\ [a_7\ P\ a_5]\ ;\ [a_8\ P\ a_5]\ ;\ [a_{21}\ P\ a_5]$$

As it can be seen clearly, although alternatives a_1, a_7, a_8 and a_{21} are preferred to a_5 according to PROMETHEE I results, they are assigned to a worse category. Same conclusions can be drawn for a_2. In spite of the fact that a_2 is preferred to a_9 and a_{18}, it is assigned to a worse category than them. In the light of these results, we can say that PROMETHEE TRI may not assign the alternatives to the categories fully consistent with PROMETHEE results.

On the other hand, assignments of PROMSORT are consistent with PROMETHEE results. It should be remembered that PROMSORT guarantees that given any two alternatives a_1 and a_5 such that $a_1\ P\ a_5$, a_5 is not classified to a better category than a_1. Since PROMSORT uses preference relation to sort alternatives into ordered categories, whereas PROMETHEE TRI uses a kind of similarity based measurement. Additionally, it should be noted that the assignments of both methods are not so different, except the abovementioned suppliers. Therefore, PROMSORT seems to be a reliable tool to assign alternatives to the ordered categories.

According to the results, it should be mentioned that except supplier 15, all assignments done by PROMSORT are inside the range of ELECTRE TRI assignments. At first glance one can easily say that the assignment of suppliers to the categories is quite similar in the two approaches. However, some alternatives were assigned to different classes by the two approaches as expected since both approaches are not based on the same methodological framework in evaluating the alternatives. In addition, ELECTRE TRI optimistic and pessimistic procedures assigned the supplier 6 to the classes in wide range. In the pessimistic procedure, a_6 is assigned to the worst (Class 1) class as a pruning supplier. Contrarily, ELECTRE TRI optimistic procedure assigned it to the third class (Class 3) as a promising supplier. ELECTRE TRI results were only given for λ (cutting level) = 0.85. If λ were set a higher value (e.g. 0.95), most comparisons performed between alternatives and limit profiles would give the incomparability results and would assign most of the alternatives to the best two classes in optimistic procedure and the worst two classes in the pessimistic procedure.

6.3.5 Sensitivity analysis

In this section, we also test the robustness of the proposed MCS method by means of a given supplier selection example. Every multicriteria sorting method requires the determination of some parameters (e.g. thresholds, weights,…). Since generally decision makers cannot fix correctly their exact values, it is important to know the influence they have on the classifications when small changes occur in their values (Brans et al., 1986). The robustness of the classification must be demonstrated by analyzing the sensitivity in the change of the parameters (Merad et al., 2004).

Besides the ‘‘basic solution’’ (parameters presented as in Table 6.2), a number of sensitivity analyses were carried out on the supplier selection problem presented (as in Georgopoulou et al., 2003):

• Increased values of both thresholds, compared to the ‘‘basic solution’’ – by +10%, +30% and +50%.

• Decreased values of both thresholds, compared to the ‘‘basic solution’’ – by -10%, -30% and -50%.

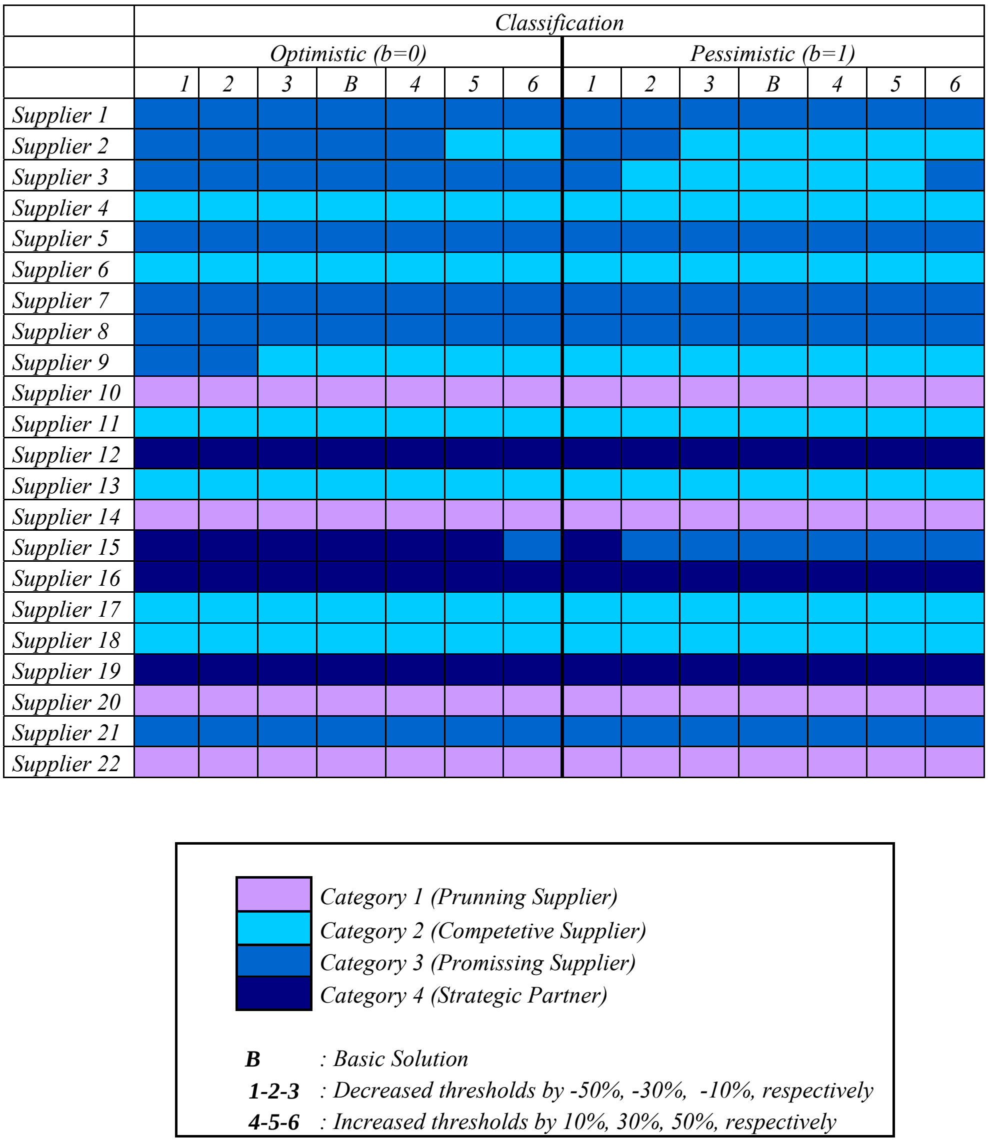


Figure 6.10 Results of the Sensitivity Analysis

Table 6.10 Sensitivity for all suppliers

Category	*Stable*	*Unstable*
Class 4 (Strategic Partner)	a_{12}, a_{16}, a_{19}	
		a_{15}
Class 3 (Promissing Supplier)	$a_1, a_5, a_7, a_8, a_{21}$	
		a_2, a_3, a_9
Class 2 (Competetive Supplier)	$a_4, a_6, a_{11}, a_{13}, a_{17}, a_{18}$	
Class 1 (Prunning Supplier)	$a_{10}, a_{14}, a_{20}, a_{22}$	

The results of the sensitivity analyses are seen in Figure 6.10 and summarized in Table 6.10. The results indicate that the classification of suppliers a_2, a_3, a_9 and a_{15} oscillates between two successive classes. The classification of other suppliers remains insensitive to parameter changes. Therefore, we can say that the small changes in the values of parameters do not have a strong effect on the results of the proposed method.

6.4 Summary

Selection and evaluation of suppliers have always been considered as an important function for the companies. Collaborating with the right suppliers and managing them are getting more important now with the strategic partnerships being implemented with suppliers to achieve a competitive advantage and the involvement of suppliers in product development stages. Therefore effective methodologies that have the capability of evaluating and continually monitoring suppliers' performance are still needed.

In this research, we proposed a supplier evaluation and management methodology for the product development process, in which suppliers are categorized and compared according to their performances on several design based criteria, potential causes for differences in suppliers' performances are identified, and performances of the suppliers are improved by applying supplier development programs. The proposed methodology considers the strategic partnership and concurrent product development concepts to identify the supplier selection criteria rather than the traditional selection criteria.

Different from the previous approaches used for prequalification of suppliers, this research offers the use of a new MCS method, called as PROMSORT, in sorting the suppliers based on their preference relations, which assists management in selecting suppliers for strategic partnership ("perfect" suppliers), supplier development programs ("good" suppliers), competitive partnership ("moderate" suppliers) and pruning ("bad" suppliers).

As discussed in Chapter 2, once the selected set of suppliers (a subset of the base) is determined, the firm must allocate orders to them. In the next chapter, an integrated multi-criteria decision making (MCDM) methodology for supplier (or outsourcing) management that incorporates PROMETHEE and interactive fuzzy goal programming (IFGP) approaches for the selection of strategic partners and order allocation will be presented.

CHAPTER SEVEN
AN INTEGRATED MULTI-CRITERIA DECISION-MAKING METHODOLOGY FOR SUPPLIER MANAGEMENT

7.1 Introduction

As discussed in the earlier chapters, most important purchasing decisions are maintaining close relationship with a few suppliers, identifying appropriate suppliers and allocating order quantities to them. The preceding chapter of this dissertation has been devoted to explain the strategic supplier evaluation and management system (SSEMS) proposed to select the strategic partners and manage the reduced supply base effectively. With the selection of strategic suppliers by applying the methodology described in the previous chapter, the most important remaining decision is to allocate the order quantities to the appropriate suppliers.

As stated in the first chapter, once the supply base of the firm is reduced to a manageable size, the firm must allocate orders to them. The literature review presented in Section 2.4 of this dissertation reveals that the problem of order allocation is generally handled by mathematical programming (MP).

As mentioned in the previous chapter, when reducing the supply base, companies' long term expectations and design based capabilities and abilities should be considered. On the other hand, short-term allocation decisions of the orders should be based on both traditional item-specific criteria such as quality, delivery and cost and the strategic partnership scores of the selected suppliers. In the purchasing literature, overall score of a supplier, which is a measure of working with a good supplier, has largely been ignored in the decision models that deals with order allocation problem. This problem is recognized by some researchers (e.g., Ghodsypour and O'Brien ,1998; Çebi and Bayraktar, 2003; Wang et al., 2004) who proposed integrated methods that use analytic hierarchy process (AHP) and linear and goal programming (GP) to deal with both qualitative and quantitative criteria. In general, the first phase of such approaches deals with obtaining the score of suppliers, then selecting the appropriate suppliers and allocating the order quantities to them are performed by using MP techniques. However, in these studies, it is assumed that the problem is fully understood and decision maker's aspiration levels are known exactly.

In the current chapter, we propose an integrated methodology for supplier selection and order allocation. The proposed methodology is based on PROMETHEE and fuzzy goal programming (FGP). As an extension of SSEMS described in the previous chapter, it evaluates the existing suppliers in terms of company's goals, selects the most appropriate suppliers for strategic partnership as well as allocating the ordered quantities to them. By the help of the aforementioned methodology, it also identifies the differences in performances across suppliers, and assists decision maker in monitoring the suppliers' performances.

Different from the integrated approaches proposed in the literature, in the methodology proposed in this chapter, the overall score of each supplier is determined by using PROMETHEE method. The proposed methodology deals with all stages of supplier selection process: prequalification of the existing suppliers, rating of the selected suppliers, and allocating the orders to them. It also differs itself from the other approaches by using fuzzy MP techniques in the order allocation stage. By this way, the decision maker's imprecise aspiration levels are incorporated through the goals into the model.

As discussed in Chapter 2, some researchers have employed the fuzzy decision of Belman and Zadeh (1970), which is discussed in Section 4.2, to tackle with the imprecise and vague information of the objectives and constraints of the supplier selection problem. Differently, in this dissertation, we assert that interactive FGP (IFGP) approaches provide more effective solutions for the supplier selection and order allocation problem than the fuzzy approaches used in the supplier selection literature. If the decision maker is not satisfied with the current optimal solution, IFGP approaches allow the decision maker to control the search direction via updating the membership functions. Among the numerious interactive approaches, we suggest to use Abd El-Wahed & Lee's (2006) approach in the order allocation phase.

This chapter is organized as follows: Section 2 is devoted to explain the proposed integrated methodology for supplier management. Section 3 demonstrates how the proposed methodology can be applied to order allocation problem by means of a hypothetical example. In section 3, the suggested IFGP approach is also analyzed and the comparison with other FGP approaches is also performed. In Section 4, another case study that includes real data is illustrated to emphasize the applicability of the proposed methodology. Finally, Section 5 presents the summary and concluding remarks.

7.2 An integrated multi-criteria decision making methodology for supplier management

As an extension of the SSEMS described in the previous chapter, the integrated methodology is based on PROMETHEE and FGP. There are three major phases in the methodology proposed. As shown in Figure 7.1, these are *prequalification–evaluation*, *supplier management* and *final selection* phases respectively.

The *prequalification–evaluation* and *supplier management* phases are very similar to the phases of SSEMS. If the decision maker selects PROMSORT method to classify the suppliers into the classes, benchmark the suppliers' performances with profile limits or the performances of other suppliers and monitor the performance of suppliers, SSEMS can be used to perform the tasks defined in the prequalification–*evaluation* and *supplier management* phases of this methodology. However, it is not necessary to use PROMSORT method in the proposed methodology. The set of appropriate suppliers can be determined by another approach as described in the previous chapter, it may be too clear which suppliers should be pruned from supply base or the suppliers whom they can turn into strategic partners may have already been determined. In such cases, PROMETHEE method can be utilized to evaluate and manage the supply base. The following subsections explain the phases of the proposed methodology in detail.

7.2.1 Prequalification – evaluation phase

At first hand data belonging to suppliers and supplied items are collected from the system. Then company managers determine the factors to take as the basis of supplier evaluation. Among these factors, with an agreement of the company managers, some of them are set as evaluation criteria for the suppliers and some others are determined to be the objectives of the company. This differentiation is necessary since the evaluation criteria and the objectives would be used in different steps of the study (Evaluation criteria would be required in the evaluation phase by PROMETHEE; objectives would be required in the FGP phase). By this way, duplication of information would be avoided in the following phases.

As discussed earlier, the overall scores of suppliers should be companies' long term expectations and design based capabilities and abilities. After setting the evaluation criteria, performance measures of all suppliers are computed accordingly. Then the preference functions, indifference and preference threshold are determined again by the managers of the company. All these parameters are input into PROMETHEE which provides us both the overall scores of suppliers and their separate performances on each criterion.

At this point, some of the suppliers (if any) that cannot be satisfactory at all may be taken out from the supplier base by the company managers according to the PROMETHEE scores. If it is not clear which supplier should be reduced from supplier base according to PROMETHEE scores, the use of a PROMETHEE based multicriteria sorting procedure, PROMSORT, is suggested to sort the suppliers into the predefined ordered categories, such as good, moderate, and bad. Then the rest of the suppliers go into analysis by PROMETHEE again for re-computation of scores. If the company does not want to prune any supplier from the base, overall scores of the existing suppliers are obtained by PROMETHEE.

7.2.2 Supplier management phase

In the same manner with the SSEMS methodology discussed in the previous chapter, the managerial decisions about individual suppliers are addressed in the *supplier management* phase. As discussed in the previous chapter, if PROMSORT is used to sort the suppliers into predefined classes, it provides valuable information to the decision maker about the managerial decisions on individual suppliers and supplier classes.

Contrarily, if PROMSORT is not used in the problem, as stated earlier, PROMETHEE provides both overall scores of suppliers' and individual performances on each criterion and visualizes these scores on figures that represent the profiles of suppliers. Looking at these figures, the roles of the supplier management system is to identify differences in the performances across suppliers, to provide feedback to suppliers about their weaknesses, to assist suppliers by providing knowledge, skills and experience via various development programs, and to monitor suppliers' performance after providing support. As in the SSEMS, after a specified period of support and assistance, manufacturers again evaluate suppliers' performance by PROMETHEE to see whether there is a positive trend in the score of suppliers. If so, the company will further develop the strategic long-term relationship with them. If not, the company will reduce the scope of the partnership.

7.2.3 Order allocation phase

As an extension of the SSEMS described in the previous chapter, the final step of the proposed methodology is to select the suppliers and to allocate the ordered quantities to them using IFGP approach. PROMETHEE II net flows that represent overall scores of suppliers are used as coefficients of an objective function in FGP model. In addition, other objectives which are determined at the beginning of the methodology (e.g. total cost) are included in the model. By including all objective functions and constraints, the fuzzy model can allocate order quantities among the favorable suppliers. If the decision maker is satisfied with the solutions, the procedure stops. However, if the solutions are not found satisfactory by the decision maker, lower bounds, upper bound and / or aspiration levels of goals are restated. Then the fuzzy model is resolved with the new parameters. The procedure is repeated until the decision makers are totally satisfied. In other words, Abd El-Wahed and Lee's (2006) IFGP approach is employed in the proposed methodology.

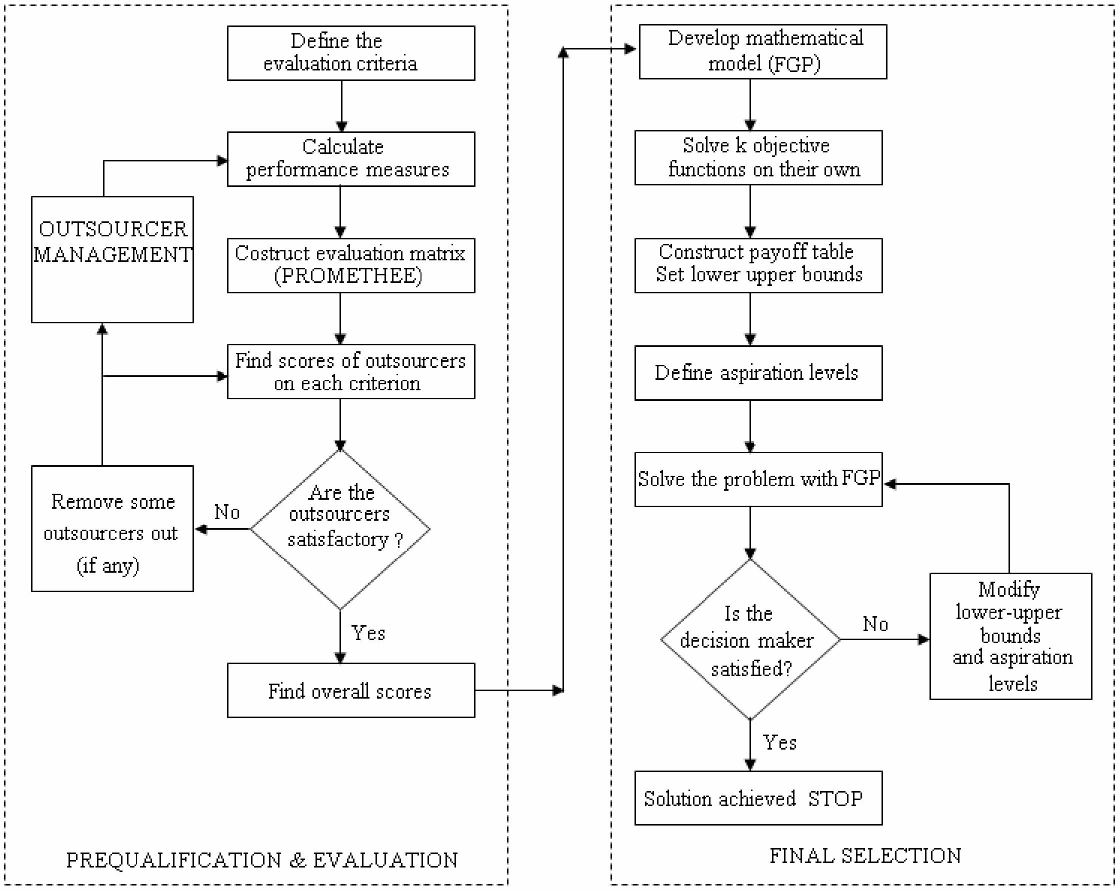


Figure 7.1 Flow diagram of proposed methodology

As discussed earlier, the main advantage of interactive approaches is that the decision maker controls the search direction during the solution procedure and achieves the preferred solution considering his/her preferences (Abd El-Wahed and Lee, 2006). Therefore, we assert that IFGP approaches provide more effective solutions for supplier selection and order allocation problem than the fuzzy approaches used in the supplier selection literature by allowing the decision maker to select the preferred compromise solution.

The order allocation phase of the proposed methodology based on IFGP can be summarized in the following steps:

- Step 1: Develop a multiobjective linear programming model. In the modeling phase, k objectives are developed by the company managers.

$$\begin{array}{ll} \textit{Maximize} & Z_1, Z_2, ..., Z_h \\ \textit{Minimize} & Z_{h+1}, Z_{h+2}, ..., Z_k \\ s.t.: & g_j(x) \le b_j \qquad j = 1,2,...,J \end{array} \tag{7.1}$$

where, $g_j(x)$ is the jth inequality constraint and b_j is the resource available of inequality constraint j.

The first objective function is simply the weighted sum of quantities ordered from each supplier. In other words it is a measure of working with good suppliers which are candidate strategic partners. Hence this objective is named as Total Value of Strategic Partnership (TVSP). The weight set is the set of net flows calculated by PROMETHEE. The goal is to maximize this summation, in other words, to set the ordered quantities to the highest performing suppliers as much as possible.

$$\text{Maximize } Z_1 = \sum_i \sum_j W_j * X_{ij} \tag{7.2}$$

where, X_{ij} denotes the units of item i ordered from supplier j and W_j denotes PROMETHEE II net flow of the supplier j.

Other objectives are determined by the company managers considering the item specific requirements.

- Step 2: Solve the first objective function as a single objective problem. Continue this process K times for the K objective functions. If all the solutions are the same, select one of them as an optimal compromise solution and go to Step 8. Otherwise, go to Step 3.

- Step 3: Evaluate the objective function at the K^{th} solution and determine the best lower bound (l_k) and the worst upper bound (u_k).

- Step 4: Define the membership function of each objective function as follows:

For a maximization type objective function *h*;

$$\mu_{z_h}(x) = \frac{Z_h(x) - l_h}{u_h - l_h} \tag{7.3}$$

For a minimization type objective function *k*;

$$\mu_{z_k}(x) = \frac{u_k - Z_k(x)}{u_k - l_k} \tag{7.4}$$

- Step 5: Develop the following linear problem and solve it as a linear programming problem.

$$\left.\begin{array}{lll}
\text{Max} & Z = \lambda & \\
\text{s.t.} & & \\
& \lambda \le \mu_{Z_k} & k = 1,\ldots,K \\
& g_j(x) \le b_j & j = 1,\ldots, J \\
& x \ge 0 & \\
& \lambda \in [0,1]. &
\end{array}\right\} \tag{7.5}$$

- Step 6: Present the solution to the decision maker. If the decision maker accepts it, go to Step 8. Otherwise, go to Step 7.

- Step 7: Evaluate each objective function of the solution. Determine the most important objective function to be improved further. Assuming the less preferred to more, compare the upper bound of the selected objective with the new value of the objective function. If the new value is lower than the upper bound, consider this as a new upper bound. Otherwise, keep the old one as is and determine the second most important objective function. Repeat this process until one of the upper bounds is updated and go to Step 4.

- Step 8: Stop.

As stated in Chapter 4 of this dissertation, the IFGP procedure used in the proposed methodology is slightly different from Abd El-Wahed and Lee (2006)'s IFGP approach. In their approach, at each iteration Abd El-Wahed and Lee (2006) change all membership functions of the goals simultaneously and the procedure stops when the decision maker is satisfied or an infeasible solution is obtained. However, it is obvious that, when the number of objectives is more than two and the strong trade-offs exist between objectives, the procedure easily reaches an infeasible solution and the decision maker can not effectively control the search direction. In order to avoid finding an infeasible solution and increase the flexibility of the decision maker in acting the search direction, we allow the decision maker to change only one of the membership functions at each iteration.

In the next section, the proposed methodology will be illustrated with a numerical example. In order to confirm the viability of the proposed methodology, solution of the presented numerical example are also performed by using other fuzzy MP approaches used in the literature and the results are discussed.

7.3 Computational Experiments

In this section, to be able to demonstrate the applicability of the proposed methodology to order allocation problem, we reconsider our hypothetic strategic sourcing problem presented in Section 6.3. As it is remembered, CI Inc. is a manufacturer working in the field of electronic industry and company managers apply SSEMS described in the previous chapter to evaluate supplier's performance, to select key suppliers for strategic partnership, develop promising suppliers for strategic partnership, monitor the supplier's overall performance, co-design contribution, and the support of supplier in concurrent engineering activities, and provide feedback to suppliers about their weaknesses. In the previous chapter, a numerical example was given to show how the proposed methodology can help CI Inc. company to effectively deal with these problems.

Now, it is assumed that CI Inc. has five parts to be supplied with different quantities and wants to answer following questions:

- Which suppliers should be selected as supply source?
- How order quantities should be allocated among the selected suppliers?

Assume that the company wants to supply these parts from the strategic partners and promising suppliers, which are assigned to the fourth and third classes, respectively. As it is recalled from Section 6.3, these supplier groups are identified by PROMSORT method and suppliers 12, 15, 16, and 19 are categorized in the best class as strategic partners while suppliers 1, 2, 3, 5, 7, 8, and 21 are assigned as the promising suppliers. Therefore, only 11 suppliers are considered to allocate the orders.

Since the *prequalification–evaluation* and *supplier management* phases have already been performed by SSEMS as in the case study given in the previous chapter, in this section, we only focus on the order allocation phase. However, as discussed above, the order allocation phase requires the determination of overall scores of suppliers. As it is recalled from Section 6.3, concurrent design team determines a set of ten criteria to evaluate suppliers' performance. It should be remembered that all of these criteria reflect the company's long-term expectations and suppliers' capabilities. In the same manner, 11 suppliers qualified in the prequalification phase are evaluated considering the same set of criteria by

PROMETHEE for re-computation of overall scores. The following figure illustrates the results of PROMETHEE II. In Figure 7.2 below, the suppliers are listed in order from the most superior to the least in terms of overall scores.

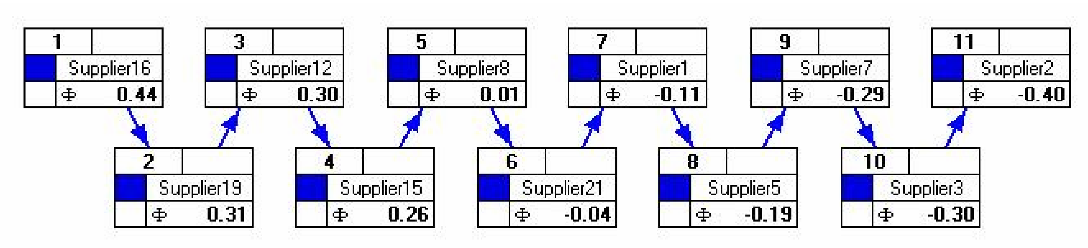


Figure 7.2 PROMETHEE II output: Final scores of suppliers after prequalification

After obtaining the overall score of each supplier, solution of order allocation problem by using IFGP approach is presented in the following.

- Step 1:

As mentioned earlier, in the first step, the development of a multiobjective linear model is required. We assumed that four objectives are developed by the company managers. The first objective function is simply the weighted sum of quantities ordered from each supplier. The weight set is the set of net flows calculated by PROMETHEE (Figure 7.2). The second objective is to maximize the percentage of accepted units in the quality control. The third objective is to maximize the delivery performance by increasing the percentage of units arriving on-time. The last objective is to minimize the total monetary cost. The model is coded using LINGO 8.0 (LINDO, 2003) format and LINGO code is presented in Appendix B. The details of the model are given in the following.

Sets:

i: Number of suppliers, i=1..11

j: Number of items, j=1..5

Decision Variables:

X_{ij} units of items j ordered from supplier i

Y_{ij} binary variable that indicates whether ith supplier selected for item j

Parameters:

M a very large number

D_j Quantity demanded of item j

Q_{ij} Minimum order quantity from supplier i for item j

C_i Capacity of supplier i for item j

F_{ij} Percentage of Quality level of supplier i on item j

S_{ij} Percentage of Delivery level of supplier i on item j

P_{ij} Net price of item j from supplier i.

W_i PROMETHEE II net flow of the supplier j.

W = [-0.11 -0.40 -0.30 -0.19 -0.29 0.01 0.30 0.26 0.44 0.31 -0.04]

Objective Functions:

$$Z1= \sum_i \sum_j W_i * X_{ij} \qquad (7.6)$$

$$Z2= \sum_i \sum_j F_{ij} * X_{ij} \qquad (7.7)$$

$$Z3= \sum_i \sum_j S_{ij} * X_{ij} \qquad (7.8)$$

$$Z4= \sum_i \sum_j P_{ij} * X_{ij} \qquad (7.9)$$

S.t.:

$$\sum_i X_{ij} = D_j \qquad \forall \text{ j} \qquad (7.10)$$

$$X_{ij} \le C_{ij} \qquad \forall \text{ i, j} \qquad (7.11)$$

$$Y_{ij} * M \ge X_{ij} \qquad \forall \text{ i, j} \qquad (7.12)$$

$$Y_{ij} * Q_{ij} \le X_{ij} \qquad \forall \text{ i, j} \qquad (7.13)$$

$$\sum_i Y_{ij} \ge 2 \qquad \forall \text{ j} \qquad (7.14)$$

$$X_{ij} \ge 0 \ and \ Y_{ij} \ 0 \ or \ 1 \qquad (7.15)$$

Constraint set (7.10) assures that demands are satisfied. Constraint set (7.11) means that the order quantity of each item of each supplier should be less than or equal to its capacity. Minimum and maximum order quantities of each supplier for each item are ensured by constraint sets (7.13) and (7.12), respectively. Constraint sets (7.14) are concerned with number of suppliers to be selected. Constraint set (7.15) prohibits the negative orders and presents the binary variables.

The values of quality and delivery level of suppliers for each item and the net prices offered by the suppliers for each item are given in Table 7.1, 7.2 and 7.3, respectively. The capacities of suppliers for each item and the quantity demanded of each item are shown in Table 7.4.

Table 7.1 Percentage of quality level of suppliers on each item

	Items				
Suppliers	1	2	3	4	5
1	0.92	0.89	0.83	0.86	0.95
2	0.70	0.87	0.67	0.74	0.82
3	1.00	0.86	0.83	0.90	0.85
5	0.65	0.76	0.66	0.85	0.61
7	0.94	0.94	0.96	0.97	0.92
8	0.87	0.86	0.85	0.86	0.89
12	0.97	0.95	0.87	0.93	0.93
15	0.89	0.93	1.00	0.88	0.90
16	0.99	0.97	0.93	1.00	0.98
19	0.83	0.85	0.81	0.93	0.93
21	0.89	0.86	0.94	0.95	0.93

Table 7.2 Percentage of delivery level of suppliers on each item

	Items				
Suppliers	1	2	3	4	5
1	0.93	0.95	0.98	0.92	0.95
2	0.96	0.95	0.93	0.93	0.96
3	0.82	0.99	0.93	0.87	0.95
5	0.76	0.94	0.88	0.93	0.87
7	0.86	0.94	0.96	0.92	0.82
8	1.00	0.95	0.96	0.99	0.99
12	0.95	0.98	0.96	0.99	1.00
15	0.93	0.96	1.00	0.97	0.96

16	0.93	0.98	0.91	0.90	1.00
19	0.99	0.93	0.95	0.98	0.99
21	0.98	0.98	0.97	0.95	0.98

Table 7.3 Prices of items offered by each supplier

			Items		
Suppliers	1	2	3	4	5
1	9.80	11.08	5.43	28.77	7.82
2	6.35	13.89	7.93	29.55	10.36
3	9.71	7.79	14.49	24.24	12.16
5	6.34	7.51	6.50	20.53	14.58
7	6.14	13.39	6.20	24.54	7.58
8	10.08	12.89	6.15	15.32	11.00
12	13.05	10.66	12.55	27.41	14.90
15	10.38	13.90	12.46	15.92	5.57
16	12.76	11.87	10.45	12.53	7.22
19	14.35	10.91	12.88	28.08	13.54
21	11.33	14.59	8.04	29.32	7.42

Table 7.4 Capacities of suppliers for each item and quantity demanded

			Items		
Suppliers	1	2	3	4	5
1	4500	5000	4500	4500	1000
2	4000	6200	2500	8000	4500
3	1500	5000	4800	5000	2350
5	1400	6400	2200	4500	4500
7	7500	3000	3750	3500	3000
8	7500	1500	6000	3250	6000
12	7250	5500	2000	5500	4500
15	4500	5500	10000	10000	2000
16	10000	10000	10000	7500	6000
19	5500	5500	5500	8000	8000
21	2000	8000	7000	2000	5500
Demand	15000	22000	28000	12500	14000

- Step 2:

As mentioned previously in Section 4.4.1, decision maker constructs the pay-off table to see efficient extreme solutions. Once the multiobjective programming model is developed, it is solved with each of the objective functions by themselves. In other words first Z1 is set as the objective and the model is solved. Then Z2, Z3 and Z4 are all set as objective one by one and solved. For each solution the value of the objective and the other Z function values are recorded. By this way the payoff table is constructed as follows:

Table 7.5 Pay-off Table

	Objective Functions			
Value	Z_1	Z_2	Z_3	Z_4
Z_1	32644.76*	15015.53	14855.73	3672.9$^+$
Z_2	84801	87670*	83703.5	82155$^+$
Z_3	87774	87095	90257.5*	86422.5$^+$
Z_4	1153910*	1079460	1126289	789131.5$^+$

*: Upper Bounds; + :Lower Bounds

- Step 3:

Considering the values of objective functions in the pay-off table, the lower bound (l_k) and the upper bound (u_k) for each objective function can be determined as follows:

Table 7.6 Lower and Upper bounds of the objectives

Objectives	Lower Bound	Upper Bound
Z_1	3672.90	32644.76
Z_2	82155.00	87670.00
Z_3	86422.50	90257.50
Z_4	789131.50	1153910.00

- Step 4:

Looking at the lower bound (l_k) and the upper bound (u_k) values determined in the previous step, the membership functions of each objective can be defined as follows:

$$\mu_{z_1}(x) = \begin{cases} 1 & if \quad Z_1(x) \geq 32644.76, \\ \dfrac{Z_1(x) - 3672.90}{32644.76 - 3672.90} & if \quad 3672.90 < Z_1(x) < 32644.76, \\ 0 & if \quad Z_1(x) \leq 3672.90. \end{cases}$$

$$\mu_{z_2}(x) = \begin{cases} 1 & if \quad Z_2(x) \geq 87670, \\ \dfrac{Z_2(x) - 82155}{87670 - 82155} & if \quad 484066 < Z_2(x) < 87670, \\ 0 & if \quad Z_2(x) \leq 82155. \end{cases}$$

$$\mu_{z_3}(x) = \begin{cases} 1 & if \quad Z_3(x) \geq 90257.50, \\ \dfrac{Z_3(x) - 86422.50}{90257.50 - 86422.50} & if \quad 86422.5 < Z_2(x) < 90257.50, \\ 0 & if \quad Z_2(x) \leq 86422.5. \end{cases}$$

$$\mu_{z_4}(x) = \begin{cases} 1 & if \quad Z_4(x) \leq 789131.50, \\ \dfrac{1153910 - Z_4(x)}{1153910 - 789131.50} & if \quad 789131.50 < Z_4(x) < 528663, \\ 0 & if \quad Z_4(x) \geq 1153910. \end{cases}$$

- Step 5:

Considering the membership functions constructed in the previous step, FGP model can be developed as follows:

$$\left. \begin{array}{ll} Max & Z = \lambda \\ & s.t. \\ & \mu_{Z_1} \geq \lambda, \\ & \mu_{Z_2} \geq \lambda, \\ & \mu_{Z_3} \geq \lambda, \\ & \mu_{Z_4} \geq \lambda, \\ & 0 \leq \lambda \leq 1 \\ & \text{Sytems constraints from (7.10) to (7.15)} \end{array} \right\} \quad (7.16)$$

- Step 6:

In this step, the FGP model developed in the previous step is solved and the following results are achieved:

Table 7.7 Results of the first Iteration

Objective Function	Value
Z_1 (TVSP)	19828.61
Z_2 (TotalQuality)	85230.36
Z_3 (TotalDelivery)	88561.03
Z_4(TotalCost)	950496.9
μ_{z1}	0.557635
μ_{z2}	0.557635
μ_{z3}	0.557635
μ_{z4}	0.557635

After this iteration, the results are presented to the decision maker and it is assumed that the decision maker is not satisfied with the current results and he/she firstly wants to improve the performance of TVSP objective.

- Step 7:

At this step, the lower bound is revised with the value achieved for TVSP. That is the new lower bound for the first objective became 19828.61. This means that the membership function of TVSP objective must be reconstructed as follows:

$$\mu_{z_1}(x) = \begin{cases} 1 & \text{if} \quad Z_1(x) \geq 32644.76, \\ \dfrac{Z_1(x) - 19828.61}{32644.76 - 19828.61} & \text{if} \quad 19828.61 < Z_1(x) < 32644.76, \\ 0 & \text{if} \quad Z_1(x) \leq 19828.61. \end{cases}$$

The model is resolved with the new membership function and the following results are obtained:

Table 7.8 Results of the second Iteration

Objective Function	Value
Z_1 (TVSP)	25705.6
Z_2 (TotalQuality)	84683.97
Z_3 (TotalDelivery)	88181.08
Z_4(TotalCost)	986636.7
μ_{z1}	0.760486
μ_{z2}	0.458561
μ_{z3}	0.458561
μ_{z4}	0.458561

If the results of the first iteration are compared to those of the second iteration, it can be seen that the value of TVSP objective is increased from 19828,61 to 25705,6 and a substantial improvement (36.37 %) can be provided in achievement level of the membership function of TVSP (μ_{z1}) objective. After this iteration, the results are again presented to the decision maker and it is assumed that the decision maker is not satisfied with the current results as well and he/she still thinks that the performance of TVSP objective should be further improved. In the same manner, the lower bound is revised with the value achieved for TVSP. That is the new lower bound for the first objective became 25705.6. The procedure is followed until the decision maker is satisfied. It is assumed that the decision maker considers TVSP objective as the most important objective followed by Total Quality, Total Delivery and Total Cost. Let's suppose that the decision maker controls the search direction based on his/her preferences and accepts the results of the model in iteration 14. We refer this solution as preferred compromise solution. The solutions of all iterations are given in Table 7.9.

The results of iteration 14 represent that the achievement level of TVSP objective is more than Total Quality objective and the achievement level of Total Quality objective is more than Total Delivery objective. Among the objectives, Total cost objective has the lowest achievement level. It means that the achievement level of the objective functions is consistent with the decision maker's preferences. Figure 7.3 represents the achievement level variations of membership functions according to the iterations. It is clear from Figure 7.3 that decision maker can easily control the search direction and act to the results whenever it is necessary.

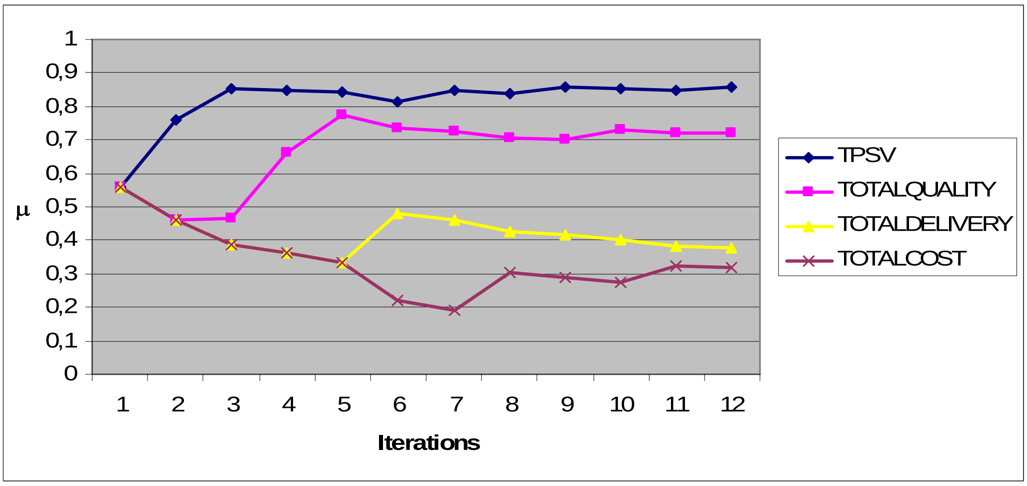


Figure 7.3 Degree of achievement levels of objective functions

Since the decision maker accepts the solution, the procedure is terminated at Step 8. The solution results of the order allocation problem are presented in Table 7.10. To evaluate the performance of the suggested interactive approach, we will consider the solution of the illustrative example by using different fuzzy MP methods in the next section.

Table 7.9 Results of the Iterations

	Iterations													
Objectives	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Z_1	19828.61	25705.6	28408.68	28220.34	28031.64	27223.63	28258.5	27970.12	28526.44	28446.66	28287.6	28548.89	28523.75	28429.48
Z_2	85230.36	84683.97	84727.39	85793.79	86422.7	86204.24	86151.95	86052.14	86017.07	86185.57	86129.33	86116.19	86200.4	86166.78
Z_3	88561.03	88181.08	87916.38	87812.3	87708.01	88265.74	88194.69	88059.07	88011.42	87967.91	87881.16	87860.9	87846.19	87924.71
Z_4	950496.9	986636.7	1011814	1021715	1031635	1074110	1084276	1043635	1049151	1054189	1036188	1038294	1039823	1045558
μ_{z1}	0.557635	0.760486	0.853786	0.847286	0.840772	0.812883	0.848603	0.838649	0.857851	0.855097	0.8496071	0.858626	0.8577583	0.8545042
μ_{z2}	0.557635	0.458561	0.466436	0.659798	0.773836	0.734222	0.724741	0.706644	0.700285	0.730838	0.7206399	0.7182581	0.7335276	0.7274315
μ_{z3}	0.557635	0.458561	0.389539	0.362399	0.335205	0.480637	0.462111	0.426747	0.414321	0.402975	0.3803544	0.3750714	0.3712358	0.3917096
μ_{z4}	0.557635	0.458561	0.389539	0.362399	0.335205	0.218763	0.190895	0.302308	0.287184	0.273375	0.322723	0.3169487	0.3127564	0.2970343

Table 7.10 The solution results of the order allocation problem

Objectives	Z_1=28429.48; Z_2= 86166.78; Z_3=87924.71; Z_4=1045558				
Achievement Levels	μ_{z1}=0.855; μ_{z2}= 0.727; μ_{z3}= 0.392; μ_{z4}= 0.297				
X_{ij}	X(6, 3)	3381.775	Y_{ij}	Y(6, 3)	1
	X(6, 4)	1579.090		Y(6, 4)	1
	X(7, 1)	7250.000		Y(7, 1)	1
	X(7, 2)	5500.000		Y(7, 2)	1
	X(8, 2)	4300.000		Y(8, 2)	1
	X(8, 3)	10000.00		Y(8, 3)	1
	X(8, 4)	3420.910		Y(8, 4)	1
	X(8, 5)	1832.138		Y(8, 5)	1
	X(9, 1)	7750.000		Y(9, 1)	1
	X(9, 2)	10000.00		Y(9, 2)	1
	X(9, 3)	7618.225		Y(9, 3)	1
	X(9, 4)	7500.000		Y(9, 4)	1
	X(9, 5)	6000.000		Y(9, 5)	1
	X(10, 2)	2200.000		Y(10, 2)	1
	X(10, 5)	6167.862		Y(10, 5)	1
	X(11, 3)	7000.000		Y(11, 3)	1

7.3.1 Comparison of the results

In this section, solution of the illustrative example is performed by using six different fuzzy MP approaches and the results are compared to that of the preferred compromise solution obtained from suggested interactive approach. The fuzzy MP approaches selected for comparison are Zimmerman's (1978) max-min approach, additive approach, Tiwari et al.'s (1987) weighted additive approach, Chen and Tsai's (2001) preemptive approach, Lin's (2004) weighted max-min approach and Aköz and Petrovic's (2006) approach. As it is recalled, the detailed explanations of these approaches are given in Section 4.2.

- *Application of Zimmerman's max-min approach*

As described in Secion 4.4.2, the illustrative example can be formulated using Zimmerman's approach as follows:

$$\left.\begin{aligned}
Max \quad & Z = \lambda \\
& s.t. \\
& \mu_{Z_1} \geq \lambda, \\
& \mu_{Z_2} \geq \lambda, \\
& \mu_{Z_3} \geq \lambda, \\
& \mu_{Z_4} \geq \lambda, \\
& 0 \leq \lambda \leq 1 \\
& \text{Sytems constraints from (7.10) to (7.15)}
\end{aligned}\right\} \quad (7.17)$$

As discussed earlier, Abd El-Wahed & Lee's (2006) IFGP approach starts the iterations by applying the Zimmerman's max-min approach. Therefore, Zimmerman's approach provides the same results with the first iteration of the proposed approach. The results are given in the following table;

Table 7.11 The results of the illustrative example using max-min approach

Z_1	Z_2	Z_3	Z_4	μ_{z1}	μ_{z2}	μ_{z3}	μ_{z4}
19828.61	85230.36	88561.03	950496.9	0.558	0.558	0.558	0.558

It should be noted that Zimmerman's approach has already been applied to supplier selection problem by Kumar et al. (2004, 2006).

- *Additive approach*

As it is called from Section 4.4.2, using additive approach, the problem can be formulated as follows:

$$\left.\begin{aligned}
Max \quad & Z = \mu_{z1} + \mu_{z2} + \mu_{z3} + \mu_{z4} \\
& s.t. \\
& \mu_{Z_1}, \mu_{Z_2}, \mu_{Z_3}, \mu_{Z_4} \in [0,1], \\
& \text{Sytems constraints from (7.10) to (7.15)}
\end{aligned}\right\} \quad (7.18)$$

Since any relative priority is not attained to the objectives, the additive approach tries to maximize the sum of the achievement level. It is clear that the results are not consistent with the decision maker's preferences. The following table summarizes the results.

Table 7.12 The results of the illustrative example using additive approach

Z_1	Z_2	Z_3	Z_4	μ_{z1}	μ_{z2}	μ_{z3}	μ_{z4}
21073.94	86271	88495	990056	0.601	0.746	0.540	0.449

- *Application of Tiwari et al.'s weighted additive approach*

As it is recalled from Section 4.4.2, different from additive approach, Tiwari et al.'s approach maximizes the weighted sum of the achievement levels. Using this approach, we can formulate the illustrative example as follows:

$$\left.\begin{array}{ll} Max & Z = 0.4 * \mu_{z1} + 0.3 * \mu_{z2} + 0.2 * \mu_{z3} + 0.1 * \mu_{z4} \\ & s.t. \\ & \mu_{Z_1}, \mu_{Z_2}, \mu_{Z_3}, \mu_{Z_4} \in [0,1], \\ & \text{Sytems constraints from (7.10) to (7.15)} \end{array}\right\} \quad (7.19)$$

As discussed in the earlier sections, we assumed that the decision maker considers TVSP objective as the most important objective followed by Total Quality, Total Delivery and Total Cost. In Tiwari et al.'s approach, the relative priorities among the goals are reflected to the model using the weights. Let's suppose that the weights are determined by the decision maker as 0.4, 0.3, 0.2 and 0.1, respectively. So, the following results are obtained using weighted additive approach.

Table 7.13 The results of the illustrative example using weighted additive approach

Z_1	Z_2	Z_3	Z_4	μ_{z1}	μ_{z2}	μ_{z3}	μ_{z4}
29349.35	86942.5	87911	1125538	0.886	0.868	0.388	0.078

As it can be seen from Table 7.13 the achievement levels of the objective functions match the preferences of the decision maker. However, the achievement level of Total Cost objective is obtained as 0.078. In the weighted additive approach, such unacceptable solutions can be obtained because of the fully compensatory nature of the objective function.

Tiwari et al.'s weighted additive approach has already been applied to supplier selection problem by Amid et al. (2006). In order to tackle the problems caused by the compensatory nature of the objective function of the weighted additive approach, they reformulate the presented approach, such that the achievement level of membership functions should not be less than an allowed value. They utilized the α-cut approach to ensure that the degree of achievement for any goals should not be less than a minimum allowed value α. This process, which can be seen as a sensitivity analysis, helps the decision maker to understand the relative importance of the objectives in the model. However, the solutions obtained are still based on the weights initially determined and the determination of the weights is a difficult task.

- *Application of Chan and Tsai's approach*

As explained in Section 4.4.2, Chan and Tsai's (2001) approach requires the determination of the following relationship for the respective achievement degrees for the goals according to the priority structure of decision maker:

$$\mu_{z1} \geq \mu_{z2}$$
$$\mu_{z2} \geq \mu_{z3}$$
$$\mu_{z3} \geq \mu_{z4}$$

After adding the above relationship to the model, the illustrative example can be formulated as follows;

$$\left.\begin{array}{ll} Max & Z = \mu_{z1} + \mu_{z2} + \mu_{z3} + \mu_{z4} \\ & s.t. \\ & \mu_{z1} \geq \mu_{z2} \\ & \mu_{z2} \geq \mu_{z3} \\ & \mu_{z3} \geq \mu_{z4} \\ & \mu_{Z_1}, \mu_{Z_2}, \mu_{Z_3}, \mu_{Z_4} \in [0,1], \\ & \text{Sytems constraints from (7.10) to (7.15)} \end{array}\right\} \tag{7.20}$$

The solution of the model obtained using the Chan and Tsai's additive approach are as follows:

Table 7.14 The results of the illustrative example using Chan and Tsai's additive approach

Z_1	Z_2	Z_3	Z_4	μ_{z1}	μ_{z2}	μ_{z3}	μ_{z4}
24859.39	86188.00	88277.11	1019193	0.731	0.731	0.484	0.369

- *Application of Lin's approach*

Lin's (2004) weighted max-min approach is explained in Section 4.4.2 in detail. Similar with Tiwari et al.'s approach, this approach requires the determination of the objective weights. As mentioned above, we assumed that the weights are determined by the decision maker as 0.4, 0.3, 0.2 and 0.1, respectively. Using these weights, we can formulate the problem as follows:

$$\left.\begin{array}{ll} Max & Z = \lambda \\ & \mu_{Z_1} \geq \lambda * 0.4, \\ & \mu_{Z_2} \geq \lambda * 0.3, \\ & \mu_{Z_3} \geq \lambda * 0.2, \\ & \mu_{Z_4} \geq \lambda * 0.1, \\ & \mu_{Z_1}, \mu_{Z_2}, \mu_{Z_3}, \mu_{Z_4} \in [0,1], \\ & \text{Sytems constraints from (7.10) to (7.15)} \end{array}\right\} \tag{7.21}$$

The results are presented in the following table.

Table 7.15 The results of the illustrative example using Lin's approach

Z_1	Z_2	Z_3	Z_4	μ_{z1}	μ_{z2}	μ_{z3}	μ_{z4}
29213.31	85801.35	88112.89	1073517	0.882	0.661	0.441	0.220

- *Application of Aköz and Petrovic's approach*

As explained in Section 4.4.2, different from aforementioned approaches, Aköz and Petrovic's (2006) approach allows the decision maker to use the linguistic terms such as 'slightly more important than', 'moderately more important than' or 'significantly more important than' when expressing the fuzzy importance relation between objectives. Considering the weights of the objectives used in abovementioned approaches, let's assume that the importance relation between the objectives is set to "significantly more important than" type. Employing Aköz and Petrovic's (2006) approach, the problem can be formulated as follows:

$$\left.\begin{aligned} Max \quad & Z = \lambda * (\mu_{z1} + \mu_{z2} + \mu_{z3} + \mu_{z4}) + (1-\lambda) * (\mu_{R1} + \mu_{R2} + \mu_{R3}) \\ & s.t. \\ & \mu_{z1} - \mu_{z2} \geq \mu_{R1} \\ & \mu_{z2} - \mu_{z3} \geq \mu_{R2} \\ & \mu_{z3} - \mu_{z4} \geq \mu_{R3} \\ & \mu_{Z_1}, \mu_{Z_2}, \mu_{Z_3}, \mu_{Z_4}, \mu_{R1}, \mu_{R2}, \mu_{R3} \in [0,1], \\ & \text{Sytems constraints from (7.10) to (7.15)} \end{aligned}\right\} \quad (7.22)$$

As it can be seen from the above formula, Aköz and Petrovic's (2006) approach requires the determination of an additional parameter λ. As the value of parameter λ decreases, the sum of the achievement degrees decreases. However, in this case the importance relations are weighted more. Similar with Tiwari et al.'s weighted additive approach, the results of this approach should be subject to sensitivity analysis. The results of the illustrative numerical example obtained using Aköz and Petrovic's approach are given in Table 7.16.

Table 7.16 The results of the illustrative example using Aköz and Petrovic's approach

Z_1	Z_2	Z_3	Z_4	μ_{z1}	μ_{z2}	μ_{z3}	μ_{z4}
26663.43	86531.41	88005.85	1039683	0.794	0.794	0.413	0.313

Table 7.17 summarizes the results of the fuzzy MP approaches presented in this section and the suggested IFGP approach. Graphical representation of the solutions by these approaches is given in Figure 7.4. The solution results of the order allocation problem by all fuzzy approaches are presented in Appendix C.

Table 7.17 Comparison of solutions by different fuzzy modeling approaches

	Z_1	Z_2	Z_3	Z_4	μ_{z1}	μ_{z2}	μ_{z3}	μ_{z4}
Max-Min Approach	19828.61	85230.36	88561.03	950496.9	0.558	0.558	0.558	0.558
Additive Approach	21073.94	86271	88495	990056	0.601	0.746	0.540	0.449
Weighted Add. Approach	29349.35	86942.5	87911	1125538	0.886	0.868	0.388	0.078
Chen and Tsai's Approach	24859.39	86188.00	88277.11	1019193	0.731	0.731	0.484	0.369
Lin's Approach	29213.31	85801.35	88112.89	1073517	0.882	0.661	0.441	0.220
Aköz and Petrovic's Approach	26663.43	86531.41	88005.85	1039683	0.794	0.794	0.413	0.313
IFGP Approach	28429.48	86166.78	87924.71	1045558	0.855	0.728	0.392	0.297

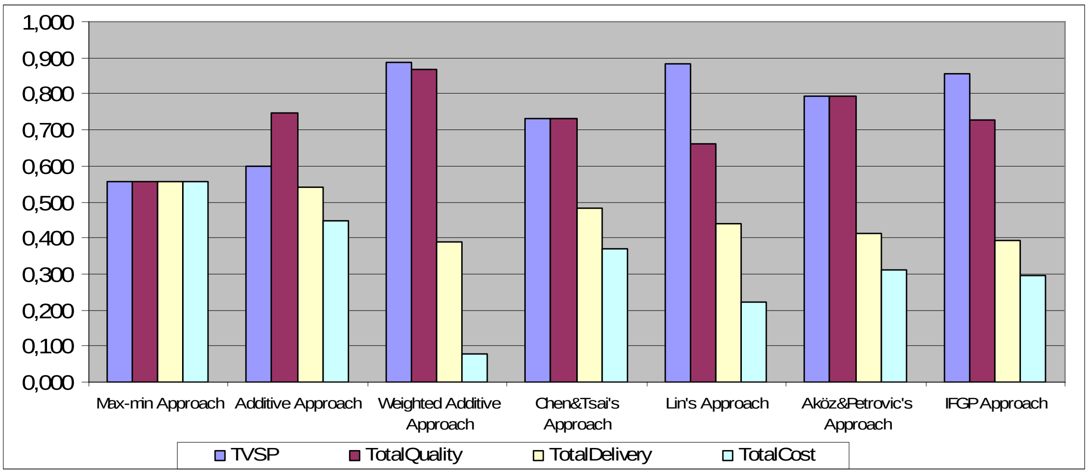


Figure 7.4 Graphical representations of the solutions by different approaches in terms of achievement level of each objective

In the light of the results presented in Table 7.17 and illustrated in Figure 7.4, we can say that all approaches provide different compromise (non-dominated) solutions. In such cases, the question should be which compromise solution is the most preferred by the decision maker. Since max-min approaches do not trade off the goals with high degree of achievement level against the goals with a low degree of achievement level, Zimmerman's max-min approach provides totally balanced solution. However, this solution can not be acceptable for the illustrated example, because the objectives are not equally important.

Contrarily, additive approach is totally compensatory and allows that the goals with high degree of achievement can be traded off against the goals with lower degree of membership. However, it doesn't consider the relative priorities among the objectives. It can be easily seen from Figure 7.4 that although the TVSP objective is more important than Total Quality objective, additive approach provides better results for Total Quality objective.

In the same manner, Tiwari et al.'s weighted additive approach is compensatory. Different from additive approach, the goals with high degree of achievement level are traded off against the goals with low degree of achievement level considering the weights of the goals. Therefore, this approach provides consistent results with the decision maker's preferences. However, it should be noted that it may provide totally unbalanced results and the results of this approach strongly depend on the weights given. Hence, the results of this approach should be subject to sensitivity analysis. Same conclusions can be drawn for Lin's approach.

It can be seen that the results obtained from Chan and Tsai's approach and Aköz and Petrovic's approach provide alternative solutions compared to the results presented above. However, in Chan and Tsai's approach, TVSP objective is satisfied with a low degree and this result also prevents obtaining better achievement degrees for Total Quality objective. Additionally, it should be pointed out that the alternative solutions can be achieved by Aköz and Petrovic's approach by changing the importance relation between objectives. However, it strongly requires the sensitivity analysis.

Different from all of the abovementioned approaches, Abd El-Wahed and Lee's (2006) IFGP approach, which is based on Zimmerman's max-min approach, doesn't need the determination of any parameter (e.g., weights, compensatory coefficient, etc.). The decision maker controls the search direction during the solution procedure and achieves the preferred solution considering his/her preferences. As it can be seen from the results presented in Table 7.17 and illustrated in Figure 7.4, the achievement level of the objective functions are consistent with the decision maker's preferences. It appears in the results that the IFGP approach is able to generate the preferred compromise solutions and more flexible decision tool for the decision maker than the other fuzzy approaches that have already been applied to supplier selection problems.

Comparison of solutions can also be performed by using some distance based techniques. Abd-El Wahed and Lee (2006) offered to use the degree of closeness of the results to the ideal solution in order to compare the solution approaches. The degree of closeness of the results to the ideal solution can be represented as follows (Steuer, 1986):

$$D_p(\lambda, K) = \left[\sum_{k=1}^{K} \lambda_k^p (1 - d_k)^p \right]^{1/p} \tag{7.23}$$

where d_k represents the degree of closeness of the preferred compromise solution to the optimal solution with respect to the k^{th} objective function. $\lambda = (\lambda_1, \lambda_2, .., \lambda_K)$ denotes the vector of objectives aspiration levels. The power p represents a distance parameter $1 \leq p \leq \infty$. For p=1,2 and ∞, degree of closeness can be written as follows (Abd-El Wahed and Lee, 2006):

$$D_1(\lambda, K) = 1 - \sum_{k=1}^{K} \lambda_k d_k \tag{7.24}$$

$$D_2(\lambda, K) = \left[\sum_{k=1}^{K} \lambda_k^2 (1 - d_k)^2 \right]^{1/2} \tag{7.25}$$

$$D_\infty(\lambda, K) = \max_k \left[\lambda_k (1 - d_k) \right] \tag{7.26}$$

where, in minimization problems, d_k can be defined as:

d_k= (the optimal solution of Z_k)/(the preferred compromise solution Z_k) (7.27)

Abd-El Wahed and Lee (2006) state that one approach is better than the others if: Min $D_p(\lambda, K)$ is achieved by its solution with respect to some p. We also compared the solutions obtained by using abovementioned fuzzy approaches based on this measure. The ideal solution contains the optimum solution of each objective function and can be obtained from the pay-off table presented in Table7.5. Table 7.18 summarizes the comparison of the solutions.

As can be seen from Table 7.18, the IFGP approach suggested provides a preferred compromise solution which is better than the solution by all approaches for D_1 and D_2 distance functions. According to the D_∞ distance function, Chen and Tsai's approach and Aköz and Petrovic's approach is slightly better than the IFGP suggested. However, it should be noted that we didn't take the weights of the objectives into consideration when determining the weights. If the aforementioned weights are considered, it is clear that the weighted additive approach provides the most preferred solution.

In the light of the above discussions, in this dissertation, we assert that IFGP approaches provide more effective solutions for supplier selection and order allocation problem than the fuzzy approaches used in the supplier selection literature. Therefore, IFGP approaches are suggested to be used in the order allocation phase of the proposed methodology. More specifically, we suggest using Abd El-Wahed and Lee's (2006) IFGP approach in supplier selection problems.

Table 7.18 Comparison of solutions by different fuzzy modelling approaches

	Max-Min Approach	Additive Approach	Weighted Add. Approach	Chen and Tsai's Approach	Lin's Approach	Aköz and Petrovic's Approach	IFGP Approach	Ideal Solution
Z_1	19828.61	21073.94	29349.35	24859.39	29213.31	26663.43	28429.48	32644.76
Z_2	85230.36	86271	86942.5	86188.00	85801.35	86531.41	86166.78	87670
Z_3	88561.03	88495	87911	88277.11	88112.89	88005.85	87924.71	90257.5
Z_4	950496.9	990056	1125538	1019193	1073517	1039683	1045558	789131.5
D_1	0.152	0.148	0.109	0.126	0.104	0.116	0.104	--
D_2	0.107	0.102	0.079	0.082	0.072	0.076	0.070	--
$D\infty$	0.098	0.089	0.075	0.060	0.067	0.060	0.061	--

To better understand the advantages of the proposed integrated supplier management system, a real-life case study will be given in the next section.

7.4 Real-life case study

In this section, to demonstrate the applicability of the proposed methodology to supplier selection and order allocation problem, the proposed integrated methodology has been applied to the supplier selection and order allocation problem of a textile company. The company under study produces sports outer clothing of knitted fabric and works with outsourcing firms for some of its products. Fabric and the necessary accessories are sent to the outsourcing firm. The firm produces final products and delivers them back to the company. More detailed information about the firm and data used can be found in Araz et al. (2006).

There are 14 different types of products purchased from 10 different outsourcing suppliers. Within the 10 outsourcing firms, each of them supply some of the 14 items under study. The list of suppliers and the items they are able to supply are listed in Table 7.19 below.

Table 7.19 List of outsourcing firms and the items they are able to produce for the company.

Outsourcers	Items Offered
S1	1-8-9-10-11
S2	1-2-4-9-12-13
S3	1-2-3-4-5-6-7
S4	3-5-8-10-12-14
S5	3-6-7-12-13
S6	2-3-5-6-7-9-10-12-14
S7	4-5-11-13
S8	8-10-11-14
S9	2-5-7-11
S10	1-6-10

7.4.1 Defining the evaluation criteria:

The outsourcers are evaluated under four main categories. These are financial, managerial, quality and delivery categories. Under these four categories totally 10 different evaluation criteria are defined. These include both quantitative and qualitative measures. The qualitative performances are rated with a five point likert scale; {Very good, Good, Moderate, Bad, Very bad}. Below are the definitions of all 10 evaluation criteria and the calculation methods of quantitative ones. They can be seen in Figure 7.5.

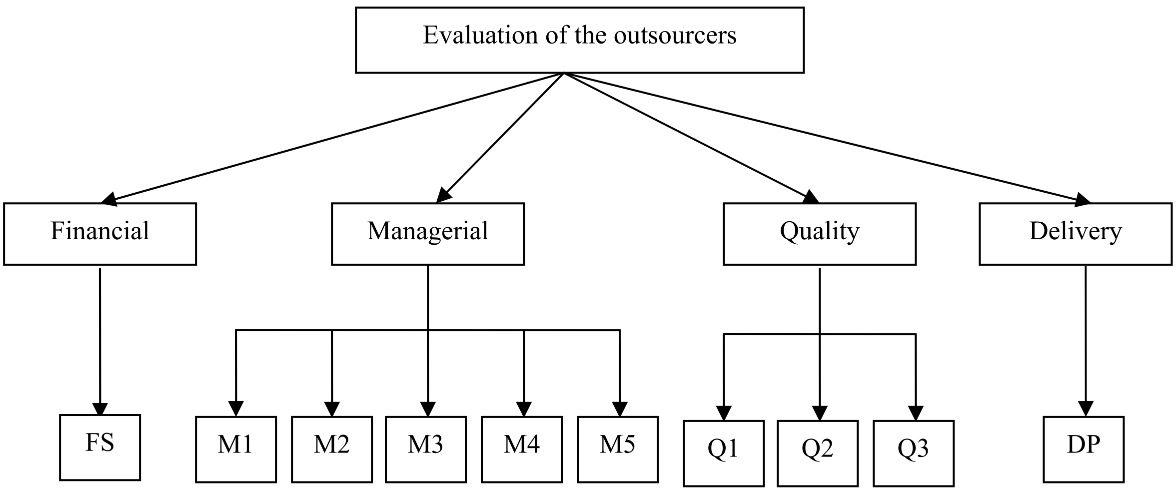


Figure 7.5 Evaluation criteria of the company

- Financial: In this category is the qualitative measure of financial strength (FS) of outsourcing firms.

- Managerial: Under this category five different criteria are defined as M1, M2, M3, M4 and M5.

M1: Capacity Utilization: Percentage of the capacity of the outsourcing firm employed by the company under study.

$$M1_j = \frac{\text{Total units received from outsourcer } j}{\text{Yearly capacity of outsourcer } j * (6/12)} \tag{7.28}$$

(Time interval that the study is based on is 6 months. Therefore the capacity of the supplier is for 6 months.)

M2: Ratio of university graduates to the total number of employees.

$$M2_j = \frac{\text{Number of university graduates of outsourcer } j}{\text{Total number of employees of outsourcer } j} \tag{7.29}$$

M3: Reliability: This criterion measures the dependability of the outsourcer for the company. It is rated by company managers qualitatively.

M4: Flexibility: This criterion is a qualitative measure stating how fast the outsourcer can adapt its system to changes.

M5: Information Flow: This is also a qualitative criterion. It measures how fast the information flow between the company and its outsourcer is.

- Quality: There are three separate criteria under this category.

Q1: Comparison of in-line and final inspection. The company employs quality control specialists who follow the production at the outsourcing supplier. The in-line and final inspection results are recorded. This criterion is defined as follows:

$$C = \left[\frac{\begin{matrix}\text{Number of damages appeared in} \\ \text{in - line inspection}\end{matrix} - \begin{matrix}\text{Number of damages appeared} \\ \text{in final inspection}\end{matrix}}{\text{Number of damages appeared in in - line inspection}} \right] \qquad (7.30)$$

If all the damages appeared in in-line inspection are repaired then the value of this criterion is defined as 1.

$$Q1_j = (\textstyle\sum_{\forall \text{ orders of outsourcer } j} [C]) / \text{Number of orders of outsourcer } j \qquad (7.31)$$

Q2: Ratio of non-damaged items. The company sends fabric and accessories to its outsourcing suppliers necessary for the order. For example, if an order of 1000 units is placed, the company sends fabric and accessories sufficient for about 1100 units. This is because it is thought that some of the materials sent may be damaged during production. This criterion is the ratio of delivered units from the supplier to the amount sent by the company. It is computed as follows.

$$G = \left[\frac{\text{Quantity received}}{\text{Quantity that the company sent material for}} \right] \qquad (7.32)$$

$$Q2_j = (\textstyle\sum_{\forall \text{ orders of outsourcer } j} [G]) / \text{Number of orders of outsourcer } j \qquad (7.33)$$

Q3: This criterion gives the number of quality certificates that the outsourcer owns.

- Delivery: Under this category only the on-time delivery performance (DP) of outsourcers are included. That is the ratio of units arriving on-time to total number of units received.

$$DP_j = \frac{\text{Number of units on - time (delivered by outsourcer } j\text{)}}{\text{Total units delivered by outsourcer } j} \qquad (7.34)$$

Each of the ten outsourcing suppliers is analyzed in terms of these performance criteria. All values of performance measures are listed in Table 7.20.

Table 7.20 Performance values of outsourcing firms

	Financial	Managerial					Quality			Delivery
Suppliers	**FS**	**M1**	**M2**	**M3**	**M4**	**M5**	**Q1**	**Q2**	**Q3**	**DP**
S1	Very Bad	0,515	0,118	Moderate	Good	Moderate	1,000	0,965	0,000	0,164
S2	Good	0,366	0,109	Good	Good	Good	0,946	0,974	1,000	0,365
S3	Very Good	0,258	0,120	Very Good	Good	Very Good	1,000	0,968	2,000	0,645
S4	Moderate	0,233	0,104	Very Good	Very Good	Good	1,000	0,976	0,000	0,324
S5	Very Bad	0,272	0,156	Moderate	Moderate	Moderate	0,855	0,970	0,000	0,534
S6	Very Good	0,392	0,114	Moderate	Moderate	Very Good	0,988	0,977	1,000	0,297
S7	Moderate	0,255	0,079	Moderate	Moderate	Moderate	1,000	0,949	0,000	0,573
S8	Bad	0,197	0,171	Very Bad	Moderate	Moderate	1,000	0,952	0,000	0,508
S9	Bad	0,220	0,000	Very Bad	Bad	Very Bad	0,760	0,910	0,000	0,102
S10	Very Bad	0,156	0,000	Very Bad	Bad	Very Bad	0,682	0,865	0,000	0,110

7.4.2 Finding the overall performance of outsourcers by PROMETHEE:

After determining the evaluation criteria and computing performance of outsourcers according to these criteria, the overall performance of each outsourcer is found by PROMETHEE using Decision Lab 2000 software (Decision Lab, 2000).

PROMETHEE parameters such as weights, preference functions, indifference and preference thresholds for each criterion are listed in Table 7.21.

Table 7.21 Parameters for PROMETHEE analysis.

	FS	**M1**	**M2**	**M3**	**M4**	**M5**	**Q1**	**Q2**	**Q3**	**DP**
Weights (%)	11	5	5	5	5	5	12	15	10	27
Preference Function	Level	Linear	V shape	Level	Level	Level	V shape	V shape	Level	Usual
Indifference Threshold	1	0,03	-	1	1	1	-	-	1	-
Preference Threshold	2	0,1075	0,0573	2	2	2	0,1172	0,0361	2	-

The parameters in Table 7.21 are input to PROMETHEE. Then it is worked and the solutions are achieved. In Figure 7.6 below, the outsourcers are listed in order from the most superior to the least in terms of overall scores.

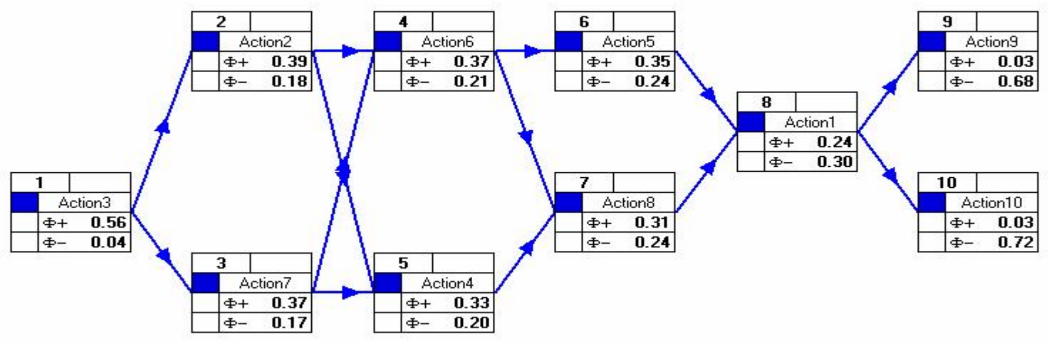


Figure 7.6 PROMETHEE output: Order of outsourcers from best to worst overall score.

As seen from the figure above the marginal decrement in scores when going down the order is very small until outsourcer 9 (Action 9 in PROMETHEE). Score of outsourcer 1 and 9 (Sequence number 8 and 9 in the figure) is -0,06 (=+0,24-0,30) and -0,65 (=+0,03-0,68) respectively. Overall performance value shows a steep decrement when going from outsourcer 1 to outsourcer 9. This means that the last two outsourcers in sequence, outsourcer 9 and 10, show really low performance in their deliveries. Therefore, these two suppliers are far away from getting into track and it is decided to remove them out of the supplier base.

If Promsort is used to sort the outsourcers into three predefined ordered categories (i.e good, moderate, and bad outsourcers) by defining the profile limits as in Table 7.22, one can find that only the outsourcer 9 and 10 is classified as bad outsourcers whereas outsourcer 3 is classified as good and the others as moderate. These results also support the idea that outsourcer 9 and 10 should be dropped from the supplier base.

Table 7.22 Performance values of profile limits.

	Financial	Managerial					Quality			Delivery
Profiles	FS	M1	M2	M3	M4	M5	Q1	Q2	Q3	DP
Profile 1 that distinguishes category good from category moderate	Good	0,35	0,15	Good	Good	Good	0,98	0,975	2,000	0,5
Profile 2 that distinguishes category moderate from category bad	Bad	0,15	0,05	Bad	Bad	Bad	0,90	0,900	1,000	0,35

After this prequalification step, the new set of outsourcers is reanalyzed by PROMETHEE since the number in the list has been decreased. Similar to the previous analysis, parameters determined in Table 7.21 are employed. The results of PROMETHEE II are given in Figure 7.7 below.

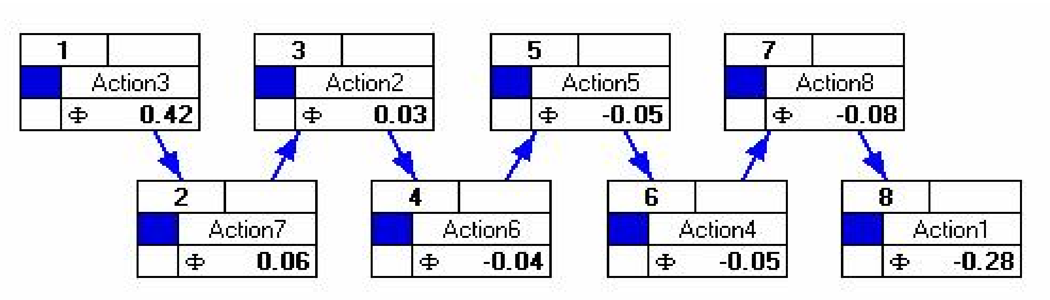


Figure 7.7 PROMETHEE II output: Final scores of outsourcers after prequalification.

The overall scores achieved by PROMETHEE II are set as the weights of outsourcers and integrated in an additive fashion. The objective function developed is the objective of FGP model in final selection phase.

7.4.3 Outsourcer Management:

As discussed in Section 2 of this chapter, it is not necessary to select PROMSORT to manage the supply base. In this case, PROMETHEE method is utilized to evaluate and manage the supply base. As mentioned in Section 3.2.2.3, PROMETHEE analysis provides each outsourcers performance on each criterion by means of single criterion net flows. In other words the individual outsourcer score cards are computed by PROMETHEE. In Figure 7.8, these evaluations can be seen. The scores are between +1 (being the best) and -1 (being worst). With these evaluations the strong and the weak sides of each outsourcer are known in advance. Hence the company supplies feedback to its outsourcers to keep the positive sides in track and to improve the negative sides.

It can be seen from Figure 7.8 that even though outsourcer 3 is the strongest outsourcer according to the overall scores, it is quite weak in the capacity utilization performance. When the second strongest outsourcer is considered (outsourcer 7), it is seen that the ratio of university graduates in the firm and the ratio of non-damaged items is quite low. Therefore especially the causes of damages in the manufacturing process should be identified and straightened. If these two outsourcers can improve their performance in these categories a little more, then they may be set as strategic partners of the company.

The third in the list of performances is outsourcer 2. This looks like an average firm in all perspectives. It shows neither too bright nor too low performances. However, if the outsourcer improves its delivery performance (which is the most important criterion) and in-line and final inspection results, it may become the strongest supplier in the base.

Other than these two outsourcers, it is seen from Figure 7.8 that the delivery performance of outsourcers 1, 4 and 6 need careful inspection. They should improve their performance in delivering the products on-time. That means they should improve their planning processes within the firm. In addition, outsourcers 1, 5 and 8 should be informed to take precautions for their financial positions. Outsourcer 5 is also the worst performer for the comparison of in-line and final inspection criterion. That means it cannot fix the damages appearing during in-line inspection properly. Therefore, managers of outsourcer 5 should spend more effort on producing good-shape products.

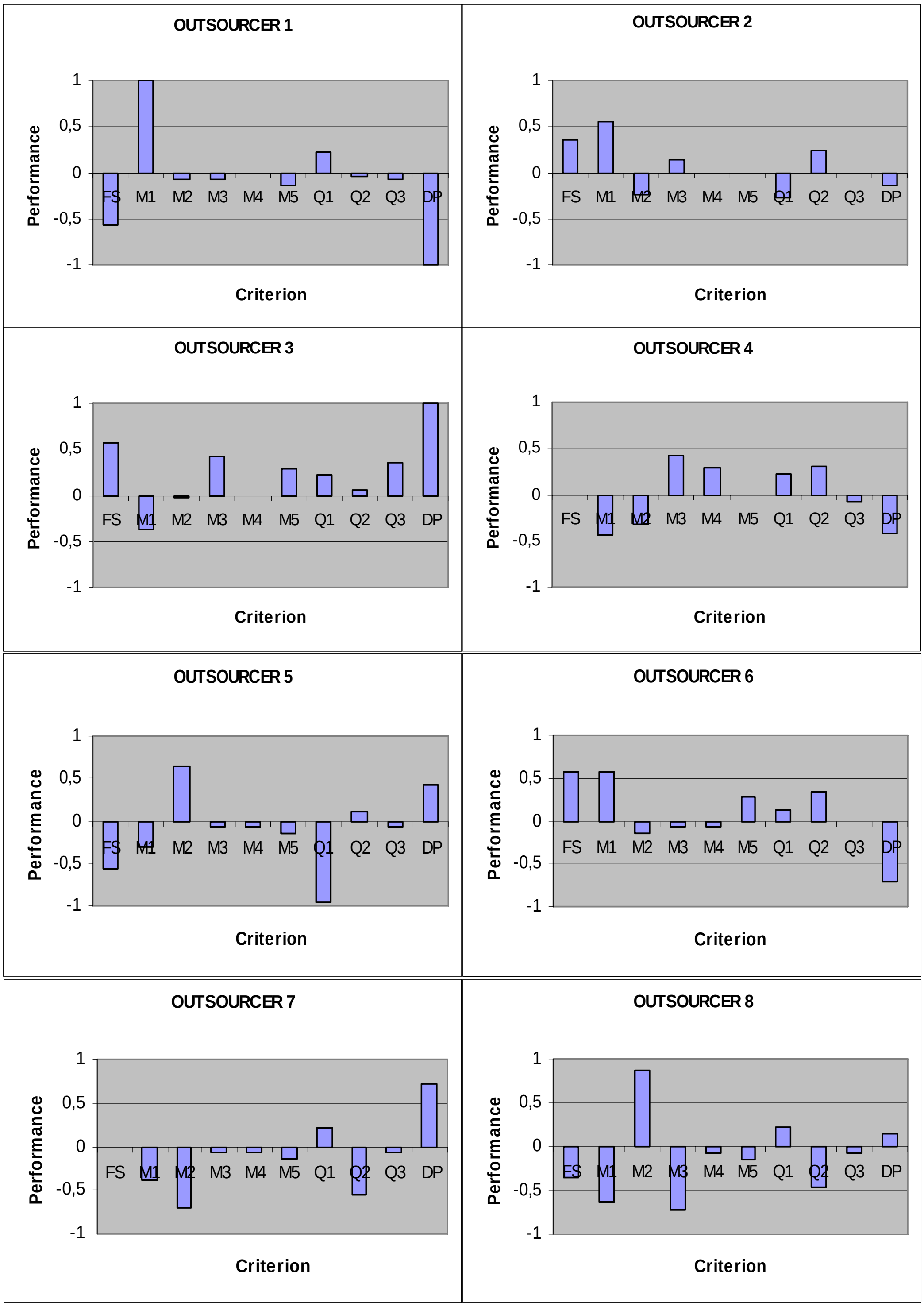


Figure 7.8 Performance of Outsourcers in terms of single criterion net flows.

7.4.4 Order allocation phase:

In the modeling phase, four objectives are developed. As discussed earlier, the first objective function is simply the weighted sum of quantities ordered from each outsourcer. As it can be remembered, this objective is named as Total Value of Strategic Partnership (TVSP). The weight set is the set of net flows calculated by PROMETHEE (Figure 7.7). The goal is to maximize this summation or, in other words, to set the ordered quantities to the highest performing suppliers as much as possible.

The second objective function gives the number of units accepted in the incoming quality control. All received lots go through inspection in the incoming quality control. Some lots are rejected here. The objective is to maximize the number of accepted units as much as possible. This objective function is calculated through the ratio of accepted units in the incoming quality control (K):

$$K_{ij} = \frac{\text{Number of accepted units of item } i \text{ (delivered by outsourcer } j\text{)}}{\text{Total units (of item } i\text{) delivered by outsourcer } j} \tag{7.35}$$

Similar to the first objective function, the second one is also the weighted sum of quantities ordered from each outsourcer where the weight set is the set of K_{ij}'s.

The third objective is the measure of units arriving on-time. It is calculated through the ratio of units arriving on-time. This ratio is similar to the delivery performance (DP) criterion defined in step 1. However this one is computed on item basis. In other words, ratio of units arriving on-time for every item from every outsourcer is calculated (Equation 22).

$$L_{ij} = \frac{\text{Number of units of item } i \text{ on-time (delivered by outsourcer } j\text{)}}{\text{Total units (of item } i\text{) delivered by outsourcer } j} \tag{7.36}$$

The goal is to maximize the weighted sum of quantities ordered from each outsourcer where the weight set is the set of L_{ij}'s.

The fourth and the last objective is to minimize the total purchasing cost of all orders. At first hand, the mathematical model is developed as integer programming. The data used is given in Appendix D. The details of the model are given in the following.

Sets:

- i: Number of items, i=1..14
- j: Number of outsourcing suppliers, j=1..8
- k: Number of periods , k=1..6

Decision Variables:

X_{ijk} units of items i ordered from supplier j in month k

Y_{ijk} binary variable that indicates whether j^{th} outsourcer selected for item i in month k

Parameters:

MRj= Monthly capacity of supplier j. (Known with certainty)

$QDik$= Quantity demanded of item i in month k. (Known with certainty)

Kij = Ratio of accepted units of item i delivered by outsourcer j.

Lij = Ratio of units on-time of item i delivered by outsourcer j.

$Costij$= Purchasing cost of item i from outsourcer j.

Wj = PROMETHEE II net flow of the outsourcer j.

W = [-0.28 0.03 0.42 -0.05 -0.04 0.06 -0.08]

Objective Functions:

Objective 1: Maximize $Z_1= \sum_i \sum_j \sum_k W_j * X_{ijk}$ (7.37)

Objective 2: Maximize $Z_2= \sum_i \sum_j \sum_k K_{ij} * X_{ijk}$ (7.38)

Objective 3: Maximize $Z_3 = \sum_i \sum_j \sum_k L_{ij} * X_{ijk}$ (7.39)

Objective 4: Minimize $Z_4 = \sum_i \sum_j \sum_k Cost_{ij} * X_{ijk}$ (7.40)

Subject to:

$\sum_j X_{ijk} = QD_{ik}$ $\forall$ i, k (7.41)

$\sum_i X_{ijk} \le MR_j$ $\forall$ j, k (7.42)

$\sum_j Y_{ijk} = 2$ $\forall$ i, k (7.43)

$Y_{ijk} * M \ge X_{ijk}$ $\forall$ i, j, k (7.44)

$(0.10) * QD_{ik} * Y_{ijk} \le X_{ijk}$ $\forall$ i, j, $\forall$k where QD(i,k) $\neq$0 (7.45)

X_{ijk} are integers, Y_{ijk} are binary. (7.46)

Among the system constraints, constraint set (7.41) assures that demands are satisfied. The sum of ordered quantities to the suppliers should exactly be equal to the quantity demanded for all materials. Constraint set (7.42) is the set of capacity constraints. The quantity ordered to a supplier in a month should not be greater than its monthly capacity. All items are manufactured by the same processes. Therefore, the capacity is distributed between all items. At this circumstance, the monthly quantities of all items ordered to an outsourcing supplier should not exceed its monthly capacity.

Constraint sets (7.43), (7.44) and (7.45) are all concerned with number of suppliers to be selected. By set (7.43), two outsourcers should be selected for every item in each month. If a supplier is not selected, quantity ordered to that supplier should be zero. Constraints in (7.44) ensure this property (M is a very large number.). Also, if a supplier is selected, minimum number of units outsourced from that supplier should be at least 10% of minimum demand. This characteristic is incorporated into the model with constraint set (7.45). These constraints will be valid for months that the demand is nonzero. Finally, the integer variables and binary variables are set with constraints in (7.46).

The model is coded using LINGO 8.0 (LINDO, 2003) format and LINGO code is presented in Appendix B. Once the integer programming model is developed, it is solved with each of the objective functions by themselves. In other words first Z_1 is set as the objective and the model is solved. Then Z_2, Z_3 and Z_4 are all set as objective one by one and solved. For each solution the value of the objective and the other Z function values are recorded. By this way the payoff table is constructed which is given in Table 7.23 below.

Table 7.23 Pay-off Table

	The Objective Function			
Value	**Z_1**	**Z_2**	**Z_3**	**Z_4**
Z_1	***137195****	41682+	73237	47121
Z_2	529523	***529675****	484066+	494107
Z_3	267120	160848+	***346893****	174126
Z_4	520931	525328	528663*	***496523+***

*: Upper Bounds; + :Lower Bounds

Looking at the figures in Table 7.23, the best lower bound *(l_k)* and the worst upper bound *(u_k)* are determined. Then the membership functions of each objective can be defined as follows:

$$\mu_{z_1}(x) = \begin{cases} 1 & if \quad Z_1(x) \geq 137195, \\ \dfrac{Z_1(x) - 41682}{137195 - 41682} & if \quad 41682 < Z_1(x) < 137195, \\ 0 & if \quad Z_1(x) \leq 41682. \end{cases}$$

$$\mu_{z_2}(x) = \begin{cases} 1 & if \quad Z_2(x) \geq 529675, \\ \dfrac{Z_2(x) - 484066}{529675 - 484066} & if \quad 484066 < Z_2(x) < 529675, \\ 0 & if \quad Z_2(x) \leq 484066. \end{cases}$$

$$\mu_{z_3}(x) = \begin{cases} 1 & if \quad Z_3(x) \geq 346893, \\ \dfrac{Z_3(x) - 160848}{346893 - 160848} & if \quad 160848 < Z_3(x) < 346893, \\ 0 & if \quad Z_3(x) \leq 160848. \end{cases}$$

$$\mu_{z_4}(x) = \begin{cases} 1 & if \quad Z_4(x) \le 496523, \\ \dfrac{528663 - Z_4(x)}{528663 - 496523} & if \quad 496523 < Z_4(x) < 528663, \\ 0 & if \quad Z_4(x) \ge 528663. \end{cases}$$

Then the FGP model is developed.

$$\left.\begin{array}{ll} Max & Z = \lambda \\ & s.t. \\ & \mu_{Z_1} \ge \lambda, \\ & \mu_{Z_2} \ge \lambda, \\ & \mu_{Z_3} \ge \lambda, \\ & \mu_{Z_4} \ge \lambda, \\ & 0 \le \lambda \le 1 \\ & \text{Sytems constraints from (7.41) to (7.46)} \end{array}\right\} \qquad (7.47)$$

The model developed is solved by IFGP presented in this Chapter.

At first iteration of the solution approach the results achieved are given in Table 7.24.

Table 7.24 Results of first iteration

Objective Function	**Value**
Z_1	104416
Z_2	525585
Z_3	283043
Z_4	507554

After this iteration, the decision maker is not satisfied with the TVSP objective. At this step, the lower bound is revised with the value achieved for TVSP. That is the new lower bound for the first objective became 104416. The model is resolved with the new parameters.

The procedure is followed until the decision maker is satisfied. The preferred compromise solution is obtained in iteration 11. The solutions of all iterations are given in Table 7.25 and the achievement levels of the objective functions are illustrated in Figure 7.9. The solution results of the order allocation problem are presented in Appendix E.

Table 7.25 Iterative results

	Iteration Number									
Objective	2	3	4	5	6	7	8	9	10	**11**
Z1	123099	119786	117356	116218	121990	120025	119279	121449	120879	**121348**
Z2	526247	521502	519569	523208	522350	521404	521044	520793	520472	**519860**
Z3	266889	304404	321177	319703	316095	312114	317189	316326	319056	**319856**
Z4	510344	513593	515976	517091	519820	515592	516421	516999	517739	**519150**

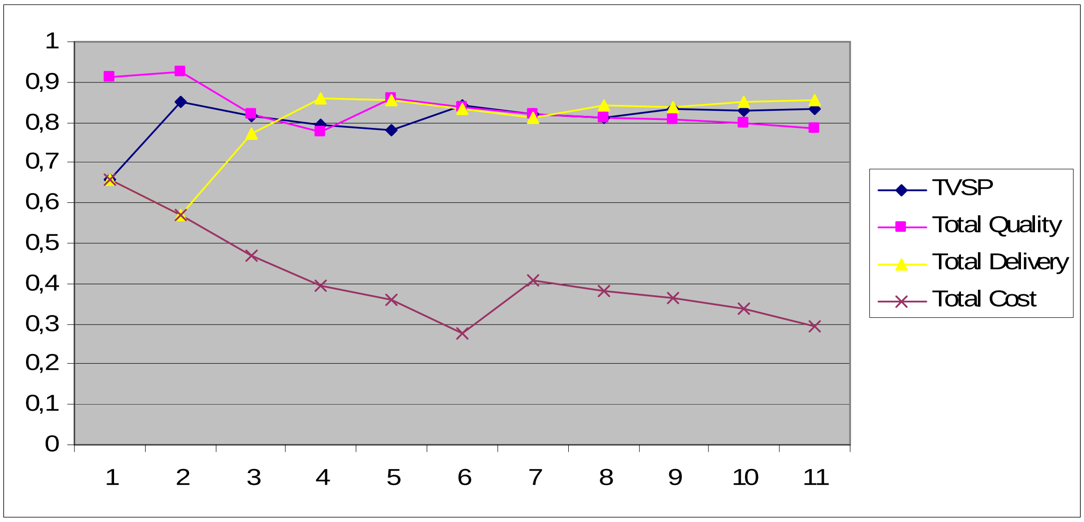


Figure 7.9 Degree of achievement levels of objective functions

The results achieved in the last iteration are compared with the solutions obtained using other fuzzy modeling approaches used in the literature to solve supplier selection problem. As can be remembered, these are Zimmerman's max-min approach and Tiwari et al.'s weighted additive approach. It can be seen from Figure 7.9 that total delivery objective has highest achievement level in the preferred compromised solution. It is followed by TVSP, total quality and total cost objectives. Therefore, when employing the weighted additive approach, the weights are set as

0.3 for TVSP objective, 0.2 for total quality objective, 0.4 for total delivery objective and 0.1 for total cost objective.

Table 7.26 summarizes the results of the fuzzy MP approaches presented in this section and the IFGP approach suggested. Graphical representation of the achievement levels of the objectives obtained by these approaches is given in Figure 7.10.

As can be seen from Table 7.26 and Figure 7.10, IFGP approach outperforms both methods. Max-min approach doesn't consider the relative priorities among the objectives, it provides unacceptable results. On the other hand, although the weights of the objectives are taken into consideration in the weighted additive approach, this approach has failed to provide consistent results with the decision maker's preferences.

Table 7.26 Comparison of solutions by different fuzzy modelling approaches

	Z_1	Z_2	Z_3	Z_4	μ_{z1}	μ_{z2}	μ_{z3}	μ_{z4}
Max-Min Approach	104415.6	525584.4	283043.5	507553.6	0.657	0.910	0.657	0.657
Weighted Add. Approach	120695.7	528514.7	310598.1	519449	0.827	0.975	0.805	0.287
IFGP Approach	121348.4	519859.7	319856.4	519150.1	0.834	0.785	0.855	0.296

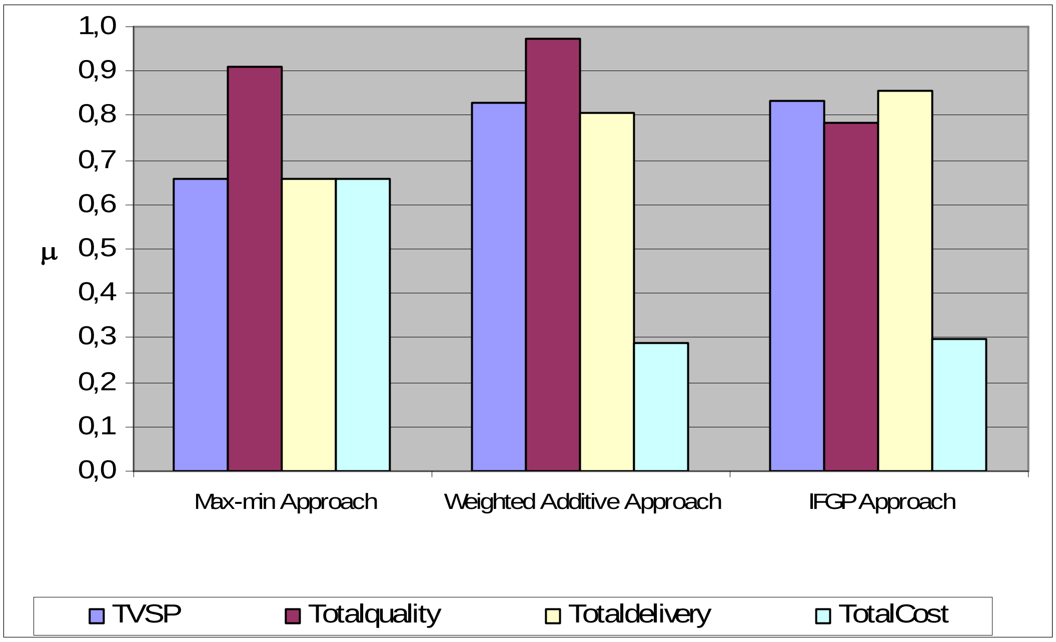


Figure 7.10 Graphical representation of the solution by different approaches

In the light of the results of the cases illustrated in this section, we assert that, with the use of the proposed methodology, firms can monitor its outsourcers continuously. By this way, the performance of purchasing can be improved even more in near future.

In addition, there are various benefits of the proposed methodology to the firms. The existing outsourcers are evaluated systematically using a multicriteria decision aid method. It helps the firms to monitor outsourcers avoiding the subjective human decisions. The proposed methodology also helps the firms to find the appropriate strategic partners and to improve relationships with these outsourcers, since the methodology informs the firms about the weaknesses and strength of the outsourcers.

7.5 Summary and Concluding Remarks

With the increasing importance of long-term strategic partnership with suppliers, supplier evaluation and selection become a more important part of supply chain management. In particular, searching appropriate suppliers for strategic partnership, monitoring the performance of these companies continuously and assisting these companies about their weaknesses are necessearcy tasks for a successfull outsourcing manufacturing system. For the firms interested in developing and implementing strategic partnership with their outsourcers, an effective supplier management system is needed.

In this Chapter, we proposed an integrated supplier evaluation and management methodology, in which outsourcers are evaluated and compared according to their performances on several criteria. Potential reasons for differences in outsourcer performance are identified, performances of the outsourcers are fed back to them and the ordered quantities are allocated to the selected outsourcers. The proposed methodology is based on PROMETHEE and FGP.

Different from other integrated approaches suggested in the literature, the proposed methodology deals with all stages of supplier selection process: prequalification of the existing suppliers, rating of the selected suppliers, and allocating the orders to them. The proposed approach also uses PROMETHEE method to obtain the overall score of each supplier. It also differs from the other approaches by the inclusion of the FGP model to select the most appropriate outsourcers suitable to be strategic partners with the company and simultaneously allocate the quantities to be ordered to them in the order allocation stage. By this way, it is allowed to incorporate the decision maker's imprecise aspiration levels for the goals into the model.

The proposed methodology also distinguishes from the others by the FGP approach suggested. As mentioned before, some researchers have employed traditional FGP approaches for the supplier selection problem to tackle with the imprecise and vague information of the objectives and constraints of the supplier selection problem. Differently, in this dissertation, it is asserted that IFGP approaches provide more effective solutions for the supplier selection and order allocation problem than the fuzzy approaches used in the supplier selection literature. As discussed earlier, if the decision maker is not satisfied with the current optimal solution, IFGP approaches allows the decision maker to control the search direction by updating the membership functions.

In order to be able to demonstrate the applicability of the proposed methodology to supplier selection and order allocation problem, we consider both a hypothetic strategic sourcing problem and an illustrative case problem in which real data is used. The results of implementation indicate that the proposed methodology is a useful tool for firms to select the strategic partners, to manage their supplier base and to allocate the orders to the most appropriate ones.

CHAPTER EIGTH
CONCLUSION

8.1 Summary and concluding remarks

In today's highly competitive and global operating environment, due to high variety of customer demands, advances in technologies and the increasing importance of communication and information systems, companies have been forced to focus on supply chain management (SCM). The rapid pace of technological change and the recent trend on just-in-time (JIT) manufacturing philosophy identifies the necessity of establishment of strategic sourcing strategies (Andersen and Rask, 2003). Such a sourcing strategy should ensure to establish long-term relationship with a selected group of competitive suppliers (Andersen and Rask, 2003; Chan and Kumar, 2006).

Strategic sourcing is one of the most vital actions of companies in a supply chain. Selecting the wrong sourcing strategy or managing it badly could be enough to deteriorate the whole supply chain's financial and operational position. In today's competitive and global business environment, it is impossible to improve supply chain performance without well-managed sourcing strategy.

Strategic sourcing decisions include the selection of the potential strategic suppliers, the implementation of the long-term strategic partnership with the suppliers selected, the establishment of necessary supplier development programs to increase supplier performance and the assignment of the order quantities to the appropriate suppliers.

As evidenced by the explosion of research on strategic sourcing and the literature review presented, there are five important and emerging viewpoints in the current purchasing literature:

- It is crucial for a firm to collaborate with suppliers during the design stage in order to gain various benefits of design collaboration (Chopra and Meindl, 2004). The literature also pointed out that strategic supplier selection and evaluation decisions need to incorporate design criteria into the assessment process (Humphreys et al., 2005). However, little research has been devoted to research on how to analytically evaluate the support given by suppliers in new product development activities.

- One of the most important purchasing decisions is still undoubtedly evaluating and selecting the suppliers and maintaining long-term relationship with a few and high quality suppliers (Aissaoui et al., 2006). Although numerous methods have been proposed, supplier evaluation and management systems that compare suppliers, identify potential reasons for differences in supplier performance and help in monitoring supplier performances have not been fully explored in the literature (Talluri and Narasimhan, 2004).

- With the growing importance of JIT philosophy, there is a strong need for firms to reduce the number of suppliers (Andersen and Rask, 2003) and an emerging trend to classify supplier into two or more categories (Choy et al., 2005). Although a number of methods have been proposed for supply base reduction, most of them are not based on the multi-criteria evaluation of suppliers.

- There is a strong need for a systematic approach to purchasing decision making especially in the area of identifying appropriate suppliers and allocating order quantities to them (Aissaoui et al., 2006). On the other hand, there is a clear trend in the purchasing literature to develop integrated methods which simultaneously consider prequalification and order allocation decisions.

- In a real world supplier selection problem, many input information are not known precisely (Amid et al., 2006). In the purchasing literature, the imprecision and uncertainty involved in the final supplier selection and order allocation decisions have been taken into consideration by embedding the fuzzy set theory (FST) into the decision models. However, to our knowledge, any methodology, which applies FST, has not yet been developed to sort the suppliers based on their fuzzy performances and to allocate order quantities to the selected suppliers simultaneously.

The main objective of this research is to develop novel methodologies for the strategic sourcing problems that can be characterized by aforementioned viewpoints. This research presents two methodologies for strategic sourcing problems. The first methodology, which is named as strategic supplier evaluation and management system (SSEMS), is based on multi-criteria evaluation of suppliers. It is a flexible method that helps concurrent design teams to classify suppliers into different categories (e.g., strategic partners, the promising suppliers which are possible candidates for supplier development programs, competitive suppliers and the suppliers to be pruned), identify the differences in performances across supplier classes, to monitor the suppliers' performances and to make decisions about necessary development programs.

The SSEMS methodology offers to use a multi-criteria sorting (MCS) procedure to determine supplier classes and reduce a large set of initial suppliers to a manageable number. Instead of using the MCS methods that exist in the current literature, we propose a new MCS methodology, which is named as PROMSORT, to overcome the limitations and disadvantages of the existing methods. PROMSORT procedure is based on a well-known multi-criteria decision making (MCDM) method PROMETHEE. In order to test the efficiency of the proposed sorting procedure, we applied it to the business failure risk assessment problem and compared with other sorting procedures, PROMETHEE TRI and ELECTRE TRI, that operate in similar way. The results of the case problem have shown that PROMSORT is an effective tool to assign the alternatives to the ordered categories and provides reliable classification in terms of the preference relation between alternatives. It also provides valuable information to the decision maker about the weaknesses and strength of the alternatives and features of the categories. Additionally, in this dissertation, a basic software coded in Visual Basic 6.0 that allows the decision maker to sort alternatives to the predefined ordered classes by using PROMSORT methodology is presented.

Subsequently, by means of a hypothetic strategic supplier selection problem, we showed how the SSEMS methodology and PROMSORT procedure can help concurrent design teams to manage their supply base and to evaluate supplier's overall performance, co-design contribution, and the support of supplier in concurrent engineering activities. We also test the robustness of PROMSORT using the aforementioned supplier selection example. Additionally, it should be noted that the SSEMS methodology emphasizes early involvement of suppliers into design stages and to incorporate design criteria into the supplier evaluation process.

In this dissertation, another focus is placed on developing a fuzzy MCS procedure to solve supplier classification problems at the early product development stages. As an extension of proposed MCS method, a new fuzzy MCS procedure in assigning alternatives to predefined ordered categories where the performance of alternatives can be defined as fuzzy numbers is also developed. Subsequently, the effects of the fuzzy performances of suppliers on the classification are investigated by a numerical example. Results of the computational experiment performed point out that it is easier to define the profiles alternatives with fuzzy numbers and the fuzzy version of PROMSORT is an effective decision making tool when the uncertainty and imprecision exist in the sorting process.

Secondly, this dissertation presents an integrated MCDM methodology for strategic sourcing that enables the decision maker to reflect his/her fuzzy objectives into the sourcing process. The proposed methodology introduces an interactive fuzzy goal programming (IFGP) model for the order allocation problem. As an extension of SSEMS described above, it evaluates the existing suppliers in terms of company's goals, selects the most appropriate suppliers for strategic partnership as well as allocating the ordered quantities to them. Apart from other integrated approaches developed in the purchasing literature, it is asserted that vagueness of the decision makers' aspiration levels can be taken into consideration by the IFGP approach suggested. IFGP approaches provide more effective solutions for supplier selection and order allocation problem than the fuzzy approaches used in the supplier selection literature by allowing the decision maker to select the preferred compromise solution.

In order to demonstrate the applicability of the proposed methodology for the order allocation problem, we consider a hypothetic strategic sourcing problem. The results of implementation indicate that the proposed methodology is a useful tool for firms to select the strategic partners, manage their supplier base and allocate the orders to the most appropriate ones. Furthermore, computational experiments were conducted for the comparison of the performance of IFGP approach and other fuzzy solution approaches.

Results of the computational experiments show that the IFGP approach suggested is able to generate the preferred compromise solutions and is more flexible decision tool for the decision maker than other fuzzy approaches that have already been applied to supplier selection problems.

Finally, the applicability of the proposed methodology to supplier selection and order allocation problem is also tested by an illustrative case problem in which real data is used. Results of the case pointed out that the proposed methodology is capable of evaluating the existing suppliers, monitor them by avoiding the subjective human decisions and allocating the order quantities to the appropriate suppliers.

8.2 Original contributions

The contribution of the research proposed in this dissertation can be summarized as in the following:

- A new MCS procedure named as PROMSORT, which is an extension of well-known PROMETHEE (Brans et al., 1986) method, is proposed.

  In multi-criteria classification (MCC) literature, it is assumed that the classification problem is based on absolute judgments. In this case the classification rule, usually, does not depend on the set of alternatives being evaluated (Doumpos and Zopounidis, 2002). Of course, this assumption is valid for some classification problems such as financial classification problems, medical diagnosis problems etc. For instance, Doumpos and Zopounidis explain this case with the following example (Doumpos and Zopounidis, 2002, p. 3):

  "*a firm may fulfill the necessary requirements for its financing by a credit institution and these requirements are independent of the population of firms seeking financing*."

  However, we asserted that this assumption is no longer valid for supplier classification problem and traditional sorting algorithms do not always provide effective results for this problem. On the other hand, the classification results of the proposed sorting algorithm are based on relative judgments and depend on the alternatives being evaluated. As it can be recalled from earlier chapters, the results of the computational experiments showed that PROMSORT is an effective tool to assign the alternatives to the ordered categories, provides reliable classification and valuable information to the decision maker about the weaknesses and strength of the alternatives and features of the categories.

- A new supplier evaluation and management methodology is proposed, in which suppliers are categorized and compared according to their performances on several design based criteria, potential reasons for differences in supplier performance are identified, and performances of the suppliers are improved by applying supplier development programs.

  To the best of our knowledge, MCS methods have not yet been applied for strategic sourcing problems. The application of the proposed methodology, PROMSORT, in strategic sourcing problem is the first time a MCS methodology is utilized for such a problem.

- An integrated MCDM methodology for supplier management is proposed. For the first time, an integrated approach that incorporates a MCS procedure and IFGP is used to select the strategic partners and to allocate the appropriate orders to them simultaneously.

  Different from the integrated approaches proposed in the literature, in the methodology proposed in this chapter, the overall score of each supplier is determined by using PROMETHEE method. The proposed methodology deals with all stages of supplier selection process: prequalification of the existing suppliers, rating of the selected suppliers, and allocating the orders to them. It also differs itself from the other approaches by using fuzzy MP techniques in the order allocation stage. By this way, the decision maker's imprecise aspiration levels are incorporated through the goals into the model.

- In the light of our literature review on supplier selection, only two researchers have employed traditional fuzzy approaches to tackle the imprecise and vague information of the objectives and constraints of the supplier selection problem. Differently, in this dissertation, we assert that IFGP approaches provide more effective solutions for supplier selection and order allocation problem than the fuzzy approaches used in the supplier selection literature. If the decision maker is not satisfied with the current optimal solution, IFGP approaches allow the decision maker to control the search direction via updating the membership functions.

- A new fuzzy MCS procedure: Fuzzy-PROMSORT is proposed. PROMSORT is extended so that it can handle fuzzy input data.

  In most of the MCS methods, it is assumed that the performances of an alternative on a set of criteria are known exactly. There are numerious fuzzy ranking approaches in the literature, however, only few attention has been paid to develop fuzzy ordinal classification methods.

- F-PROMSORT was applied to the strategic supplier selection problem. A synthesis of the literature review presented reveals that the traditional methods used to reduce the number of suppliers assume that the suppliers are fully understood and are described by crisp values of attributes. Furthermore, up to date, the effects of incomplete or imprecise nature of available information on the pre-qualification process have not been fully explored in the literature. To our knowledge, it is the first attempt that a fuzzy MCS method is used in the pre-qualification phase of supplier selection problem considering suppliers' fuzzy performances.

- In order to validate the effectiveness of the proposed sorting methodology, PROMSORT was also applied to financial classification problems besides supplier selection.

8.3 Directions for future research

The main objectives of this research are twofold. The first one is to develop novel methodologies for strategic sourcing problems. The second one is to develop a MCS procedure that can handle both fuzzy and crisp input data and that can be used to solve many real world classification problems besides supplier selection. While this research was conducted, several areas that can be investigated in the future have come to light. Topics worthy of future investigation are shown separately for the strategic sourcing methodologies and MCS procedures proposed as follows:

Strategic Sourcing Methodologies:

- Although this research proposes systematic methodologies for strategic supplier selection problem, it assumes that there is only one decision maker or decision makers can easily reach consensus on the parameters used. However, if the group members have significantly different objectives and cannot meet to discuss the decision, the complete set of chosen parameters could not represent anybody. Developing a group decision support system based on proposed methodologies can be considered as a topic for future research.

- Since this research mainly focuses on developing general strategic sourcing methodologies, modeling of complex lot-sizing, inventory management and supplier selection environments was beyond the scope of this research. However, developing more complex mathematical programming models is still open for future research.

- Another interesting area for future research should be to improve the proposed fuzzy modeling approach so that it can deal with the uncertainties of the parameters of the supplier selection problem as well.

- The systematic methodologies for supplier selection and evaluation presented in this research can be easily extended to the analysis of other management decision problems such as selection and evaluation of investment decision alternatives, human resource management, etc.

MCS procedures:

As it is recalled from Section 5.4, obviously, there are some limitations, disadvantages and open problems of the proposed sorting procedures need to be considered in the future research. Since, in this dissertation, we mainly focus on strategic sourcing problems, further researches on the proposed sorting methodologies are not within the objectives of this research. Some of these open problems and disadvantages lead to several avenues for future research. The following section summarizes these issues.

- The major drawback of PROMSORT, like other MCS methods, is that the decision maker must specify the considerable amount of information. The decision maker should assign values to profiles, weights and thresholds. Although the parameters used in PROMSORT have clear economical explanations, one of the further research studies should be to develop an indirect estimation procedure for the parameters specified by the decision maker using a set of training samples.

- Since PROMSORT is based on PROMETHEE methodology, it inherits all advantages and disadvantages of it. As discussed in Section 5.4, in the present version of PROMSORT, addition of a new alternative, which are not actually contained in the initial data set, requires the re-computation of the PROMETHEE scores. It is clear that PROMETHEE based sorting methods may have this kind of problems (See Figueira et al., 2004). One of the further research studies should be to solve this problem.

- In some cases, a decision maker may not want to assign an alternative having superior performances in almost all criteria to a good category because of the too low performances of this alternative in a specific criterion. ELECTRE TRI method deals with such situations using *veto thresholds*. Since, in contrary to ELECTRE methods, PROMETHEE does not use the concept of "*veto*", this version of PROMSORT is unable to respond such requests. The extension of the proposed method which can handle veto situation may give more realistic results for some real-life sorting problems such as supplier classification.

- As discussed in Chapter 5, since the known fuzzy versions of PROMETHEE method use center of area method in the defuzzification phase, F-PROMSORT has some limitations due to the defuzzification method used. This problem can be solved by developing a new fuzzy PROMETHEE method that uses a different type defuzzification method.

REFERENCES

Abd El-Wahed, W. F., & Abo-Sinna, M. A. (2001). A hybrid fuzzy-goal programming approach to multiple objective decision making problems. *Fuzzy Sets and Systems*, *119* (1), 71-85.

Abd El-Wahed, W. F., & Lee, S. M. (2006). Interactive fuzzy goal programming for multi-objective transportation problems. *Omega*, *34* (2), 158-166.

Aissaoui, N., Haouari, M., & Hassini, E. (2006). Supplier selection and order lot sizing modeling: A review. *Computers & Operations Research*, in press.

Aköz, O., & Petrovic, D. (2006). A fuzzy goal programming method with imprecise goal hierarchy. *European Journal of Operational Research*, in press.

Albino, V., & Garavelli, A.C. (1998). A neural network application to subcontractor rating in construction firms. *International Journal of Project Management*, 16 (1), 9-14.

Almeida, A.T. (2006). Multicriteria decision model for outsourcing contracts selection based on utility function and ELECTRE method. *Computers & Operations Research,* in press.

Amid A., Ghodsypour, S.H., & O'Brien, C.O. (2006). Fuzzy multiobjective linear model for supplier selection in a supply chain, *International Journal of Production Economics,* in press.

Andersen, P.H., & Rask, M. (2003). Supply chain management: new organisational practices for changing procurement realities. *Journal of Purchasing & Supply Management*, 9, 83–95.

Anthony, T.F., & Buffa, F.P. (1977). Strategic purchasing scheduling. *Journal of Purchasing and Material Management,* 13 (3), 27–31.

Araz, C., & Ozkarahan, I. (2005). A multicriteria sorting procedure for financial classification problems: the case of business failure risk assessment. *Lecture Notes in Computer Science*, 3578, 563-70.

Araz, C., & Ozkarahan, I. (2006). Supplier evaluation and management system for strategic sourcing based on a new multicriteria sorting procedure. *International Journal of Production Economics*, in press.

Araz, C., Ozfirat, P.M., & Ozkarahan, I. (2006). An integrated multicriteria decision-making methodology for outsourcing management. *Computers & Operations Research*, in press.

Archer, N.P., & Wang, S. (1993). Application of the back propagation neural networks algorithm with monotonicity constraints for two-group classification problems. *Decisions Sciences*, 24, 60-75.

Arıkan, F., & Güngör, Z. (2001). An Application of fuzzy goal programming to a multiobjective project network problem. *Fuzzy Sets and Systems*, 119, 49-58.

Aziz, S.A., & Parthiban, J. (1996). Fuzzy logic and its uses. Retrieved December 25, 2006 from http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/sbaa/report.html.

Baptistella, L.F.B., & Ollero, A. (1980). Fuzzy methodologies for interactive multicriteria optimization. *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-10, 355-365.

Barbarosoglu, G., & Yazgaç, T. (1997). An application of analytic hierarchy process to the supplier selection problem. *Production and Inventory Management Journal*, 1st quarter, 14-21.

Basnet, C., & Leung, J.M.Y. (2005). Inventory lot-sizing with supplier selection. *Computers and Operations Research*, 32, 1–14.

Beamon, B.M. (1999). Measuring supply chain performance. International Journal of Operations & Production Management, 19(3), 275-292.

Belacel, N. (2000). Multicriteria assignment method PROAFTN: Methodology and medical application. *European Journal of Operations Research*, 125, 175-183.

Belacel, N., & Boulassel, M.R. (2004). Multicriteria fuzzy classification procedure PROCFTN: methodology and medical application. *Fuzzy Sets and Systems,* 141 203–217.

Belacel, N., Raval, H.B., & Punnen, A.P. (2007). Learning multicriteria fuzzy classification method PROAFTN from data. *Computers & Operations Research*, 34(7), 1885-1898.

Bellman, R. E., & Zadeh, L. A. (1970). Decision-making in a fuzzy environment. *Management Science*, 17, 141-164.

Benayoun, R., De Montgolfier, J., Tergny, J., & Larichev, O. (1971). Linear programming with multiple objective function : Stem method (STEM). Mathematical programming, 1(3), 366-375.

Bevilacqua, M., & Petroni, A., (2002). From traditional purchasing to supplier management: A fuzzy logic-based approach to supplier selection. *International Journal of Logistics: Research and Applications*, 5(3), 236-250.

Bezdek, J. C. (1993). Editorial: Fuzzy models-what are they, and why? IEEE Transactions on Fuzzy Systems, 1 (1), 1-6.

Bhutta, K.S., & Huq, F. (2002). Supplier selection problem: a comparison of the total cost of ownership and analytic hierarchy process approaches. *Supply Chain Management: An international Journal*, 7(3), 126-135.

Bonaccorsi, A. & Lipparini, A. (1994). Strategic partnership in new product development: an Italian case study. *Journal of Product Innovation Management*, 11, 134-145.

Bonser, J.S., & Wu, S.D. (2001). Procurement planning to maintain both short-term adaptiveness and long-term perspective. *Management Science*, 47, 769–786.

Bortolan, G., & Degani, R. (1985). A review of some methods for ranking fuzzy subsets, 15, 1-19.

Bottani, E., & Rizzi, A. (2006). A fuzzy TOPSIS methodology to support outsourcing of logistics services. *Supply Chain Management: An International Journal*, 11(4), 294-308.

Bozdağ, C.F., Kahraman, C., & Ruan, D. (2003). Fuzzy group decision making for selection among computer integrated manufacturing systems. *Computers in Industry*, 51, 13-29.

Brans, J.P. & Mareschal, B. (1992). PROMETHEE V: MCDM problems with segmentation constraints. *INFOR* 1992; 30: 85–96.

Brans, J.P., & Vincke, P.H. (1985). A preference ranking organisation method: The PROMETHEE method for MCDM. *Management Science*, 31(6), 647-656.

Brans, J.P., Vincke, P.H., & Mareschal, B. (1986). How to select and how to rank projects: The PROMETHEE method. *European Journal of Operational Research*, 24, 228-238.

Buffa, F.P., & Jackson, W.M. (1983). A goal programming model for purchase planning. *Journal of Purchasing and Materials Management*, 19, 27-34.

Burke, G.J. (2005). *Sourcing strategies in a supply chain*. PhD. Thesis. University of Florida, USA.

Catelani, M., & Fort, A. (2000). Fault diagnosis of electronic analog circuits using a radial basis function network classifier. *Measurement*, 28(3), 147-158.

Çebi, F. & Bayraktar, D. (2003). An integrated approach for supplier selection. *Logistics Information Management*, 16, 395-400.

Chan, F.T.S. (2003). Interactive selection model for supplier selection process: an analytical hierarchy process approach. *International Journal of Production Research*, 41, 3549-3579.

Chan, F.T.S., & Kumar, N. (2007). Global supplier development considering risk factors using fuzzy extended AHP-based approach. *Omega*, 35, 417-431.

Chaudhry, S.S., Forst, F.G., & Zydiak, J.L. (1993). Vendor selection with price breaks. *European Journal of Operational Research,* 70, 52-66.

Chen, C.-T., Lin, C.-T., & Huang, S.-F. (2006). A fuzzy approach for supplier evaluation and selection in supply chain management. *International Journal of Production Economics*, 102, 289–301.

Chen, L.H., & Tsai, F.C., (2001). Fuzzy Goal Programming with Different Importance and Priorities. *European Journal of Operation Research*, 133, 548-556.

Chen, M., & Wang, W. (1997). A linear programming model for integrated steel production and distribution planning. *International Journal of Operations and Production Management*, *17* (6), 592-610.

Chen, Y., Kilgour, D.M., & Hipel, K.W. (2006). Multiple criteria classification with an application in water resources planning. *Computers & Operation Research*, 33, 3301-3323.

Chopra, S., & Meindl, P. (2004). Supply chain management (2nd ed.). NJ: Pearson Prentice Hall.

Choy, K.L., Lee, W.B., & Lo, V. (2002). An intelligent supplier management tool for benchmarking suppliers in outsource manufacturing. *Expert Systems with Applications*, 22, 213-224.

Choy, K.L., Lee, W.B., & Lo, V. (2003). Design of a case based intelligent supplier relationship management system-the integration of supplier rating system and product coding system. *Expert Systems with Applications*, 25, 87-100.

Choy, K.L., Lee, W.B., Lau, H.C.W., & Choy, L.C. (2005). A Knowledge-based supplier intelligence retrieval system for outsource manufacturing. *Knowledge-Based Systems*, 18, 1-17.

Choy, K-L.T. (2003). *An intelligent supplier management system for outsource manufacturing*. PhD Thesis, The Hong Kong Polytechnic University, Hong Kong.

Christopher, M. (1998). *Logistics and supply chain management: Strategies for reducing cost and improving service* (2nd ed.). NJ: Prentice-Hall.

Chuang, C.L. (2004). *Supplier selection and order allocation in supply chain management*, PhD Thesis, University of Iowa, USA.

Chung, A., & Kim, G.M. (2003). Performance effects of partnership between manufacturers and suppliers for new product development: the supplier's standpoint. *Research Policy*, 32, 587-603.

Cook, R.L. (1997). Case-based reasoning systems in purchasing: applications and development. *International Journal of Purchasing and Materials Management,* 33 (1), 32-39.

CramaY., Pascual, R.J., & Torres A. (2004). Optimal procurement decisions in the presence of total quantity discounts and alternative product recipes. *European Journal of Operational Research*, 159(2),364-378.

Croom, S. (2001). The dyadic capabilities concept: examining the processes of key supplier involvement in collaborative product development. *European Journal of Purchasing & Supply Management*, 7, 29-37.

Crow, L.E., Olshavsky, R.W., & Summers, J.O. (1980). Industrial buyer choice strategies: a protocol analysis. *Journal of Marketing Research*, 17, 34–44.

Dahel, N.E. (2003). Vendor selection and order quantity allocation in volume discount environment. *Supply Chain Management: An International Journal*, 8(4), 335-342.

Damart, S., Dias, L.C., & Mousseau, V. (2006). Supporting groups in sorting decisions: Methodology and use of a multi-criteria aggregation/disaggregation DSS. *Decision Support Systems*, in press.

De Boer, L., Labro, E., & Morlacchi, P. (2001). A review of methods supporting supplier selection. *European Journal of Purchasing & Supply Management*, 7, 75-89.

De Boer, L., Van der Wegen, L., & Telgen, J. (1998). Outranking methods in support of supplier selection. *European Journal of Purchasing & Supply Management*, 4(2/3), 109-118.

De Leeneer, I. & Pastijn, H., (2002). Selecting land mine detection strategies by means of outranking MCDM techniques. *European Journal of Operational Research*, 139(2), 327-338.

De Smet, Y., & Gilbart, F. (2001). A class definition method for country risk problems. Technical Report SMG 2001/13, Universit´e Libre de Bruxelles.

De Smet, Y., & Montano-Guzman, L. (2004). Towards multicriteria clustering: An extension of the k-means algorithm. *European Journal of Operational Research*, 158, 390-398.

De Toni, A., & Nassimbeni, G. (2001). A method for the evaluation of suppliers' co-design effort. *International Journal of Production Economics*, 72, 169-180.

Decision Lab 2000 (2000). Visual decision Inc., Canada.

Degraeve, Z., & Roodhooft, F. (1999). Improving the efficiency of the purchasing process using total cost of ownership information: the case of heating electrodes at Cockerill Sambre S. A.. *European Journal of Operational Research*, 112(1), 42-53.

Degraeve, Z., Labro, E., & Roodhooft, F. (2000). An evaluation of vendor selection models from a total cost of ownership perspective. *European Journal of Operational Research*,125, 34–58.

Demirtas, E.A., & Üstün, Ö. (2006). An integrated multiobjective decision making process for supplier selection and order allocation. *Omega*, in press.

Diakoulaki, D., Zopounidis, C., Mavrotas, G., & Doumpos, M. (1999). The use of a preference disaggregation method in energy analysis and policy making. *Energy-The International Journal,* 24(2), 157-166.

Dias, L.C., & Mousseau, V. (2003). IRIS: a DSS for multiple criteria sorting problems, *Journal of Multi-Criteria Decision Analysis*, 12, 285–298.

Dickson, G.W. (1966). An analysis of vendor selection systems and decisions. *Journal of Purchasing*, 2(1), 5-17.

Dimitras, A.I., Zopounidis, C., & Hurson, C. (1995). A multicriteria decision aid method for the assessment of business failure risk. *Foundations of Computing and Decision Sciences*, 20(2), 99-112.

Dogan, I., & Sahin, U. (2003). Supplier selection using activity-based costing and fuzzy present-worth techniques. *Logistics Information Management*, 16(6), 420-426.

Doumpos, M., & Zapounidis, C. (2001). Assessing financial risks using a multicriteria sorting procedure: the case of country risk assessment. *Omega*, 29, 97-109.

Doumpos, M., & Zapounidis, C. (2004). A Multicriteria classification approach based on pairwise comparisons. *European Journal of Operational Research*, 158, 378-389.

Doumpos, M., & Zopounidis, C. (2002). *Multicriteria decision aid classification methods*. The Netherlands: Kluwer Academic Publishers.

Doumpos, M., Zanakis, S., & Zapounidis, C. (2001). Multicriteria preference disaggregation for classification problems with an application to global investing risk. *Decision Sciences*, 32(2), 33-385.

Dowlatshahi, S. (2000). Design-buyer-supplier interface: Theory versus practice. *International Journal of Production Economics*, 63, 111-130.

Dubois, D., & Prade, H. (1978). Operations on fuzzy numbers. *International Journal of Systems Science,* 9, 613-626.

Dulmin, R., & Mininno, V. (2003). Supplier selection using a multi-criteria decision aid method. *Journal of Purchasing & Supply Management*, 9, 177-187.

Ellram, L.M. (1995). Total cost of ownership: an analysis approach for purchasing. *International Journal of Physical Distribution & Logistics Management*, 25(8).

Figueira, J. (2006). Private Communication.

Figueira, J., Greco, S., & Ehrgott, M. (2004). *Multiple Criteria Decision Analysis:State of the Art Surveys*. New York: Springer.

Figueira, J., Smet Y., & Brans, J.-P. (2004). *MCDA methods for sorting and clustering problems: Promethee TRI and Promethee CLUSTER*. Universite Libre de Bruxelles, Working Paper 2004/02 Retrieved January 1, 2005 from http://www.ulb.ac.be/polytech/smg/indexpublications.htm.

Fleischmann, B., Meyr, H., & Wagner, M. (2002). Advanced Planning. In H. Stadtler & C. Kilger (Ed.). *Supply chain management and advanced planning* (2nd ed.) (71-95). New York: Springer-Verlag.

Freytag, P.V., & Kirk, L. (2003). Continuous strategic sourcing. Journal of *Purchasing and Supply Management*, 9(3), 135-150.

Ganeshan, R., Jack, E., Magazine, M. J., & Stephens, P. (1999). A taxonomic review of supply chain management research, in S. Tayur, R. Ganeshan & M. Magazine (eds.), *Quantitative models for supply chain management* (pp. 840-879). Boston, MA: Kluwer Academic Publishers.

Gelderman, J., Spengler,T., & Rentz, O. (2000). Fuzzy outranking for environmental assessment. Case study: iron and steel making industry. *Fuzzy Sets and Systems,* 115, 45-65.

Georgopoulou, E., Lalas D., & Papagiannakis L. (1997). A multicriteria decision aid approach for energy planning problems: The case of renewable energy option. *European Journal of Operational Research*, 103 (1), 38-54.

Georgopoulou, E., Sarafidis, Y., Mirasgedis, S., Zaimi, S., & Lalas, D.P. (2003). A multiple criteria decision-aid approach in defining national priorities for greenhouse gases emissions reduction in the energy sector. *European Journal of* Operational Research, 146, 199–215.

Ghodsypour, S.H. & O'Brien, C. (2001). The total cost of logistics in supplier selection, under conditions of multiple sourcing, multiple criteria and capacity constraints. *International Journal of Production Economics,* 73, 15-27.

Ghodsypour, S.H., & O'Brien, C.O. (1998). A decision support system for supplier selection using an integrated analytical hierarchy process and linear programming. *International Journal of Production Economics*, 56-57 (1-3), 199-212.

Gochet, W., Stam, A., Srinivasan, V., & Chen, S. (1997). Multigroup discriminant analysis using linear programming. *Operations Research*, 45(2), 213-225.

Grando, A. & Sianesi, A. (1996). Supply management: a vendor rating assessment, *CEMS Business Review*, 1, 199-212.

Handfield, R.B., & Pannesi, R.T. (1994). Managing component life cycles in dynamic technological environments. *International Journal of Purchasing and Materials Management*, 30(2), 19-27.

Hannan E. L. (1981). Some further comments on fuzzy priorities. *Decision Science*, 13, 337-339.

Hinkle, C.L., Robinson, P.J., & Green, P.E. (1969). Vendor evaluation using cluster analysis. *Journal of Purchasing*, 5, 49–58.

Hokkanen, J., & Salminen, P. (1997). Choosing a solid waste management system using multicriteria decision analysis. *European Journal of Operational Research*, 98 (1), 19-36.

Hokkanen, J., & Salminen, P. (1997). Locating a waste treatment facility by multicriteria analysis. *Journal of Multi-Criteria Decision Analysis*, 6, 175-184.

Holt, G.D. (1998). Which contractor selection methodology?. *International Journal of Project Management*, 16,153–164.

Hong, G.H., Hark, S.C., Jang, D.S., & Rho, H.M. (2005). An effective supplier selection method for constructing competitive supply-relationship. *Expert Systems with applications*, 28, 629-39.

Hong, J., & Hayya, J.C. (1992). Just-in-time purchasing: single or multiple sourcing. *International Journal of Production Economics*, 27, 175–81.

Huang, S.H., & Keskar, H. (2006). Comprehensive and configurable metrics for supplier selection. *International Journal of Production Economics*, in press.

Humphreys, P., Huang, G., & Cadden, T. (2005). A web-based supplier evaluation tool for the product development process. *Industrial Management & Data Systems*, 105(2), 147-163.

Ignizio, J. P. (1982). On the rediscovery of fuzzy goal programming. *Decision Science*, 13, 331-336.

Inuiguchi, M., & Ramik, J. (2000). Possibilistic linear programming: A brief review of fuzzy mathematical programming and a comparison with stochastic programming in portfolio selection problem. *Fuzzy Sets and Systems*, *111* (1), 3-28.

Işıklar, G., Alptekin, E., & Büyüközkan, G. (2006).Application of hybrid intelligent decision support model in logistics outsourcing. *Computers & Operation Research*, in press.

Jayaraman, V., Srivastava, R., & Benton, W.C. (1999). Supplier selection and order quantity allocation: a comprehensive model. *The Journal of Supply Chain Management*, 35, 50–58.

Jharkharia, S., & Shankarb, R. (2007). Selection of logistics service provider: An analytic network process (ANP) approach. *Omega*, 35, 274 – 289.

Kahraman, C., Cebeci, U., & Ulukan, Z. (2003). Multi-criteria supplier selection using fuzzy AHP. *Logistic Information Management*, 16(6), 382-394.

Karagiannidis, A., & Moussiopoulos, N. (1997). Application of ELECTRE III for the integrated management of municipal solid wastes in the greater Athens area. *European Journal of Operational Research*, 97 (3), 439-449.

Karpak, B., Kumcu, F., & Kasuganti, R. (1999). An application of visual interactive goal programming: a case in vendor selection decisions. *Journal of Multi-Criteria Decision Analysis,* 8, 93-105.

Keeney, R.L., & Raiffa, H. (1993). *Decisions with Multiple Objectives: Preferences and Value Trade-Offs*. Cambridge University Press.

Köksalan, M., & Ulu, C. (2003). An interactive approach for placing alternatives in preference classes. *European Journal of Operation Research*, 144, 429-439.

Kumar, M., Vrat, P., & Shankar, V. (2003). A fuzzy goal programming approach for vendor selection problem in a supply chain. *Computers and Industrial Engineering*, 46(1), 69-85.

Kumar, M., Vrat, P., & Shankar, V. (2006). A fuzzy programming approach for vendor selection problem in a supply chain. *International Journal of Production Economics*, 101, 273-285.

Kwong, C.K., Ip, W.H., & Chan, J.W.K. (2002). Combining scoring method and fuzzy expert systems approach to supplier assessment: a case study. *Integrated Manufacturing Systems*, 13(7), 512-519.

Le Téno, J.F., & Mareschal, B. (1998). An interval version of PROMETHEE for the comparison of building products' design with ill-defined data on environmental quality. *European Journal of Operational Research*, 109, 522–529.

Lee, E.K., Ha, S., & Kim, S.K. (2001). Supplier selection and management system considering relationships in supply chain management. *IEEE Transactions on Engineering Management*, 48(3), 307-318.

Leger, J., & Martel, J.M. (2002). A Multicriteria assignment procedure for a nominal sorting problematic. *European Journal of Operation Research*, 138, 349-364.

Liao, Z., & Rittscher, J. (2006). A multi-objective supplier selection model under stochastic demand conditions. *Int. J. Production Economics*, in press.

Lin, C. C. (2004). A weighted max–min model for fuzzy goal programming. *Fuzzy Sets and Systems*, 142, 407-420.

LINGO 8.0 (2003). Lindo Sys., Inc., Chicago, USA

Liu, F.-H. F., & Hai, H.L. (2005). The voting analytical hierarchy process method for selecting supplier. *International Journal of Production Economics*, 97, 308-317.

Macharis, C., Siprigael, J., De Brucker, K., & Verbeke, A. (2004). PROMETHEE and AHP: The design of operational synergies in multicriteria analysis. strengthening PROMETHEE with ideas of AHP. *European Journal of Operational Research*, 153(2), 307-317.

Maffin, D., & Braiden, P. (2001). Manufacturing and supplier roles in product development. *International Journal of Production Economics*, 69, 205-213.

Mandal, A., & Deskmukh, S.G. (1994). Vendor selection using Interpretive Structural Modeling (ISM). *International Journal of Operations and Production Management*, 14(6), 52-59.

Mareschal, B., & Brans, J.P. (1988). Geometrical representations for MCDA. *European Journal of Operational Research*, 34, 69-77.

Martin, J.M., Fajardo, W., Blanco, A., & Requena1, A. (2003). Constructing linguistic versions for the multicriteria decision support systems preference ranking organization method for enrichment evaluation I and II. *International Journal of Intelligent Systems*, 18, 711-731.

Masella, C., & Rangone, A. (2000). A contingent approach to the design of vendor selection systems for different types of cooperative customer/supplier. *International Journal of Operations and Production Management*, 20, 70–84.

Massaglia, M., & Ostanello, A. (1991). N-TOMIC: A decision support for multicriteria segmentation problems. In P. Korhonen, (Ed.), *International Workshop on Multicriteria Decision Support*. Lecture Notes in Economics and Mathematics Systems, Springer, (Berlin), 356, 167–174.

Meixell, M.J., & Gargeya, V.B. (2005). Global supply chain design: A literature review and critique. *Transportation Research Part E*, 41, 531–550.

Merad, M.M., Verdel, T., Roy, B., & Kouniali, S. (2004). Use of multi-criteria decision-aids for risk zoning and management of large area subjected to mining-induced hazards. *Tunnelling and Underground Space Technology*, 19, 125–138.

Min, H. (1994). International supplier selection: a multi-attribute utility approach. *International Journal of Physical Distribution and Logistics Management*, 24, 24–33.

Mohamed, R. H. (1997). The relationship between goal programming and fuzzy programming. *Fuzzy Sets and Systems*, 89, 215-222.

Mohamed, Z. M. (1999). Integrated production-distribution model for a multi-national company operating under varying exchange rates. *International Journal of Production Economics*, *58* (1), 81-92.

Mohammed, W. (2000). Chance constrained fuzzy goal programming with right-hand side uniform random variable coefficients. *Fuzzy Sets and Systems*, 109, 107-110.

Monczka, R.M., & Trecha, S.J. (1988). Cost-based supplier performance evaluation. *Journal of Purchasing and Materials Management*, 24 (2), 2-7.

Mousseau, R., Slowinski, R., & Zielniewicz, P. (2000). A user-oriented implementation of the ELECTRE TRI method integrating preference elicitation support. *Computers and Operations Research*, 27(7-8), 757-777.

Mousseau, V., & Słowinski, R. (1998). Inferring an ELECTRE TRI model from assignment examples. *Journal of Global Optimization,* 12 (2), 157–174.

Mousseau, V., Figueira, J., & Naux, J. (2001). Using assignment examples to infer weights for ELECTRE TRI method: Some experimental results. *European Journal of Operational Research,* 130 (2), 263–275.

Narasimhan R., & Rubin P. A. (1984). Fuzzy goal programming with nested priorities. *Fuzzy Sets and Systems*, 14, 115-129.

Narasimhan, R. (1980). Goal programming in a fuzzy environment. *Decision Science*, 11, 325-336.

Narasimhan, R. (1983). An analytic approach to supplier selection. *Journal of Purchasing & Supply Management*, 1, 27-32.

Narasimhan, R., & Stoynoff, K. (1986). Optimizing aggregate procurement allocation decisions. *Journal of Purchasing and Material Management*, 22, 23–30.

Ng, S.T., & Skitmore, R.M. (1995). CP-DSS: decision support system for contractor prequalification. *Civil Engineering Systems: Decision Making Problem Solving*, 12(2), 133-160.

Nieddu, L., & Patrizi, G. (2000). Formal methods in pattern recognition: A review. *European Journal of Operational Research*, 120, 459-495.

Nydick, R.L., & Hill, R.P. (1992). Using the analytic hierarchy process to structure the supplier selection procedure. *International Journal of Purchasing and Materials Management,* 28(2), 31-36.

Ohta H., & Yamaguchi T. (1996). Linear fractional goal programming in consideration of fuzzy solution. *European Journal of Operational Research*, 92, 157-165.

Olson, D. L. (2006). Evaluation of ERP outsourcing. *Computers & Operations Research*, in press.

Ostermark, R. (1999). A fuzzy neural network algorithm for multigroup classification. Fuzzy Sets and Systems, 105, 113-122.

Pan, A.C. (1989). Allocation of order quantities among suppliers. *Journal of Purchasing and Materials Management*, 25(2), 36-39.

Pasiouras, F., Gaganis, C., & Zopounidis, C. (2006). Multicriteria decision support methodologies for auditing decisions: The case of qualified audit reports in the UK. *European Journal of Operational Research*, in press.

Pasiouras, F., Tanna, S., & Zopounidis, C. (2006). The identification of acquisition targets in the EU banking industry: An application of multicriteria approaches. *International Review of Financial Analysis*, in press.

Petroni, A., & Braglia, M. (2000). Vendor selection using principal component analysis. *The Journal of Supply Chain Management: A Global Review of Purchasing and Supply,*36, 63–69.

Prahinski, C., & Benton, W.C. (2004). Supplier evaluations: communication strategies to improve supplier performance. *Journal of Operations Management*, 22, 39-62.

Primo, M.A.M., & Amundson, S.D. (2002). An exploratory study of the effects of supplier relationships on new product development outcomes. *Journal of Operations Management*, 20, 33-52.

Ramik J. (2000). Fuzzy goals and fuzzy alternatives in goal programming problems. *Fuzzy Sets and Systems*, 111, 81-86.

Rao S. S., Tiwari, R. N., & Mohanty, B. K. (1988). A preference structure on aspiration levels in a goal programming problem - a fuzzy approach. *Fuzzy Sets and Systems*, 25, 175-182.

Ripley, B.D. (1996). *Pattern Recognition and Neural Networks*, Cambridge University Press, Cambridge.

Rodhe, J., Meyr, H., & Wagner, M. (2000). Die supply chain planning matrix. *PPS Management*, 5(1), 10-15.

Rogers, M., & Bruen, M. (2000). Using ELECTRE III to choose route for Dublin port motorway. *Journal of Transportation Engineering*, 126 (4), 313-323.

Rosenblatt, M.J., Herer, Y.T., & Hefter I. (1998). An acquisition policy for a single item multi-supplier system. *Management Science* , 44, 96–100.

Rosenthal, E.C., Zydiak, J.L., & Chaudhry, S.S. (1995). Vendor selection with bundling. *Decision Sciences,* 26 (1), 35-48.

Roy, B. & Vanderpooten, D. (1996). The european school of MCDA: Emergence, basic features and current works. *Journal of Multi-Criteria Decision Analysis*, 5(1), 22-37.

Roy, B. (1968). Classement et choix en presence de points de vue multiples: La methode ELECTRE. *R.I.R.O.*, 8, 57-75.

Roy, B. (1991). The outranking approach and the foundations of ELECTRE methods. *Theory and Decision*, 31(1), 49-73.

Roy, B. (1996). *Multicriteria Methodology for Decision Aiding. Nonconvex Optimization and its Applications*. Dordrecht: Kluwer Academic Publishers.

Saaty, T.L. (1980). *The Analytic Hierarchy Process*. New York: Mc Graw-Hill.

Sadrian, A.A., & Yoon, Y.S. (1994). A procurement decision support system in business volume discount environments. *Operations Research*, 42 (1), 14-23.

Saen, R.F. (2006). A new mathematical approach for suppliers selection: Accounting for non-homogeneity is important. *Applied Mathematics and Computation*, in press.

Sakawa, M. (1993). *Fuzzy sets and interactive multiobjective optimization*. NY: Plenum Press.

Sarkar, A., & Mohapatra, P.K.J. (2006). Evaluation of supplier capability and performance: A method for supply base reduction. *Journal of Purchasing & Supply Management*, in press.

Sharma, D., Benton, W.C., & Srivastava, R. (1989). Competitive strategy and purchasing decision. *Proceedings of the 1989 Annual Conference of the Decision Science Institute*, 1088–1090.

Shen, L., Tay, F.E.H., Qu, L. & Shen, Y. (2000). Fault diagnosis using rough set theory. *Computers in Industry*, 43, 61-72.

Sheth, J., & Sharma, A. (1997). Supplier relationships: Emerging issues and challenges. *Industrial Marketing Management*, 26, 91-10.

Shin, H., Collier, D.A., & Wilson, D.D. (2000). Supply management orientation and supplier/buyer performance. *Journal of Operations Management*, 18, 317-333.

Shyur, H.-J., & Shih, H.-S. (2006). A hybrid MCDM model for strategic vendor selection. *Mathematical and Computer Modelling*, 44, 749-761.

Siskos, Y., Grigoroudis, E., Zopounidis, C., & Saurais, O. (1998). Measuring customer satisfication using a survey based preference disaggregation model. *Journal of Global Optimization*, 12(2), 175-195.

Smytka, D.L., Clemens, M.W. (1993). Total cost supplier selection model: a case study. *International Journal of Purchasing and Materials Management*, 29 (1), 42-49.

Soukup, W.R. (1987). Supplier selection strategies. *Journal of Purchasing and Materials Management*, 23 (3), 7-12.

Stadtler, H. (2002). Supply chain management – An overview. In H. Stadtler & C. Kilger (Ed.). *Supply chain management and advanced planning* (2nd ed.) (7-28). New York: Springer-Verlag.

Stam, A., Sun, M., & Haines, M. (1996). Artificial neural network representations for hierarchical preference structures. *Computers and Operations Research*, 23(12), 1191–1201.

Sucky, E. (2006). A model for dynamic strategic vendor selection. *Computers & Operation Research*, in press.

Talluri, S., & Narasimhan, R. (2004). A Methodology for strategic sourcing. *European Journal of Operational Research*, 154, 236-250.

Tam, M.C.Y., & Tummala, V.M.R. (2001). An application of the AHP in vendor selection of a telecommunications system. *Omega*, 29, 171–182.

Terano, T., Asai, K., & Sugeno, M. (1992). *Fuzzy systems theory and its applications*. San Diego: Academic press Inc.

Thompson, K. (1991) Scaling evaluative criteria and supplier performance estimates in weighted pint prepurchase decision models. *International Journal of Purchasing and Materials Management*, 27(1), 27-36.

Timmerman, E. (1986). An approach to vendor performance evaluation. *Journal of Purchasing and Supply Management*, 1, 27-32.

Tiwari, R. N., Dharmar, S., & Rao, J. R. (1986). Priority structure in fuzzy goal programming. *Fuzzy Sets and Systems*, 19, 251-259.

Tiwari, R.N., Dharmar, S., & Rao, J.R. (1987). Fuzzy goal programming: An additive method. *Fuzzy Sets and Systems*, 24, 27-34.

Triantaphyllou, E. & Lin, C.-T. (1996). Development and Evaluation of Five Fuzzy Multi-Attribute Decision-Making Methods. *Approximate Reasoning*, 14(4), 281-310.

Tsai,W.-C. (1999). *A procedure for the supplier evaluation problem under risk using fuzzy sets*. PhD. Thesis, University of Alabama, USA.

Valk, W.V.D., & Wynstra, F. (2005). Supplier involvement in new product development in the food industry. *Industrial Marketing Management*, 34, 681-694.

Valls, A., & Torra, V. (2000). Using classification as an aggregation tool in MCDM. *Fuzzy Sets and Systems*, 115, 159-168.

Vokurka, R.J., Choobineh, J., & Vadi, L. (1996). A prototype expert system for the evaluation and selection of potential suppliers. *International Journal of Operations and Production Management*, 16(12), 106-127.

Wadhwa, V., & Ravindran, A.R. (2006). Vendor selection in outsourcing. *Computers & Operation Research*, in press.

Wang, G., Huang, S.H., & Dismukes, J.P. (2004). Product-driven supply chain selection using integrated multi-criteria decision-making methodology. *International Journal of Production Economics*, 91(1), 1-15.

Wang, H. F., & Fu, C. C. (1997). A generalization of fuzzy goal programming with preemptive structure. *Computers & Operations Research*, 24, 819-828.

Wang, H. F., & Wang, M. L. (1997). A fuzzy multiobjective linear programming. *Fuzzy Sets and Systems*, 86, 61-72.

Wang, H.S., & Che, Z.H. (2006). An integrated model for supplier selection decisions in configuration changes. *Expert Systems with Applications*, in press.

Wang, J.-J., & Yang, D.-L. (2006). Using a hybrid multi-criteria decision aid method for information systems outsourcing. *Computers & Operations Research*, in press.

Wang, X., & Kerre, E.E. (2001). Reasonable properties of fuzzy quantities (I). *Fuzzy Sets and Systems,* 118, 375-385.

Wang, X., & Kerre, E.E. (2001). Reasonable properties of fuzzy quantities (II). *Fuzzy Sets and Systems,* 118, 385-405.

Wang, X., & Triantaphyllou, E. (2006). Ranking irregularities when evaluating alternatives by using some multi-criteria decision analysis methods. *Omega*, in press.

Weber, C.A. & Ellram, L.M. (1993). Supplier selection using multi-objective programming: a decision support system approach. *International Journal of Physical Distribution & Logistics Management* , 23(2), 3-14.

Weber, C.A., & Current, J.R. (1993). A multiple-objective approach to vendor selection. *European Journal of Operational Research*, 68, 173–184.

Weber, C.A., & Desai, A. (1996). Determination of paths to vendor market efficiency using parallel coordinates representation: a negotiation tool for buyers. *European Journal of Operational Research,* 90, 142-155.

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

Weber, C.A., Current, J.R., & Desai, A. (1998). Non-cooperative negotiation strategies for vendor selection. *European Journal of Operational Research*, 108, 208-223.

Weber, C.A., Current, J.R., & Desai, A. (2000). An optimization approach to determining the number of vendors to employ. *Supply Chain Management: An International Journal*, 5 (2), 90-98.

Werners, B. (1987). An interactive fuzzy programming system. *Fuzzy Sets and Systems*, 23, 131-147.

Williams, R.F. (1984). *Purchasing the technological product: selecting and weighting criteria for the inherently complex new product.* Ann Arbor, MI: University Microfilms International.

Wright, P. (1975). Consumer choice strategies/simplifying vs optimizing. *Journal of Marketing Research*,12, 60–67.

Wynstra, F., Weele, A.V., & Weggemann, M. (2001). Managing supplier involvement in product development: Three critical issues. *European Management Journal*, 19, 157-167.

Yahya, S., & Kingsman, B. (1999). Vendor rating for an entrepreneur development program: a case study using the analytic hierarchy process method. *Journal of* Operational Research Society, 50, 916–930.

Yu, W. (1992). *Aide multicriterea la decision dans le cadre de la problematique du tri: Concepts, methodes et applications*. PhD Thesis, Universite Paris-Dauphine.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8, 338-353.

Zimmermann, H. J. (1978). Fuzzy programming and linear programming with several objective function. *Fuzzy Sets and Systems*, 1, 45-55.

Zimmermann, H. J. (1994). *Fuzzy Set Theory – and its applications* (3rd ed.). Dordrecht: Kluwer Academic Publishers.

Zions, S., & Wallenius, J. (1976). An interactive programming method for solving the multicriteria problem. *Management Science*, 22, 652-663.

Zopounidis, C. & Doumpos, M. (2001). A preference disaggregation decision support system for financial classification problems. *European Journal of Operational Research*, 130(2), 137-148.

Zopounidis, C., & Doumpos, M. (1999). A multicriteria decision support system for sorting decision problems: the case of financial distress. *Computational Economics*, 14(3), 197-218.

Zopounidis, C., & Doumpos, M. (2000). Building additive utilities for multi-group hierarchical discrimination: The M.H.DIS method. *Optimization Methods and Software*, 14(3), 219–240.

Zopounidis, C., & Doumpos, M. (2002). Multicriteria classification and sorting methods: A literature review. *European Journal of Operational Research*, 138, 229-246.

APPENDIX A

THE SAMPLE CODES OF PROMSORT 1.0

A1. The code of "Open a New Promsort" window

```
Dim bb As String
Dim ff As String
Dim Ex10 As Excel.Application
Dim Ex20 As Excel.Application
Dim Ex30 As Excel.Application

Private Sub Cancel_Click()
Unload Form1
End Sub

Private Sub Command1_Click()
AlternatifSayisi = Val(Text1.Text)
KategoriSayisi = Val(Text2.Text)
KriterSayisi = Val(Text3.Text)
BDegeri = Val(Text4.Text)

If Text1.Text = "" Then MsgBox ("The number of alternatives must be written."): Exit Sub
If Text2.Text = "" Then MsgBox ("The number of categories must be written."): Exit Sub
If Text3.Text = "" Then MsgBox ("The number of criteria must be written."): Exit Sub

If bb = "" Then MsgBox ("You must select ranking file"): Exit Sub
If ff = "" Then MsgBox ("you must select scores file "): Exit Sub

Unload Form1
End Sub

Private Sub Command2_Click()

CommonDialog1.DialogTitle = "Select PROMETHEE Results File"
CommonDialog1.Filter = "*.htm|*.htm"
CommonDialog1.ShowOpen
a = CommonDialog1.FileName
bb = 1

ref = "FINDER;file:///" & a

Set Ex10 = New Excel.Application
With Ex10
  .Visible = False
  .Workbooks.Open ("C:\Promsoft\1.xls")
  .Sheets(1).Select


  With ActiveSheet.QueryTables.Add(Connection:= _
     ref, Destination:=Range("A1") _
     )

     .FieldNames = True
     .RowNumbers = False
```

```
        .FillAdjacentFormulas = False
        .PreserveFormatting = True
        .RefreshOnFileOpen = False
        .BackgroundQuery = True
        .RefreshStyle = xlInsertDeleteCells
        .SavePassword = False
        .SaveData = True
        .AdjustColumnWidth = True
        .RefreshPeriod = 0
        .WebSelectionType = xlAllTables
        .WebFormatting = xlWebFormattingNone
        .WebPreFormattedTextToColumns = True
        .WebConsecutiveDelimitersAsOne = True
        .WebSingleBlockTextImport = False
        .WebDisableDateRecognition = False
        .WebDisableRedirections = False
        .Refresh BackgroundQuery:=False
    End With

Range("A1:Z100").Select
Selection.Copy
End With
Form3.m2.Range("A1:A1").Paste

Application.CutCopyMode = False

ActiveWorkbook.Close False

Ex10.Quit
Form3.m2.Range("A1").Select
Form3.Show
Label6.Visible = True
End Sub

Private Sub Command3_Click()

CommonDialog2.DialogTitle = "Select PROMETHEE Single Criterion Net Flow File"
CommonDialog2.Filter = "*.htm|*.htm"
CommonDialog2.ShowOpen
c = CommonDialog2.FileName
ff = 1

ref1 = "FINDER;file:///" & c

Set Ex20 = Excel.Application
With Ex20
   .Visible = False
   .Workbooks.Open ("C:\Promsoft\2.xls")
   .Sheets(1).Select

  With ActiveSheet.QueryTables.Add(Connection:= _
        ref1, Destination:=Range("A1") _
        )

        .FieldNames = True
        .RowNumbers = False
        .FillAdjacentFormulas = False
        .PreserveFormatting = True
```

```
      .RefreshOnFileOpen = False
      .BackgroundQuery = True
      .RefreshStyle = xlInsertDeleteCells
      .SavePassword = False
      .SaveData = True
      .AdjustColumnWidth = True
      .RefreshPeriod = 0
      .WebSelectionType = xlAllTables
      .WebFormatting = xlWebFormattingNone
      .WebPreFormattedTextToColumns = True
      .WebConsecutiveDelimitersAsOne = True
      .WebSingleBlockTextImport = False
      .WebDisableDateRecognition = False
      .WebDisableRedirections = False
      .Refresh BackgroundQuery:=False
    End With

Range("A1:Z100").Select
Selection.Copy

End With
Form4.m3.Range("A1:A1").Paste
Form4.m3.Cells([1], [1]).Select

Application.CutCopyMode = False

ActiveWorkbook.Close False

Set Ex30 = Excel.Application
With Ex30
   .Visible = False
   .Workbooks.Open ("C:\Promsoft\ilktablo.xls")
   .Sheets(1).Select

  With ActiveSheet.QueryTables.Add(Connection:= _
      ref1, Destination:=Range("A1") _
      )

      .FieldNames = True
      .RowNumbers = False
      .FillAdjacentFormulas = False
      .PreserveFormatting = True
      .RefreshOnFileOpen = False
      .BackgroundQuery = True
      .RefreshStyle = xlInsertDeleteCells
      .SavePassword = False
      .SaveData = True
      .AdjustColumnWidth = True
      .RefreshPeriod = 0
      .WebSelectionType = xlAllTables
      .WebFormatting = xlWebFormattingNone
      .WebPreFormattedTextToColumns = True
      .WebConsecutiveDelimitersAsOne = True
      .WebSingleBlockTextImport = False
      .WebDisableDateRecognition = False
      .WebDisableRedirections = False
      .Refresh BackgroundQuery:=False
    End With
```

```
End With
ActiveWorkbook.Save
ActiveWindow.Close
Form4.Show
Ex30.Quit
Ex20.Quit
Label8.Visible = True

End Sub
```

A2. The code of “Solve the Problem” window

```
Dim Ex As Excel.Application
Dim Ex2 As Excel.Application
Dim Ex3 As Excel.Application
Dim Ex4 As Excel.Workbooks

Dim Action As Integer
Dim DkNegatif As Double
Dim DkPozitif As Double

Private Sub Command2_Click()
Load Form3
For i = 1 To AlternatifSayisi 'alternatifler data1 e alınır
Data1.Recordset.AddNew
Data1.Recordset![Adi] = Form3.m2.Range("a" & i + 1).Value
Data1.Recordset![Phi_Plus] = Form3.m2.Range("b" & i + 1).Value
Data1.Recordset![Phi_Minus] = Form3.m2.Range("c" & i + 1).Value
Data1.Recordset![Phi_net] = Form3.m2.Range("d" & i + 1).Value
Data1.Recordset.Update
Data1.Refresh
DBGrid1.Refresh

Next i
For i = AlternatifSayisi + 1 To AlternatifSayisi + KategoriSayisi - 1 'Kriterler data2 ye alınır
Data2.Recordset.AddNew
Data2.Recordset![Adi] = Form3.m2.Range("a" & i + 1).Value
Data2.Recordset![Phi_Plus] = Form3.m2.Range("b" & i + 1).Value
Data2.Recordset![Phi_Minus] = Form3.m2.Range("c" & i + 1).Value
Data2.Recordset![Phi_net] = Form3.m2.Range("d" & i + 1).Value
Data2.Recordset.Update
Next i
Text1.Text = Text1.Text & "* data are stored succesfully"
Print
Label2.Visible = True
End Sub

Private Sub Command3_Click()
Text1.Text = Text1.Text & Chr(13)
Text1.Text = Text1.Text & "* Comparisons based on Promethee I:"


For j = 1 To AlternatifSayisi
For i = 1 To KategoriSayisi - 1
Data1.RecordSource = "select * from Alternatifler where Adi='Action" & j & "'"
Data1.Refresh
```

```
Data2.RecordSource = "select * from Kriterler where Adi='Action" & AlternatifSayisi + i & "'"
Data2.Refresh

'''    1) aj1=bi1 ve aj2=bj2
If Data1.Recordset.Fields(1).Value = Data2.Recordset.Fields(1).Value And _
Data1.Recordset.Fields(2).Value = Data2.Recordset.Fields(2).Value Then GoTo aRb

'''    2) aj1>bi1 ve aj2>bj2
If Data1.Recordset.Fields(1).Value > Data2.Recordset.Fields(1).Value And _
Data1.Recordset.Fields(2).Value > Data2.Recordset.Fields(2).Value Then GoTo aRb

'''    3) aj1<bi1 ve aj2<bj2
If Data1.Recordset.Fields(1).Value < Data2.Recordset.Fields(1).Value And _
Data1.Recordset.Fields(2).Value < Data2.Recordset.Fields(2).Value Then GoTo aRb

If i = KategoriSayisi - 1 Then
If Data1.Recordset.Fields(1).Value < Data2.Recordset.Fields(1).Value And _
Data1.Recordset.Fields(2).Value > Data2.Recordset.Fields(2).Value Then GoTo EnKotuKategori
End If

''' aj1>bi1 ve aj2<bi2 hali
If Data1.Recordset.Fields(1).Value >= Data2.Recordset.Fields(1).Value And _
Data1.Recordset.Fields(2).Value <= Data2.Recordset.Fields(2).Value Then GoTo aPb

Next i

EnKotuKategori:
Data1.Recordset.Edit
Data1.Recordset.Fields(4).Value = KategoriSayisi
Data1.Recordset.Update
i = 1
GoTo BirsonrakiAlternatif

aRb:
Data1.Recordset.Edit
Data1.Recordset.Fields(4).Value = KategoriSayisi + 1
Data1.Recordset.Fields(5).Value = i
Data1.Recordset.Update
Text1.Text = Text1.Text & " kararsız a" & j & " "
i = 1

GoTo BirsonrakiAlternatif

aPb:
Data1.Recordset.Edit
Data1.Recordset.Fields(4).Value = i
Data1.Recordset.Update
Text1.Text = Text1.Text & "Action" & j & " iyidir B" & i & Chr(13)
i = 1

BirsonrakiAlternatif:
Next j
Data4.RecordSource = "select * from Alternatifler order by Kategori"
Data4.Refresh

Label3.Visible = True

End Sub
```

```
Private Sub Command33_Click()
Set Ex4 = Excel.Workbooks
Ex4("Raporlar.xls").Activate
Ex4.Application.Sheets(3).Select
Ex4.Application.Range("A1").Resize(KategoriSayisi + KategoriSayisi + AlternatifSayisi, KriterSayisi +
2).Select
Selection.Copy

Form5.sonuc1.Range("A1:A1").Paste
Application.CutCopyMode = False
Form5.sonuc1.Range("a1").Select
Form5.Show

End Sub

Private Sub Command6_Click()
i = 1
j = 1

Set Ex2 = Excel.Application

With Ex2
  .Workbooks.Open ("C:\Promsoft\Raporlar.xls")
  .Visible = False
End With
cikis = 1
For i = 1 To KategoriSayisi + 1
Ex2.Cells(i + 1, 1) = i
Data4.RecordSource = "select * from Alternatifler where kategori = " & i
Data4.Refresh
Data4.RecordSource = "select AVG(Phi_net) from Alternatifler where kategori = " & i
Data4.Refresh

Ex2.Cells(i + 1, 2) = Data4.Recordset.Fields(0).Value

Data1.RecordSource = "select * from Alternatifler where kategori = " & i
Data1.Refresh
j = 0
Do While Data1.Recordset.EOF = False
j = j + 1
     Ex2.Cells(i + 1, j + 2) = Data1.Recordset.Fields(0).Value
     Data1.Recordset.MoveNext
Loop
Next i

Form2.Show

Label4.Visible = True
End Sub

Private Sub Command7_Click()
Set Ex3 = Excel.Application
With Ex3
  .Visible = False
  .Sheets(2).Select
End With
```

```
DataBelirsiz.RecordSource = "select * from Alternatifler where Kategori = " & KategoriSayisi + 1
DataBelirsiz.Refresh
Belirsizmiktari = DataBelirsiz.Recordset.RecordCount
i = 1
Do While DataBelirsiz.Recordset.EOF = False
belirsizlikdegeri = DataBelirsiz.Recordset.Fields(5)
PhiNet = DataBelirsiz.Recordset.Fields(3)

Data4.RecordSource = "select * from Alternatifler where kategori= " & belirsizlikdegeri
Data4.Refresh

If Data4.Recordset.EOF = True Then

Ex3.Sheets(1).Select
DkNegatif = 0
DkPozitif = PhiNet - Ex3.Cells(belirsizlikdegeri + 2, 2)
fark = DkPozitif - DkNegatif
GoTo Atlat
End If

Data4.RecordSource = "select * from Alternatifler where kategori= " & belirsizlikdegeri + 1
Data4.Refresh
If Data4.Recordset.EOF = True Then

Ex3.Sheets(1).Select
DkNegatif = Ex3.Cells(belirsizlikdegeri + 1, 2) - PhiNet
DkPozitif = 0
fark = DkPozitif - DkNegatif
GoTo Atlat
End If

Ex3.Sheets(1).Select
DkNegatif = Ex3.Cells(belirsizlikdegeri + 1, 2) - PhiNet
DkPozitif = PhiNet - Ex3.Cells(belirsizlikdegeri + 2, 2)
fark = DkPozitif - DkNegatif

Atlat:

With Ex3
.Sheets(2).Select
.Cells(i + 1, 2) = DkNegatif
.Cells(i + 1, 3) = DkPozitif
.Cells(i + 1, 4) = fark
.Cells(i + 1, 1) = DataBelirsiz.Recordset.Fields(0)
.Cells(i + 1, 5) = DataBelirsiz.Recordset.Fields(5)
End With
If fark >= 0 And fark < 1 Then
optimistic = DataBelirsiz.Recordset.Fields(5)
pesimistic = DataBelirsiz.Recordset.Fields(5) + 1
Ex3.Cells(i + 1, 6) = optimistic
Ex3.Cells(i + 1, 7) = pesimistic
End If
  If fark >= 1 Then
  optimistic = DataBelirsiz.Recordset.Fields(5)
  pesimistic = DataBelirsiz.Recordset.Fields(5)
  Ex3.Cells(i + 1, 6) = optimistic
  Ex3.Cells(i + 1, 7) = pesimistic
  End If
```

```
        If fark < 0 Then
        optimistic = DataBelirsiz.Recordset.Fields(5) + 1
        pesimistic = DataBelirsiz.Recordset.Fields(5) + 1

        Ex3.Cells(i + 1, 6) = optimistic
        Ex3.Cells(i + 1, 7) = pesimistic
        End If
    DataBelirsiz.Recordset.Edit

    If BDegeri = 0 Then 'optimistik
    DataBelirsiz.Recordset.Fields(4).Value = optimistic
    Else
    DataBelirsiz.Recordset.Fields(4).Value = pesimistic
    End If
    DataBelirsiz.Recordset.Update
    DataBelirsiz.Recordset.MoveNext

    i = i + 1
    Loop
    Form2.Show

    Label5.Visible = True

    End Sub

    Private Sub Command7777_Click()
    Unload Form2
    End Sub

    Private Sub Command8_Click()
    On Error Resume Next
    Set Ex3 = New Excel.Application

    Set Ex4 = Excel.Workbooks
    Ex4("Raporlar.xls").Activate
    Ex3.Visible = False
    Ex3.Workbooks.Open ("C:\Promsoft\ilktablo.xls")
    satirnosu = 1
    Ex4.Application.Sheets(3).Select
     Ex4.Application.Range("A1").Resize(KategoriSayisi + KategoriSayisi + AlternatifSayisi, KriterSayisi +
2).Select

    Selection.Borders(xlDiagonalDown).LineStyle = xlNone
      Selection.Borders(xlDiagonalUp).LineStyle = xlNone
      With Selection.Borders(xlEdgeLeft)
        .LineStyle = xlContinuous
        .Weight = xlMedium
        .ColorIndex = xlAutomatic
      End With
      With Selection.Borders(xlEdgeTop)
        .LineStyle = xlContinuous
        .Weight = xlMedium
        .ColorIndex = xlAutomatic
      End With
      With Selection.Borders(xlEdgeBottom)
        .LineStyle = xlContinuous
        .Weight = xlMedium
        .ColorIndex = xlAutomatic
```

```
        End With
        With Selection.Borders(xlEdgeRight)
            .LineStyle = xlContinuous
            .Weight = xlMedium
            .ColorIndex = xlAutomatic
        End With
        With Selection.Borders(xlInsideVertical)
            .LineStyle = xlContinuous
            .Weight = xlThin
            .ColorIndex = xlAutomatic
        End With

      Ex4.Application.Range("A1").Resize(1, KriterSayisi + 2).Select
        With Selection.Borders(xlEdgeBottom)
            .LineStyle = xlContinuous
            .Weight = xlMedium
            .ColorIndex = xlAutomatic
        End With
    Ex4.Application.Sheets(3).Select
     Ex4.Application.Range("B2").Resize(KategoriSayisi + KategoriSayisi + AlternatifSayisi - 1, KriterSayisi +
1).Select
     Ex4.Application.Selection.NumberFormat = "0.0000"

    Ex3.Sheets(1).Select
     Aktarma = Ex3.Range("B1").Resize(1, KriterSayisi)
     Ex4.Application.Sheets(3).Select
     Ex4.Application.Range("C1").Resize(1, KriterSayisi) = Aktarma
     Ex4.Application.Range("C1").Resize(1, KriterSayisi).Select
     Ex4.Application.Selection.Font.FontStyle = "Bold"
    Ex4.Application.Sheets(4).Select
     Ex4.Application.Range("B1").Resize(1, KriterSayisi) = Aktarma
     Ex4.Application.Sheets(3).Select

    For kategori = 1 To KategoriSayisi

    Data5.RecordSource = "select * from Alternatifler where kategori =" & kategori
    Data5.Refresh
    Data5.Recordset.MoveLast
    Data5.Recordset.MoveFirst
    satirnosu = satirsayisi + 1

    tekraradedi = Data5.Recordset.RecordCount


    For satirsayisi = satirnosu To tekraradedi + satirnosu - 1



    With Ex3
        .Sheets(1).Select
        Aktarma = Ex3.Range("A" & Action + 1).Resize(1, KriterSayisi + 1)

        Ex4.Application.Sheets(3).Select
        Ex4.Application.Range("B" & satirsayisi + 1).Resize(1, KriterSayisi + 1) = Aktarma

    End With
    Data5.Recordset.MoveNext
    Next satirsayisi
```

```
    If tekraradedi = 0 Then
    Ex4.Application.Range("C" & satirsayisi + 1).Select
    Ex4.Application.Range("C" & satirsayisi + 1).Resize(1, KriterSayisi).Value = 0
    Ex4.Application.Range("C" & satirsayisi + 1).Resize(1, KriterSayisi).Font.FontStyle = "Bold"

    GoTo sifirdurumu
    End If

    Ex4.Application.Range("C" & satirsayisi + 1).Select
    Ex4.Application.Range("C" & satirsayisi + 1).Resize(1, KriterSayisi).FormulaR1C1 = "=AVERAGE(R[-" &
tekraradedi & "]C:R[-1]C)"
    Ex4.Application.Range("C" & satirsayisi + 1).Resize(1, KriterSayisi).Font.FontStyle = "Bold"

    sifirdurumu:

    Ex4.Application.Range("A" & satirsayisi + 1).Resize(1, KriterSayisi + 2).Select
        With Selection.Borders(xlEdgeBottom)
          .LineStyle = xlContinuous
          .Weight = xlMedium
          .ColorIndex = xlAutomatic
       End With
    Ex4.Application.Sheets(4).Select

       ActiveSheet.ChartObjects("Grafik 3").Activate
       ActiveChart.ChartArea.Select
       ActiveChart.SetSourceData Source:=Sheets("Grafik").Range("A1").Resize(KategoriSayisi + 1, KriterSayisi
+ 1), PlotBy _
          :=xlRows
    Ex4.Application.Sheets(3).Select

    Aktarma = Ex4.Application.Range("C" & satirsayisi + 1).Resize(1, KriterSayisi)
     Ex4.Application.Sheets(4).Select
     Ex4.Application.Range("B" & kategori + 1).Resize(1, KriterSayisi) = Aktarma
     Ex4.Application.Range("B" & kategori + 1).Resize(1, KriterSayisi).Select
     Ex4.Application.Selection.Font.FontStyle = "Bold"
    Ex4.Application.Range("A" & kategori + 1) = "Class " & kategori

     Ex4.Application.Sheets(3).Select

     If tekraradedi = 0 Then GoTo sifirhatasi
          Ex4.Application.Range("A" & satirsayisi - tekraradedi + 1 & ":A" & satirsayisi).Select
                With Ex4.Application.Selection
                .HorizontalAlignment = xlCenter
               .VerticalAlignment = xlCenter
                .WrapText = False
               .Orientation = 90
                  .AddIndent = False
                 .IndentLevel = 0
                .ShrinkToFit = True
                 .ReadingOrder = xlContext
                 .MergeCells = True
                .Value = "Class " & kategori
                .Font.FontStyle = "Bold"
            End With
    Ex4.Application.Range("A" & satirsayisi + 1).Select
                 With Ex4.Application.Selection
                .HorizontalAlignment = xlCenter
               .VerticalAlignment = xlCenter
```

```
            .WrapText = False
           .Orientation = 0
              .AddIndent = False
             .IndentLevel = 0
            .ShrinkToFit = True
             .ReadingOrder = xlContext
             '.MergeCells = True
            .Value = "Average " & kategori
            .Font.FontStyle = "Bold"
         End With
sifirhatasi:
If tekraradedi = 0 Then
 Ex4.Application.Range("A" & satirsayisi + 1).Select
             With Ex4.Application.Selection
            .HorizontalAlignment = xlCenter
           .VerticalAlignment = xlCenter
            .WrapText = False
           .Orientation = 0
              .AddIndent = False
             .IndentLevel = 0
            .ShrinkToFit = True
             .ReadingOrder = xlContext
             '.MergeCells = True
            .Value = "Average " & kategori
            .Font.FontStyle = "Bold"
            End With
      End If

Next kategori

Ex3.Sheets(1).Select
 Aktarma = Ex3.Range("A" & AlternatifSayisi + 2).Resize(KategoriSayisi - 1, KriterSayisi + 3)
 Ex4.Application.Sheets(3).Select
 Ex4.Application.Range("B" & satirsayisi + 2).Resize(KategoriSayisi - 1, KriterSayisi + 3) = Aktarma
Ex4.Application.Range("A" & satirsayisi + 2).Resize(KategoriSayisi - 1, KriterSayisi + 4).Select
Ex4.Application.Selection.Font.FontStyle = "Bold"
Ex4.Application.Range("A" & satirsayisi + 2).Resize(KategoriSayisi - 1, 1).Select
            With Ex4.Application.Selection
            .MergeCells = True
            .HorizontalAlignment = xlCenter
           .VerticalAlignment = xlCenter
           ' .WrapText = True
           .Orientation = 90
              .AddIndent = False
             .IndentLevel = 0
            .ShrinkToFit = True
             .ReadingOrder = xlContext
            .Value = "Profiles "
            .Font.FontStyle = "Bold"
         End With

 Ex4.Application.Columns("A:Z").EntireColumn.AutoFit

With Ex3
   .Sheets(1).Select
   .Cells.ClearContents
End With
Ex3.ActiveWorkbook.Close True
```

```
Ex3.Quit
Label6.Visible = True

End Sub

Private Sub Form_Load()
Data3.Refresh
If Data3.Recordset.RecordCount > 0 Then
Data3.Database.Execute "delete * from Alternatifler"
Data3.Database.Execute "delete * from Kriterler"
Data3.Refresh
End If

End Sub

Private Sub Form_Unload(Cancel As Integer)
On Error Resume Next
With Ex
  .ActiveWorkbook.Close False  'False değeri yaptıklarımızın kaydedilmemesi için
  .Quit
End With

End Sub

Private Sub Text3_Change()
Text3.SelStart = 6
Text3.SelLength = 3
Action = Val(Text3.SelText)
Text4.Text = Val(Text3.SelText)
End Sub
```

APPENDIX B

LINGO CODE FOR THE MODELS DEVELOPED

B.1 LINGO CODE FOR THE ORDER ALLOCATION CASE I

```
Model:
SETS:
PRODUCTS/1..5/:DEMAND;
SUPPLIER/1..11/:SPV;
SET1(SUPPLIER,PRODUCTS):X,PRICE,QUALITY,DELIVERY,CAPACITY,Y;
ENDSETS

DATA:
PRICE=
```

9.80	11.08	5.43	28.77	7.82
6.35	13.89	7.93	29.55	10.36
9.71	7.79	14.49	24.24	12.16
6.34	7.51	6.50	20.53	14.58
6.14	13.39	6.20	24.54	7.58
10.08	12.89	6.15	15.32	11.00
13.05	10.66	12.55	27.41	14.90
10.38	13.90	12.46	15.92	5.57
12.76	11.87	10.45	12.53	7.22
14.35	10.91	12.88	28.08	13.54
11.33	14.59	8.04	29.32	7.42

```
;

QUALITY=
```

0.92	0.89	0.83	0.86	0.95
0.77	0.87	0.87	0.74	0.82
1.00	0.86	0.83	0.90	0.85
0.65	0.76	0.66	0.85	0.81
0.94	0.94	0.96	0.97	0.92
0.87	0.86	0.85	0.86	0.89
0.97	0.95	0.84	0.93	0.93
0.86	0.93	1.00	0.85	0.90
0.92	0.97	0.93	1.00	0.92
0.83	0.85	0.81	0.93	0.93
0.89	0.81	0.94	0.95	0.93

```
;

DELIVERY=
```

0.93	0.95	0.98	0.92	0.95
0.96	0.95	0.93	0.93	0.96
0.82	0.99	0.93	0.87	0.95
0.76	0.94	0.88	0.93	0.87
0.86	0.94	0.96	0.92	0.82
1.00	0.95	0.96	0.99	0.99
0.95	0.98	0.96	0.99	1.00

0.93	0.96	1.00	0.97	0.96
0.93	0.98	0.91	0.90	1.00
0.99	0.93	0.95	0.98	0.99
0.98	0.98	0.97	0.95	0.98

;

CAPACITY=

4500	5000	4500	4500	1000
4000	6200	2500	8000	4500
1500	5000	4800	5000	2350
1400	6400	2200	4500	4500
7500	3000	3750	3500	3000
7500	1500	6000	3250	6000
7250	5500	2000	5500	4500
4500	5500	10000	10000	2000
10000	10000	10000	7500	6000
5500	5500	5500	8000	8000
2000	8000	7000	2000	5500

;

SPV=
-0.1092
-0.3986
-0.2983
-0.1867
-0.2896
0.0121
0.2955
0.2627
0.441
0.3114
-0.0402

;

DEMAND=

15000	22000	28000	12500	14000

;

```
ENDDATA

!objective function;

MAX=TOTALSPV;
MAX=TOTALQUALITY;
MAX=TOTALDELIVERY;
MIN=TOTALPRICE;

!Zimmerman's max-min approach;
MAX = LAMDA;
LAMDA<=1;

!Additive approach;
MAX= LAMDA1+LAMDA2+LAMDA3+LAMDA4;
LAMDA1<=1;
LAMDA2<=1;
```

```
LAMDA3<=1;
LAMDA4<=1;

LAMDA1=((TOTALSPV-3672.9)/(32644.76-3672.9));
LAMDA2=((TOTALQUALITY-82155)/(87670-82155));
LAMDA3=((TOTALDELIVERY-86422.5)/(90257.5-86422.5));
LAMDA4=((1153910-TOTALPRICE)/(1153910-789131.5));


!Tiwari et al.'s weighted additive approach;
MAX=0.4*LAMDA1+0.3*LAMDA2+0.2*LAMDA3+0.1*LAMDA4;
LAMDA1<=1;
LAMDA2<=1;
LAMDA3<=1;
LAMDA4<=1;

LAMDA1=((TOTALSPV-3672.9)/(32644.76-3672.9));
LAMDA2=((TOTALQUALITY-82155)/(87670-82155));
LAMDA3=((TOTALDELIVERY-86422.5)/(90257.5-86422.5));
LAMDA4=((1153910-TOTALPRICE)/(1153910-789131.5));

!Chan and Tsai's approach;
MAX= LAMDA1+LAMDA2+LAMDA3+LAMDA4;

LAMDA1>=LAMDA2;
LAMDA2>=LAMDA3;
LAMDA3>=LAMDA4;

LAMDA1<=1;
LAMDA2<=1;
LAMDA3<=1;
LAMDA4<=1;

LAMDA1=((TOTALSPV-3672.9)/(32644.76-3672.9));
LAMDA2=((TOTALQUALITY-82155)/(87670-82155));
LAMDA3=((TOTALDELIVERY-86422.5)/(90257.5-86422.5));
LAMDA4=((1153910-TOTALPRICE)/(1153910-789131.5));

!Lin's Approach;

MAX=LAMDA;
LAMDA1>=LAMDA*0.4;
LAMDA2>=LAMDA*0.3;
LAMDA3>=LAMDA*0.2;
LAMDA4>=LAMDA*0.1;

!Aköz and Petrovic's approach;

MAX=0.9*(LAMDA1+LAMDA2+LAMDA3+LAMDA4)+0.1*(LAMDAR1+LAMDAR2+LAMDAR3);

LAMDA1=((TOTALSPV-3672.9)/(32644.76-3672.9));
LAMDA2=((TOTALQUALITY-82155)/(87670-82155));
LAMDA3=((TOTALDELIVERY-86422.5)/(90257.5-86422.5));
LAMDA4=((1153910-TOTALPRICE)/(1153910-789131.5));

(LAMDA1-LAMDA2)>=LAMDAR1;
(LAMDA2-LAMDA3)>=LAMDAR2;
(LAMDA3-LAMDA4)>=LAMDAR3;

LAMDAR1<=1;
LAMDAR2<=1;
LAMDAR3<=1;
```

```
LAMDA1<=1;
LAMDA2<=1;
LAMDA3<=1;
LAMDA4<=1;

@SUM(SET1(I,J):PRICE(I,J)*X(I,J))=TOTALPRICE;
@SUM(SET1(I,J):QUALITY(I,J)*X(I,J))=TOTALQUALITY;
@SUM(SET1(I,J):DELIVERY(I,J)*X(I,J))=TOTALDELIVERY;
@SUM(SET1(I,J):SPV(I)*X(I,J))=TOTALSPV;

!System Constraints;

@FOR(PRODUCTS(J):@SUM(SUPPLIER(I):X(I,J))=DEMAND(J));
@FOR(SET1(I,J):X(I,J)<=CAPACITY(I,J));
@FOR(SET1(I,J):Y(I,J)*100000>=X(I,J));
@FOR(SET1(I,J):(Y(I,J)*0.10*DEMAND(J))<=X(I,J));
@FOR(PRODUCTS(J):@SUM(SUPPLIER(I):Y(I,J))>=2);
@FOR(SET1(I,J):@BIN(Y(I,J)));

END
```

B.2 LINGO CODE FOR THE ORDER ALLOCATION CASE II

```
SETS:
MODELS/1..14/;
NODES/1..9/;

SUPPLIERS/1..8/:Q, W;

SUPPLIERS1/1..3/:TK21,TT1,TY1,TCOST1;
SUPPLIERS2/1..3/:TK22,TT2,TY2,TCOST2;
SUPPLIERS3/1..4/:TK23,TT3,TY3,TCOST3;
SUPPLIERS4/1..3/:TK24,TT4,TY4,TCOST4;
SUPPLIERS5/1..4/:TK25,TT5,TY5,TCOST5;
SUPPLIERS6/1..3/:TK26,TT6,TY6,TCOST6;
SUPPLIERS7/1..3/:TK27,TT7,TY7,TCOST7;
SUPPLIERS8/1..3/:TK28,TT8,TY8,TCOST8;
SUPPLIERS9/1..3/:TK29,TT9,TY9,TCOST9;
SUPPLIERS10/1..4/:TK210,TT10,TY10,TCOST10;
SUPPLIERS11/1..3/:TK211,TT11,TY11,TCOST11;
SUPPLIERS12/1..4/:TK212,TT12,TY12,TCOST12;
SUPPLIERS13/1..3/:TK213,TT13,TY13,TCOST13;
SUPPLIERS14/1..3/:TK214,TT14,TY14,TCOST14;
MONTHS/1..6/:DEMANDMOD1,DEMANDMOD2,DEMANDMOD3,DEMANDMOD4,DEMANDMOD5,
DEMANDMOD6,DEMANDMOD7,DEMANDMOD8,DEMANDMOD9,DEMANDMOD10,DEMANDMOD11,
DEMANDMOD12,DEMANDMOD13,DEMANDMOD14;
ARC1(SUPPLIERS1,MONTHS):X1,Y1;
ARC2(SUPPLIERS2,MONTHS):X2,Y2;
ARC3(SUPPLIERS3,MONTHS):X3,Y3;
ARC4(SUPPLIERS4,MONTHS):X4,Y4;
ARC5(SUPPLIERS5,MONTHS):X5,Y5;
ARC6(SUPPLIERS6,MONTHS):X6,Y6;
ARC7(SUPPLIERS7,MONTHS):X7,Y7;
ARC8(SUPPLIERS8,MONTHS):X8,Y8;
ARC9(SUPPLIERS9,MONTHS):X9,Y9;
ARC10(SUPPLIERS10,MONTHS):X10,Y10;
ARC11(SUPPLIERS11,MONTHS):X11,Y11;
ARC12(SUPPLIERS12,MONTHS):X12,Y12;
ARC13(SUPPLIERS13,MONTHS):X13,Y13;
ARC14(SUPPLIERS14,MONTHS):X14,Y14;
```

```
ARC15(NODES,MODELS,MONTHS):SA,SE;
ENDSETS
DATA:
      W=  -0.2838 0.0273 0.4189 -0.0525 -0.0507 -0.0367 0.0614 -0.0840;


      DEMANDMOD1=39800  17914 0     2400  0     0 ;
      DEMANDMOD2=0      2130  69703 0     0     0 ;
      DEMANDMOD3=0      0     5400  3210  31668 23447 ;
      DEMANDMOD4=0      0     6693  750   0     0 ;
      DEMANDMOD5=1321   7399  18445 0     0     0 ;
      DEMANDMOD6=40030  50020 1200  2486  0     0 ;
      DEMANDMOD7=0      0     4119  2030  3036  0 ;
      DEMANDMOD8=0      0     0     0     14174 2323 ;
      DEMANDMOD9=0      1340  3927  37    0     0 ;
      DEMANDMOD10=0     0     0     31689 3097  1358 ;
      DEMANDMOD11=0     0     850   4495  0     0 ;
      DEMANDMOD12=0     1640  12583 6776  38497 27684 ;
      DEMANDMOD13=0     0     0     3150  6113  0 ;
      DEMANDMOD14=0     0     0     0     28810 8069 ;


      TK21=1.000 1.000 1.000;
      TK22=0.479 1.000 0.672;
      TK23=1.000 1.000 1.000 1.000;
      TK24=1.000 1.000 1 ;
      TK25=1.000  1.000 1.000 1.000;
      TK26=1.000 1.000 1.000;
      TK27=1.000 1.000 1.000;
      TK28=1.000 1.000 0.952;
      TK29=1.000 1.000 0.810;
      TK210=1.000  1.000 1.000 1.000;
      TK211=1.000 1.000 1;
      TK212=1.000 0.751 0.938 1.000 ;
      TK213=1.000 1.000 1.000;
      TK214=1.000 1.000 1.000;

      TT1=0.000 0.055 0.679;
      TT2=1.000 1.000 0.9;
      TT3=0.000 0.365 0.000 0.858;
      TT4=0.856   1.000 0.42;
      TT5=1.000   0.000 0.776 0.159;
      TT6=0.896   0.000 0.529;
      TT7=1.000   0.716 0.647;
      TT8=0.944   0.000 0.653;
      TT9=0.655   0.009 0.847 ;
      TT10=0.000  0.000 1.000 0.352;
      TT11=0.437  0.525 0.0;
      TT12=0.000  0.411 0.232 0.000;
      TT13=1.000  0.000 0.127 ;
      TT14=0.000  0.000 0.000;

      TCOST1=0.9751 1.0364 1.102;
      TCOST2=0.727 0.7575 0.965;
      TCOST3=1.4415 1.1212 1.326 1.4512;
      TCOST4=1.1 0.7638 0.99;
      TCOST5=0.7395 0.841 0.9 0.7214;
      TCOST6=0.85 0.6792 0.6342;
      TCOST7=1.1373 1.1764 1.000;
      TCOST8=0.7476 0.71 0.85 ;
      TCOST9=1.22 1.16 1.2475;
      TCOST10=1.1517  1.168 1.1545 1.1632;
```

```
      TCOST11=3.9318 4.215 4.52;
      TCOST12=1.05 0.98 1.1 1.03 ;
      TCOST13=1.4037 1.523 1.45;
      TCOST14=0.8277 0.7065 0.751;


ENDDATA

MAX=LAMDA;

LAMDA<=((PRO-120879.4)/(137195-120879.4));
LAMDA<=((TTQ-519569.2)/(529675.2-519569.2));
LAMDA<=((TTL-319056.3)/(346893-319056.3));
LAMDA<=((519819.8-TCOST)/(519819.8-496523.4));
LAMDA<=1;

PRO=@SUM(SUPPLIERS(I): W*Q);
TTQ=TQ1+TQ2+TQ3+TQ4+TQ5+TQ6+TQ7+TQ8+TQ9+TQ10+TQ11+TQ12+TQ13+TQ14;
TTL=TL1+TL2+TL3+TL4+TL5+TL6+TL7+TL8+TL9+TL10+TL11+TL12+TL13+TL14;
TCOST=TC1+TC2+TC3+TC4+TC5+TC6+TC7+TC8+TC9+TC10+TC11+TC12+TC13+TC14;

TC1=@SUM(SUPPLIERS1(I):TCOST1*TY1);
TC2=@SUM(SUPPLIERS2(I):TCOST2*TY2);
TC3=@SUM(SUPPLIERS3(I):TCOST3*TY3);
TC4=@SUM(SUPPLIERS4(I):TCOST4*TY4);
TC5=@SUM(SUPPLIERS5(I):TCOST5*TY5);
TC6=@SUM(SUPPLIERS6(I):TCOST6*TY6);
TC7=@SUM(SUPPLIERS7(I):TCOST7*TY7);
TC8=@SUM(SUPPLIERS8(I):TCOST8*TY8);
TC9=@SUM(SUPPLIERS9(I):TCOST9*TY9);
TC10=@SUM(SUPPLIERS10(I):TCOST10*TY10);
TC11=@SUM(SUPPLIERS11(I):TCOST11*TY11);
TC12=@SUM(SUPPLIERS12(I):TCOST12*TY12);
TC13=@SUM(SUPPLIERS13(I):TCOST13*TY13);
TC14=@SUM(SUPPLIERS14(I):TCOST14*TY14);


Q(1)= @SUM(MONTHS(K):Y1(1,K))+ @SUM(MONTHS(K):Y8(2,K))+
@SUM(MONTHS(K):Y9(1,K))+ @SUM(MONTHS(K):Y10(2,K))+
      @SUM(MONTHS(K):Y11(3,K));
Q(2)= @SUM(MONTHS(K):Y1(2,K))+ @SUM(MONTHS(K):Y2(1,K))+
@SUM(MONTHS(K):Y4(2,K))+ @SUM(MONTHS(K):Y9(2,K))+
      @SUM(MONTHS(K):Y12(4,K))+ @SUM(MONTHS(K):Y13(3,K));
Q(3)= @SUM(MONTHS(K):Y1(3,K))+ @SUM(MONTHS(K):Y2(2,K))+
@SUM(MONTHS(K):Y3(4,K))+ @SUM(MONTHS(K):Y5(4,K))+
      @SUM(MONTHS(K):Y6(3,K)) + @SUM(MONTHS(K):Y7(3,K))+
@SUM(MONTHS(K):Y4(3,K));
Q(4)= @SUM(MONTHS(K):Y3(1,K))+
@SUM(MONTHS(K):Y5(1,K))+@SUM(MONTHS(K):Y8(1,K))+
@SUM(MONTHS(K):Y10(1,K))+
      @SUM(MONTHS(K):Y12(1,K))+@SUM(MONTHS(K):Y14(1,K));
Q(5)= @SUM(MONTHS(K):Y3(2,K))+ @SUM(MONTHS(K):Y6(1,K)) +
@SUM(MONTHS(K):Y7(1,K))+@SUM(MONTHS(K):Y12(2,K))+
      @SUM(MONTHS(K):Y13(2,K));
Q(6)= @SUM(MONTHS(K):Y3(3,K))+ @SUM(MONTHS(K):Y5(3,K))+
@SUM(MONTHS(K):Y6(2,K)) + @SUM(MONTHS(K):Y7(2,K))+
      @SUM(MONTHS(K):Y10(4,K))+ @SUM(MONTHS(K):Y12(3,K)) +
@SUM(MONTHS(K):Y14(3,K))+ @SUM(MONTHS(K):Y2(3,K))+
      @SUM(MONTHS(K):Y9(3,K));
Q(7)= @SUM(MONTHS(K):Y4(1,K))+ @SUM(MONTHS(K):Y5(2,K))+
@SUM(MONTHS(K):Y11(1,K))+@SUM(MONTHS(K):Y13(1,K));
```

```
Q(8)= @SUM(MONTHS(K):Y10(3,K))+ @SUM(MONTHS(K):Y11(2,K)) +
@SUM(MONTHS(K):Y14(2,K))+ @SUM(MONTHS(K):Y8(3,K));

@FOR(SUPPLIERS1(I): TY1(I)=@SUM(MONTHS(K):Y1(I,K)));
@FOR(SUPPLIERS2(I): TY2(I)=@SUM(MONTHS(K):Y2(I,K)));
@FOR(SUPPLIERS3(I): TY3(I)=@SUM(MONTHS(K):Y3(I,K)));
@FOR(SUPPLIERS4(I): TY4(I)=@SUM(MONTHS(K):Y4(I,K)));
@FOR(SUPPLIERS5(I): TY5(I)=@SUM(MONTHS(K):Y5(I,K)));
@FOR(SUPPLIERS6(I): TY6(I)=@SUM(MONTHS(K):Y6(I,K)));
@FOR(SUPPLIERS7(I): TY7(I)=@SUM(MONTHS(K):Y7(I,K)));
@FOR(SUPPLIERS8(I): TY8(I)=@SUM(MONTHS(K):Y8(I,K)));
@FOR(SUPPLIERS9(I): TY9(I)=@SUM(MONTHS(K):Y9(I,K)));
@FOR(SUPPLIERS10(I): TY10(I)=@SUM(MONTHS(K):Y10(I,K)));
@FOR(SUPPLIERS11(I): TY11(I)=@SUM(MONTHS(K):Y11(I,K)));
@FOR(SUPPLIERS12(I): TY12(I)=@SUM(MONTHS(K):Y12(I,K)));
@FOR(SUPPLIERS13(I): TY13(I)=@SUM(MONTHS(K):Y13(I,K)));
@FOR(SUPPLIERS14(I): TY14(I)=@SUM(MONTHS(K):Y14(I,K)));


TQ1=@SUM(SUPPLIERS1(I):TK21*TY1);
TQ2=@SUM(SUPPLIERS2(I):TK22*TY2);
TQ3=@SUM(SUPPLIERS3(I):TK23*TY3);
TQ4=@SUM(SUPPLIERS4(I):TK24*TY4);
TQ5=@SUM(SUPPLIERS5(I):TK25*TY5);
TQ6=@SUM(SUPPLIERS6(I):TK26*TY6);
TQ7=@SUM(SUPPLIERS7(I):TK27*TY7);
TQ8=@SUM(SUPPLIERS8(I):TK28*TY8);
TQ9=@SUM(SUPPLIERS9(I):TK29*TY9);
TQ10=@SUM(SUPPLIERS10(I):TK210*TY10);
TQ11=@SUM(SUPPLIERS11(I):TK211*TY11);
TQ12=@SUM(SUPPLIERS12(I):TK212*TY12);
TQ13=@SUM(SUPPLIERS13(I):TK213*TY13);
TQ14=@SUM(SUPPLIERS14(I):TK214*TY14);


TL1=@SUM(SUPPLIERS1(I):TT1*TY1);
TL2=@SUM(SUPPLIERS2(I):TT2*TY2);
TL3=@SUM(SUPPLIERS3(I):TT3*TY3);
TL4=@SUM(SUPPLIERS4(I):TT4*TY4);
TL5=@SUM(SUPPLIERS5(I):TT5*TY5);
TL6=@SUM(SUPPLIERS6(I):TT6*TY6);
TL7=@SUM(SUPPLIERS7(I):TT7*TY7);
TL8=@SUM(SUPPLIERS8(I):TT8*TY8);
TL9=@SUM(SUPPLIERS9(I):TT9*TY9);
TL10=@SUM(SUPPLIERS10(I):TT10*TY10);
TL11=@SUM(SUPPLIERS11(I):TT11*TY11);
TL12=@SUM(SUPPLIERS12(I):TT12*TY12);
TL13=@SUM(SUPPLIERS13(I):TT13*TY13);
TL14=@SUM(SUPPLIERS14(I):TT14*TY14);



@FOR(MONTHS(K):(@SUM(SUPPLIERS1(I):Y1(I,K)))-DEMANDMOD1(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS2(I):Y2(I,K)))-DEMANDMOD2(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS3(I):Y3(I,K)))-DEMANDMOD3(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS4(I):Y4(I,K)))-DEMANDMOD4(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS5(I):Y5(I,K)))-DEMANDMOD5(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS6(I):Y6(I,K)))-DEMANDMOD6(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS7(I):Y7(I,K)))-DEMANDMOD7(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS8(I):Y8(I,K)))-DEMANDMOD8(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS9(I):Y9(I,K)))-DEMANDMOD9(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS10(I):Y10(I,K)))-DEMANDMOD10(K)=0);
```

```
@FOR(MONTHS(K):(@SUM(SUPPLIERS11(I):Y11(I,K)))-DEMANDMOD11(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS12(I):Y12(I,K)))-DEMANDMOD12(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS13(I):Y13(I,K)))-DEMANDMOD13(K)=0);
@FOR(MONTHS(K):(@SUM(SUPPLIERS14(I):Y14(I,K)))-DEMANDMOD14(K)=0);


@FOR(MONTHS(K):(Y3(1,K)+Y5(1,K)+Y8(1,K)+Y10(1,K)+Y12(1,K)+Y14(1,K))<
=50000);
@FOR(MONTHS(K):(Y4(1,K)+Y5(2,K)+Y11(1,K)+Y13(1,K))<=20833);
@FOR(MONTHS(K):(Y3(2,K)+Y6(1,K)+Y7(1,K)+Y12(2,K)+Y13(2,K))<=10000);
@FOR(MONTHS(K):(Y1(1,K)+Y8(2,K)+Y9(1,K)+Y10(2,K))<=8333);
@FOR(MONTHS(K):(Y10(3,K)+Y11(2,K)+Y14(2,K))<=12500);
@FOR(MONTHS(K):(Y3(3,K)+Y5(3,K)+Y6(2,K)+Y7(2,K)+Y10(4,K)+Y12(3,K)+Y1
4(3,K))<=83333);
@FOR(MONTHS(K):(Y1(2,K)+Y2(1,K)+Y4(2,K)+Y9(2,K)+Y12(4,K)+Y13(3,K))<=
70833);
@FOR(MONTHS(K):(Y1(3,K)+Y2(2,K)+Y3(4,K)+Y5(4,K)+Y6(3,K)+Y7(3,K))<=10
0000);


@FOR(MONTHS(K):(@SUM(SUPPLIERS1(I):X1(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS2(I):X2(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS3(I):X3(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS4(I):X4(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS5(I):X5(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS6(I):X6(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS7(I):X7(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS8(I):X8(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS9(I):X9(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS10(I):X10(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS11(I):X11(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS12(I):X12(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS13(I):X13(I,K)))=2);
@FOR(MONTHS(K):(@SUM(SUPPLIERS14(I):X14(I,K)))=2);



@FOR(ARC1(I,K)|DEMANDMOD1(K)#GT#0 :(240*X1(I,K)-Y1(I,K))<=0);
@FOR(ARC2(I,K)|DEMANDMOD2(K)#GT#0 :(210*X2(I,K)-Y2(I,K))<=0);
@FOR(ARC3(I,K)|DEMANDMOD3(K)#GT#0 :(540*X3(I,K)-Y3(I,K))<=0);
@FOR(ARC4(I,K)|DEMANDMOD4(K)#GT#0 :(75*X4(I,K)-Y4(I,K))<=0);
@FOR(ARC5(I,K)|DEMANDMOD5(K)#GT#0 :(130*X5(I,K)-Y5(I,K))<=0);
@FOR(ARC6(I,K)|DEMANDMOD6(K)#GT#0 :(120*X6(I,K)-Y6(I,K))<=0);
@FOR(ARC7(I,K)|DEMANDMOD7(K)#GT#0 :(200*X7(I,K)-Y7(I,K))<=0);
@FOR(ARC8(I,K)|DEMANDMOD8(K)#GT#0 :(230*X8(I,K)-Y8(I,K))<=0);
@FOR(ARC10(I,K)|DEMANDMOD10(K)#GT#0 :(130*X10(I,K)-Y10(I,K))<=0);
@FOR(ARC11(I,K)|DEMANDMOD11(K)#GT#0 :(85*X11(I,K)-Y11(I,K))<=0);
@FOR(ARC12(I,K)|DEMANDMOD12(K)#GT#0 :(160*X12(I,K)-Y12(I,K))<=0);
@FOR(ARC13(I,K)|DEMANDMOD13(K)#GT#0 :(310*X13(I,K)-Y13(I,K))<=0);
@FOR(ARC14(I,K)|DEMANDMOD14(K)#GT#0 :(800*X14(I,K)-Y14(I,K))<=0);

@FOR(ARC1(I,K): (500000*X1(I,K)-Y1(I,K))>=0);
@FOR(ARC2(I,K): (500000*X2(I,K)-Y2(I,K))>=0);
@FOR(ARC3(I,K): (500000*X3(I,K)-Y3(I,K))>=0);
@FOR(ARC4(I,K): (500000*X4(I,K)-Y4(I,K))>=0);
@FOR(ARC5(I,K): (500000*X5(I,K)-Y5(I,K))>=0);
@FOR(ARC6(I,K): (500000*X6(I,K)-Y6(I,K))>=0);
@FOR(ARC7(I,K): (500000*X7(I,K)-Y7(I,K))>=0);
@FOR(ARC8(I,K): (500000*X8(I,K)-Y8(I,K))>=0);
@FOR(ARC9(I,K): (500000*X9(I,K)-Y9(I,K))>=0);
@FOR(ARC10(I,K): (500000*X10(I,K)-Y10(I,K))>=0);
@FOR(ARC11(I,K): (500000*X11(I,K)-Y11(I,K))>=0);
```

```
@FOR(ARC12(I,K): (500000*X12(I,K)-Y12(I,K))>=0);
@FOR(ARC13(I,K): (500000*X13(I,K)-Y13(I,K))>=0);
@FOR(ARC14(I,K): (500000*X14(I,K)-Y14(I,K))>=0);

@FOR(ARC1(I,K):@BIN(X1(I,K)));
@FOR(ARC2(I,K):@BIN(X2(I,K)));
@FOR(ARC3(I,K):@BIN(X3(I,K)));
@FOR(ARC4(I,K):@BIN(X4(I,K)));
@FOR(ARC5(I,K):@BIN(X5(I,K)));
@FOR(ARC6(I,K):@BIN(X6(I,K)));
@FOR(ARC7(I,K):@BIN(X7(I,K)));
@FOR(ARC8(I,K):@BIN(X8(I,K)));
@FOR(ARC9(I,K):@BIN(X9(I,K)));
@FOR(ARC10(I,K):@BIN(X10(I,K)));
@FOR(ARC11(I,K):@BIN(X11(I,K)));
@FOR(ARC12(I,K):@BIN(X12(I,K)));
@FOR(ARC13(I,K):@BIN(X13(I,K)));
@FOR(ARC14(I,K):@BIN(X14(I,K)));

@FOR(ARC1(I,K):@GIN(Y1(I,K)));
@FOR(ARC2(I,K):@GIN(Y2(I,K)));
@FOR(ARC3(I,K):@GIN(Y3(I,K)));
@FOR(ARC4(I,K):@GIN(Y4(I,K)));
@FOR(ARC5(I,K):@GIN(Y5(I,K)));
@FOR(ARC6(I,K):@GIN(Y6(I,K)));
@FOR(ARC7(I,K):@GIN(Y7(I,K)));
@FOR(ARC8(I,K):@GIN(Y8(I,K)));
@FOR(ARC9(I,K):@GIN(Y9(I,K)));
@FOR(ARC10(I,K):@GIN(Y10(I,K)));
@FOR(ARC11(I,K):@GIN(Y11(I,K)));
@FOR(ARC12(I,K):@GIN(Y12(I,K)));
@FOR(ARC13(I,K):@GIN(Y13(I,K)));
@FOR(ARC14(I,K):@GIN(Y14(I,K)));

END
```

APPENDIX C
SOLUTION RESULTS OF DIFFERENT FUZZY GOAL PROGRAMMING APPROACHES FOR THE ORDER ALLOCATION CASE I

C1.The solution results of Zimmerman's approach

Objectives	Z_1=19828.61; Z_2= 85230.36; Z_3=88561.03; Z_4=950496.9				
Achievement Levels	μ_{z1} =0.558; μ_{z2} = 0.558; μ_{z3} = 0.558; μ_{z4} = 0.558				
X_{ij}	X(1, 3)	2800.000	Y_{ij}	Y(1, 3)	1
	X(3, 2)	2500.501		Y(3, 2)	1
	X(5, 3)	2800.000		Y(5, 3)	1
	X(6, 1)	3806.087		Y(6, 1)	1
	X(6, 3)	5942.728		Y(6, 3)	1
	X(7, 1)	7250.000		Y(7, 1)	1
	X(7, 2)	5500.000		Y(7, 2)	1
	X(8, 3)	10000.00		Y(8, 3)	1
	X(8, 4)	5000.000		Y(8, 4)	1
	X(8, 5)	2000.000		Y(8, 5)	1
	X(9, 1)	3943.913		Y(9, 1)	1
	X(9, 2)	10000.00		Y(9, 2)	1
	X(9, 4)	7500.000		Y(9, 4)	1
	X(9, 5)	6000.000		Y(9, 5)	1
	X(10, 2)	3999.499		Y(10, 2)	1
	X(10, 5)	1400.000		Y(10, 5)	1
	X(11, 3)	6457.272		Y(11, 3)	1
	X(11, 5)	4600.000		Y(11, 5)	1

C2.The solution results of the additive approach

Objectives	Z_1=21073.94; Z_2= 86271; Z_3=88495; Z_4=990056				
Achievement Levels	μ_{z1}=0.601; μ_{z2} = 0.746; μ_{z3} = 0.540; μ_{z4} = 0.449				
X_{ij}	X(3, 2)	2200.000	Y_{ij}	Y(3, 2)	1
	X(5, 3)	3750.000		Y(5, 3)	1
	X(6, 1)	6250.000		Y(6, 1)	1
	X(6, 4)	3250.000		Y(6, 4)	1
	X(7, 1)	7250.000		Y(7, 1)	1
	X(7, 2)	5500.000		Y(7, 2)	1
	X(8, 2)	4300.000		Y(8, 2)	1
	X(8, 3)	10000.00		Y(8, 3)	1
	X(8, 4)	1750.000		Y(8, 4)	1
	X(8, 5)	2000.000		Y(8, 5)	1
	X(9, 1)	1500.000		Y(9, 1)	1
	X(9, 2)	10000.00		Y(9, 2)	1
	X(9, 3)	7250.000		Y(9, 3)	1
	X(9, 4)	7500.000		Y(9, 4)	1
	X(9, 5)	6000.000		Y(9, 5)	1
	X(10, 5)	1400.000		Y(10, 5)	1
	X(11, 3)	7000.000		Y(11, 3)	1
	X(11, 5)	4600.000		Y(11, 5)	1

C3.The solution results of Tiwari et al.'s weighted additive approach

Objectives	Z_1=29349.35; Z_2= 86942.5; Z_3=87911; Z_4=1125538				
Achievement Levels	μ_{z1} =0.886; μ_{z2} = 0.868; μ_{z3} = 0.388; μ_{z4} = 0.078				
	X(5, 3)	2800.000		Y(5, 3)	1
	X(7, 1)	7250.000		Y(7, 1)	1
	X(7, 2)	5500.000		Y(7, 2)	1
	X(7, 4)	5000.000		Y(7, 4)	1
	X(8, 2)	4300.000		Y(8, 2)	1
	X(8, 3)	10000.00		Y(8, 3)	1
X_{ij}	X(9, 1)	7750.000	Yij	Y(9, 1)	1
	X(9, 2)	10000.00		Y(9, 2)	1
	X(9, 3)	10000.00		Y(9, 3)	1
	X(9, 4)	7500.000		Y(9, 4)	1
	X(9, 5)	6000.000		Y(9, 5)	1
	X(10, 2)	2200.000		Y(10, 2)	1
	X(10, 5)	8000.000		Y(10, 5)	1

C4.The solution results of Chen and Tsai's additive approach

Objectives	Z_1=24859.39; Z_2= 86188.00; Z_3=88277.11; Z_4=1019193				
Achievement Levels	μ_{z1} =0.731; μ_{z2} = 0.731; μ_{z3} = 0.484; μ_{z4} = 0.369				
	X(5, 3)	2800.000		Y(5, 3)	1
	X(6, 1)	6250.000		Y(6, 1)	1
	X(7, 1)	7250.000		Y(7, 1)	1
	X(7, 2)	5500.000		Y(7, 2)	1
	X(8, 2)	4300.000		Y(8, 2)	1
	X(8, 3)	10000.00		Y(8, 3)	1
	X(8, 4)	5000.000		Y(8, 4)	1
	X(8, 5)	2000.000		Y(8, 5)	1
X_{ij}	X(9, 1)	1500.000	Yij	Y(9, 1)	1
	X(9, 2)	10000.00		Y(9, 2)	1
	X(9, 3)	8200.000		Y(9, 3)	1
	X(9, 4)	7500.000		Y(9, 4)	1
	X(9, 5)	6000.000		Y(9, 5)	1
	X(10, 2)	2200.000		Y(10, 2)	1
	X(10, 5)	4060.960		Y(10, 5)	1
	X(11, 3)	7000.000		Y(11, 3)	1
	X(11, 5)	1939.040		Y(11, 5)	1

C5.The solution results of Lin's approach

Objectives	Z_1=29213.31; Z_2= 85801.35; Z_3=88112.89; Z_4=1073517			
Achievement Levels	μ_{z1} =0.882; μ_{z2} = 0.661; μ_{z3} = 0.441; μ_{z4} = 0.220			
	X(6, 3)	3082.181	Y(6, 3)	1
	X(7, 1)	7250.000	Y(7, 1)	1
	X(7, 2)	5500.000	Y(7, 2)	1
	X(8, 2)	4300.000	Y(8, 2)	1
	X(8, 3)	10000.00	Y(8, 3)	1
	X(8, 4)	5000.000	Y(8, 4)	1
	X(9, 1)	3164.597	Y(9, 1)	1
	X(9, 2)	10000.00	Y(9, 2)	1
	X(9, 3)	9506.881	Y(9, 3)	1
	X(9, 4)	7500.000	Y(9, 4)	1
	X(9, 5)	6000.000	Y(9, 5)	1
	X(10, 1)	4585.403	Y(10, 1)	1
	X(10, 2)	2200.000	Y(10, 2)	1
	X(10, 5)	8000.000	Y(10, 5)	1
	X(11, 3)	5410.939	Y(11, 3)	1

C6.The solution results of Aköz and Petrovic's approach

Objectives	Z_1=26663.43; Z_2= 86531.41; Z_3=88005.85; Z_4=1039683			
Achievement Levels	μ_{z1}=0.794; μ_{z2} = 0.794; μ_{z3} = 0.413; μ_{z4} = 0.313			
	X(3, 2)	2200.000	Y(3, 2)	1
	X(5, 3)	3097.037	Y(5, 3)	1
	X(7, 1)	7250.000	Y(7, 1)	1
	X(7, 2)	5500.000	Y(7, 2)	1
	X(8, 2)	4300.000	Y(8, 2)	1
	X(8, 3)	10000.00	Y(8, 3)	1
	X(8, 4)	5000.000	Y(8, 4)	1
	X(8, 5)	2000.000	Y(8, 5)	1
	X(9, 1)	7750.000	Y(9, 1)	1
	X(9, 2)	10000.00	Y(9, 2)	1
	X(9, 3)	7902.963	Y(9, 3)	1
	X(9, 4)	7500.000	Y(9, 4)	1
	X(9, 5)	6000.000	Y(9, 5)	1
	X(10, 5)	6000.000	Y(10, 5)	1
	X(11, 3)	7000.000	Y(11, 3)	1

APPENDIX D

DATA USED FOR THE ORDER ALLOCATION CASE II

D1. Ratio of accepted units of item *i* delivered by outsourcer *j* (K_{ij})

	Suppliers							
Items	1	2	3	4	5	6	7	8
1	1.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.479	1.000	0.000	0.000	0.672	0.000	0.000
3	0.000	0.000	1.000	1.000	1.000	1.000	0.000	0.000
4	0.000	1.000	1.000	0.000	0.000	0.000	1.000	0.000
5	0.000	0.000	1.000	1.000	0.000	1.000	1.000	0.000
6	0.000	0.000	1.000	0.000	1.000	1.000	0.000	0.000
7	0.000	0.000	1.000	0.000	1.000	1.000	0.000	0.000
8	1.000	0.000	0.000	1.000	0.000	0.000	0.000	0.952
9	1.000	1.000	0.000	0.000	0.000	0.810	0.000	0.000
10	1.000	0.000	0.000	1.000	0.000	1.000	0.000	1.000
11	1.000	0.000	0.000	0.000	0.000	0.000	1.000	1.000
12	0.000	1.000	0.000	0.751	0.938	1.000	0.000	0.000
13	0.000	1.000	0.000	0.000	1.000	0.000	1.000	0.000
14	0.000	0.000	0.000	1.000	0.000	1.000	0.000	1.000

D2. Ratio of units on-time of item *i* delivered by outsourcer *j* (L_{ij})

	Suppliers							
Items	1	2	3	4	5	6	7	8
1	0.000	0.055	0.679	0.000	0.000	0.000	0.000	0.000
2	0.000	1.000	1.000	0.000	0.000	0.9	0.000	0.000
3	0.000	0.000	0.000	0.365	0.000	0.858	0.000	0.000
4	0.000	0.856	1.000	0.000	0.000	0.000	0.42	0.000
5	0.000	0.000	1.000	0.000	0.000	0.776	0.159	0.000
6	0.000	0.000	0.896	0.000	0.000	0.529	0.000	0.000
7	0.000	0.000	1.000	0.000	0.716	0.647	0.000	0.000
8	0.944	0.000	0.000	0.000	0.000	0.000	0.000	0.653
9	0.655	0.009	0.000	0.000	0.000	0.847	0.000	0.000
10	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.352
11	0.437	0.000	0.000	0.000	0.000	0.000	0.525	0.0
12	0.000	0.000	0.000	0.411	0.232	0.000	0.000	0.000
13	0.000	1.000	0.000	0.000	0.000	0.000	0.127	0.000
14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

D3. Purchasing cost of item *i* delivered by outsourcer *j* ($Cost_{ij}$)

	Suppliers							
Items	1	2	3	4	5	6	7	8
1	0.9751	1.0364	1.1020	----------	----------	----------	----------	----------
2	----------	0.7270	0.7575	----------	----------	0.9650	----------	----------
3	----------	----------	1.4415	1.1212	1.3260	1.4512	----------	----------
4	----------	1.1000	0.7638	----------	----------	----------	0.9900	----------
5	----------	----------	0.7395	0.8410	----------	0.9000	0.7214	----------
6	----------	----------	0.8500	----------	0.6792	0.6342	----------	----------
7	----------	----------	1.1373	----------	1.1764	1.0000	----------	----------
8	0.7476	----------	----------	0.7100	----------	----------	----------	0.8500
9	1.2200	1.1600	----------	----------	----------	1.2475	----------	----------
10	1.1517	----------	----------	1.1680	----------	1.1545	----------	1.1632
11	3.9318	----------	----------	----------	----------	----------	4.215	4.5200
12	----------	1.0500	----------	0.9800	1.1000	1.0300	----------	----------
13	----------	1.4037	----------	----------	1.5230	----------	1.4500	----------
14	----------	----------	----------	0.8277	----------	0.7065	----------	0.7510

D4. Quantity demanded of item *i* in month *k*

	Months					
Items	1	2	3	4	5	6
1	39800	17914	0	2400	0	0
2	0	2130	69703	0	0	0
3	0	0	5400	3210	31668	23447
4	0	0	6693	750	0	0
5	1321	7399	18445	0	0	0
6	40030	50020	1200	2486	0	0
7	0	0	4119	2030	3036	0
8	0	0	0	0	14174	2323
9	0	1340	3927	37	0	0
10	0	0	0	31689	3097	1358
11	0	0	850	4495	0	0
12	0	1640	12583	6776	38497	27684
13	0	0	0	3150	6113	0
14	0	0	0	0	28810	8069

D5. Monthly capacity of supplier *j*

	Suppliers							
	1	2	3	4	5	6	7	8
Capacity	50000	20833	10000	8333	12500	83333	70833	100000

APPENDIX E

SOLUTION RESULTS FOR THE ORDER ALLOCATION CASE II

Objectives	Z_1=121348.4; Z_2= 519859.7; Z_3=319856.4; Z_4=519150.1				
Achievement Levels	μ_{z1} =0.834; μ_{z2} = 0.785; μ_{z3} = 0.855; μ_{z4} = 0.296				
X(1,2,1)	240.0000	X(7,3,2)	130.0000	X(10,8,4)	19274.00
X(1,2,2)	240.0000	X(7,3,3)	9103.000	X(10,8,5)	130.0000
X(1,2,4)	240.0000	X(6,3,1)	120.0000	X(10,8,6)	130.0000
X(1,3,1)	39560.00	X(6,3,2)	120.0000	X(11,1,3)	765.0000
X(1,3,2)	17674.00	X(6,3,3)	120.0000	X(11,1,4)	4410.000
X(1,3,4)	2160.000	X(6,3,4)	120.0000	X(11,7,3)	85.00000
X(2,2,2)	210.0000	X(6,6,1)	39910.00	X(11,7,4)	85.00000
X(2,2,3)	210.0000	X(6,6,2)	49900.00	X(12,4,3)	6426.000
X(2,3,2)	1920.000	X(6,6,3)	1080.000	X(12,4,4)	6616.000
X(2,3,3)	69493.00	X(6,6,4)	2366.000	X(12,4,5)	9260.000
X(3,4,3)	540.0000	X(7,3,3)	200.0000	X(12,4,6)	7621.000
X(3,4,4)	540.0000	X(7,3,4)	200.0000	X(12,5,2)	160.0000
X(3,4,5)	540.0000	X(7,3,5)	200.0000	X(12,5,6)	20063.00
X(3,4,6)	540.0000	X(7,6,3)	3919.000	X(12,6,2)	1480.000
X(3,6,3)	4860.000	X(7,6,4)	1830.000	X(12,6,3)	6156.000
X(3,6,4)	2670.000	X(7,6,5)	2836.000	X(12,6,4)	160.0000
X(3,6,5)	31128.00	X(8,1,5)	13944.00	X(12,6,5)	29237.00
X(3,6,6)	22907.00	X(8,1,6)	2093.000	X(13,2,4)	2840.000
X(4,3,3)	6618.000	X(8,8,5)	230.0000	X(13,2,5)	5803.000
X(4,3,4)	675.0000	X(8,8,6)	230.0000	X(13,7,4)	310.0000
X(4,7,3)	75.00000	X(9,6,2)	1340.000	X(13,7,5)	310.0000
X(4,7,4)	75.00000	X(9,6,3)	3927.000	X(14,6,5)	800.0000
X(5,3,1)	1191.000	X(9,6,4)	37.00000	X(14,6,6)	801.0000
X(5,3,2)	7269.000	X(10,6,4)	12415.00	X(14,8,5)	28010.00
X(5,3,3)	9342.000	X(10,6,5)	2967.000	X(14,8,6)	7268.000
X(7,3,1)	130.0000	X(10,6,6)	1228.000		