INTEGRATION OF QUALITY FUNCTION DEPLOYMENT WITH DATA ENVELOPMENT ANALYSIS FOR SUPPLIER EVALUATION

(TEDARİKÇİ DEĞERLENDİRMESİ İÇİN KALİTE FONKSİYONU YAYILIMI
İLE VERİ ZARFLAMA ANALİZİ ENTEGRASYONU)

by

Melih ECE, B.S.

Thesis

Submitted in Partial Fulfillment
of the Requirements
for the Degree of

MASTER of SCIENCE
in
INDUSTRIAL ENGINEERING
in the
INSTITUTE OF SCIENCE AND ENGINEERING
of
GALATASARAY UNIVERSITY

June 2013

INTEGRATION OF QUALITY FUNCTION DEPLOYMENT WITH DATA ENVELOPMENT ANALYSIS FOR SUPPLIER EVALUATION

(TEDARİKÇİ DEĞERLENDİRMESİ İÇİN KALİTE FONKSİYONU YAYILIMI İLE VERİ ZARFLAMA ANALİZİ ENTEGRASYONU)

by

Melih ECE, B.S.

Thesis

Submitted in Partial Fulfillment
of the Requirements
for the Degree of

MASTER of SCIENCE

Date of Submission : May 24, 2013

Date of Defense Examination: June 18, 2013

Supervisor : Asst. Prof. Dr. Zeynep ŞENER
Committee Members: Assoc. Prof. Dr. Y. Esra ALBAYRAK
Asst. Prof. Dr. Gönen EREN

Acknowledgments

This thesis has been result of numerous of hours spent on theoretical and practical findings. I would like to thank all of these people who supported me during my education in Galatasaray University.

First of all, I would like to express my gratitute to Prof. Dr. E. Ertuğrul KARSAK for introducing me to the topic as well for his contribution in this thesis.

Furthermore I would like to thank my supervisor Asst. Prof. Dr. Zeynep ŞENER for supporting me and for her time dedicated in my study.

Also, I like to thank Barış TUTAL, Mehmet SONGÜR and Onur ÖĞÜN who have willingly shared their experience during the investigation.

Special thanks to my brother Emre Burç ACAR who gives me a priceless friendship during my life. Without his support and courage, I would not accomplish this study.

Last but not at least, I owe more than thanks to my parents Hüsniye ECE and Ahmet ECE for their patience and encouragment throughout my life.

24/05/2013, Melih ECE

Table of Contents

List of Figures

List of Tables

Abstract

In today's competitive market environment, organizations aim to respond to the fast-changing needs of customers as soon as possible. In order to achieve this goal, supplier performaces also play a key role as well as company's own operations. Quality function deployment (QFD) is a technique which helps to meet the customer requirements in each step of supply chain by developing products and services for assuring the supplier satisfaction. This paper aims to propose a comprehensive methodology for supplier evaluation that enables customer requirements (CRs), buyer firm' s technical capabilities (TCs) and supplier characteristics (SCs) that companies request from suppliers to be taken into consideration. Data envelopment analysis (DEA) models are applied in three stages using the information from interrelated house of quality (HOQ) matrices and quantitative performance criteria to compute the efficiency scores of suppliers. The verbal assessments of decision makers are included in the decision process throughout the proposed methodology by utilizing the fuzzy set theory.

In the developed approach, evaluation criteria are derived from the customers requirements, technical capabilities of firm, and supplier characteristics using a series of house of quality matrices. House of quality matrix, which translates the customer requirements into technical attributes of company, has one the most widespread applications in QFD process. Qualitative assessments made by a joint evaluation of decision making team, are subsequently translated into mathematical expressions by utilizing from fuzzy set theory. Further, a special variant of DEA model, which can take into account crisp and fuzzy data, is introduced to determine the importance weights of criteria at each step and the performance ratings of suppliers at last.

Finally, the effectiveness of the proposed approach is supported by a real case study that pertains a pharmaceutical logistic company founded in Turkey. After the evaluation stage, managers individually arranged meetings with their suppliers to take corrective

actions considering the results of the proposed methodology. The initial improvements after taking corrective actions are presented throughout the case study.

Résumé

Dans l'environnement concurrentiel contemporain, le but des entreprises est de satisfaire le plutôt possible les besoins des clients qui peuvent se changer rapidement. Afin d'arriver à ce but, la performance des fournisseurs joue un rôle aussi important que la performance des opérations de l'entreprise lui-même. Le déploiement de la fonction qualité (DFQ) étant une technique qui est conçue pour développer des produits ou des services qui assurent la satisfaction du client, aide à satisfaire les besoins des clients à chaque étape de la chaine d'approvisionnement. Ce travail propose une approche pour l'évaluation des fournisseurs en tenant compte des besoins des clients, les compétences techniques de l'entreprise acheteuse et les exigences qu'on attend des fournisseurs. Afin de calculer le degré de performance des fournisseurs, des modèles de l'analyse de l'enveloppement des données (AED) qui comportent les informations et les données sur les critères de performance, sont utilisées dans un processus en trois étapes. L'évaluation subjective des décideurs est intégrée au modèle présenté à l'aide de l'utilisation de la théorie des sous-ensembles flous.

Dans ce travail, les critères d'évaluation des fournisseurs sont obtenues par les matrices successives du DFQ qui comportent les besoins des clients, les compétences techniques de l'entreprise acheteuse et les exigences qu'on attend des fournisseurs. La première matrice du DFQ, appelée la maison de qualité, qui traduit les besoins du client aux caractéristiques techniques est la matrice la plus utilisée dans le DFQ. Les évaluations subjectives des décideurs sont quantifiées et se sont agrégées à l'aide de la théorie des sous-ensembles flous. Ensuite, les critères se sont pondérés à chaque étape en utilisant les modèles de l'analyse de l'enveloppement des données.

Afin de présenter l'application de l'approche de décision proposée qui est basée sur les méthodes du déploiement de la fonction qualité et d'analyse de l'enveloppement des données, les fournisseurs d'une entreprise pharmaceutique-logistique se sont évalués en utilisant des données réelles. Les résultats obtenus sont présentés aux responsables de

l’entreprise qui ont organisé des réunions avec les fournisseurs pour déterminer les précautions d’assurance de qualité totale. Les premiers signes d’amélioration après l’établissement du nouveau plan sont présentés.

Özet

Günümüz rekabetçi iş çevresinde, işletmelerin amacı müşterilerin hızla değişen ihtiyaçlarını en kısa sürede karşılamaktır. Bu amacı gerçekleştirmede firmanın kendi operasyonlarının olduğu kadar tedarikçilerinin de performansı önemli rol oynamaktadır. Müşteri memnuniyetini sağlayacak ürün ve hizmetler geliştirmeye yönelik bir yöntem olan kalite fonksiyonu yayılımı (KFY) tedarik zincirinin her aşamasında müşteri beklentilerinin karşılanmasına yardımcı olmaktadır. Bu çalışma, müşteri ihtiyaçlarını, alıcı firmanın teknik becerilerini ve şirketlerin tedarikçilerden beklediği özellikleri ele alarak tedarikçi değerlendirmesi için kapsamlı bir yöntem sunmayı amaçlamaktadır. Tedarikçilerin verimliliklerini hesaplamak için veri zarflama analizi (VZA) modelleri birbirleriyle bağlantılı kalite evi matrislerindeki bilgileri ve niceliksel performans ölçütleri kullanılarak üç aşamalı bir şekilde uygulanmaktadır. Önerilen yöntemde karar vericilerin sözel değerlendirmelerinin karar sürecine dahil edilmesinde bulanık küme teorisinden yararlanılmaktadır.

Geliştirilen yaklaşımda, değerlendirme ölçütleri müşteri ihtiyaçlarının, firmanın teknik becerilerinin ve tedarikçi özelliklerinin bulunduğu seri halindeki kalite evi matrislerinden türetilmiştir. Müşteri beklentilerini teknik özelliklere dönüştüren kalite evi, KFY uygulamalarının en yaygın kullanılan matrisi olma özelliği taşımaktadır. Karar vericilerin yaptıkları farklı niteliksel değerlendirmeler bulanık küme teorisi yardımıyla sayısallaştırılarak birleştirilmiştir. Daha sonra, her bir aşamadaki ölçütlerin ağırlıkları ve son aşamada tedarikçilerin performans dereceleri, bulanık ve niceliksel verileri hesaba katabilen bir veri zarflama analizi modelinin yardımıyla elde edilmiştir.

Önerilen KFY ve VZA tabanlı karar verme yaklaşımının uygulanması amacıyla Türkiye’de kurulmuş olan bir ecza-lojistik firmasının tedarikçileri gerçek veriler kullanılarak değerlendirilmiştir. Elde edilen tedarikçi değerlendirme sonuçları firma yetkililerine iletilmiştir. Bu sonuçlar ışığında, alınabilecek ortak önleyici tedbirleri

belirlemek amacıyla ecza-lojistik firması yöneticileri tedarikçilerle birebir toplantılar düzenlemişlerdir. Alınan önlemlerin sağladığı ilk iyileşmelerden örnekler çalışmada verilmektedir.

1 INTRODUCTION

In today's turbulent business environment, organizations pursue to respond rapidly to the fast-changing needs of market. The action taking place even in an inconspicuous part of chain will increase the operational complexity across the whole supply chain network. Each organization buys materials from its upstream suppliers and acts as a supplier when it delivers products to downstream customers. At the same time, the global competition puts pressure on companies to achieve excellence in delivering low cost and high quality products to gain competitive advantages (Li & Zabinsky, 2011). In supply chains, the flow of materials is initiated by purchasing activities (Waters, 2003). Huang & Keska (2007) reported that the percentages of sales revenues spent on purchased materials varies from more than 80 percent in petroleum refining industry to 25 percent in pharmaceutical industry. Hence, the purchasing function is considered to a greater extent as a strategic issue in supply chain management.

One of the key objectives of purchasing research is to evaluate and select the right suppliers. Supplier evaluation and selection can be defined as the process through which suppliers are identified, evaluated, and negotiated on the basis of company' s requirements (Saen, 2007). Although the traditional purchasing was inclined to strike a bargain at the least cost, there have been progressive changes between companies and suppliers to establish more stable and durable relations with a specific group of suppliers in order to obtain significant cost savings and ongoing quality improvements. As an instance, Toyota expects a 3% reduction in costs each year from its suppliers (Monczka et al., 2008).

Over the last two decades, supplier evaluation and selection has been broadly studied and investigated by a number of researchers (Ho et al, 2010; Chai et al., 2013). In the current approach, supplier selection is regarded as a multi-criteria decision making

(MCDM) problem. MCDM deals with the evaluation and making a decision on a set of alternatives with respect to both tangible and intangible evaluating factors. Even though, in real life cases, cost seem to be the most distinctive factor comparing other criteria such as quality and delivery, the supplier selection problem is characterized by the presence of various amounts of decision factors and needs to make a trade-off between these tangible and intangible criteria in order to select the best supplier (Braglia and Petroni, 2000). Therefore, the analysis of the problem leads us to investigate and discover a novel solution methodology concerning the literature of decision-making methods which have been implemented in supplier selection problem by a myriad amount of researchers. Within the range of decision-making (DM) techniques implemented in supplier selection, data envelopment analysis (DEA) appears as one of the most powerful approaches, which was first developed by Charnes et al. (1974), to determine a set of optimal efficiency weights for decision making units (DMUs) with respect to the ratio of outputs they produce to inputs they consume. A typical multi-criteria decision making model is characterized as a central tendency approach and it evaluates suppliers' relative with respect to an average supplier, whereas DEA is an extreme point method and compares each supplier with only the "best" supplier. DEA is a non-parametric approach that allows efficiency to be measured without having to specify either the form of the function or the weights for different inputs and outputs chosen (Braglia & Petroni, 2000).

Under many conditions, human judgments including preferences are often vague and cannot be expressed using exact numerical values. When the data set lacks numerical values, linguistic variables are needed to represent the parameters. Linguistic assessments can be translated into mathematical expressions using fuzzy set theory (Zadeh, 1978).

Throughout supplier evaluation and selection process, firms are utilizing a variety of activities that include reducing number of suppliers, coordinating and consolidating to their suppliers, and re-configuring their existing supply base by selecting new high-performance suppliers. However, the level of customer satisfaction will determine the success or failure of any organization (Christopher, 2011). The challenge has risen to design supply chains from "customer backwards", instead of designing them from "factory outwards" (Christopher, 2011). The main reason to identify different responses of customers is to decide proper match between the firm and its suppliers that can suit the needs of customers and enhance their values to the firm (Chan, 2003). Therefore, firms should take into account customer requirements while analyzing the trade-off among several evaluation criteria of suppliers. Philips had lost about $40 million in sales, since they were not able to evaluate the trade-off between the utility of managing a few selected suppliers and the risk of fluctuating customer demands (Li & Zabinsky, 2011).

This study aims to propose a comprehensive methodology to evaluate the suppliers that allows for customer requirements (CRs), the technical capabilities of company (TCs), and further, supplier characteristics (SCs) that a company request from suppliers to be taken into consideration, and deploys this information throughout the supplier selection process. The proposed framework integrates quality function deployment (QFD) with DEA for supplier selection. QFD is not only a superior design tool to prioritize the attributes of a company, but it is also used as an evaluation technique to assess the supplier performances with respect to technical attributes of company and customer requirements. To establish the relevant supplier assessment criteria, we model a simple supply chain considering three levels in which three HOQ matrices represent the design of qualitative information. However, since HOQ is constituted on the basis of decision makers' subjective judgments, fuzzy logic deals with intrinsic qualitative nature of assessment. As a relative evaluation technique, DEA can incorporate both the information from QFD and quantitative evaluation factors of suppliers. In this paper, DEA is implemented in supplier evaluation using the data from the developed HOQs and quantitative factor components related to suppliers. The DEA model deploys various CRs, TCs and SCs from the HOQ matrices and tangible evaluation factors of suppliers as the output and input parameters for suppliers. The effectiveness of the proposed approach is supported by a real case study that pertains a pharmaceutical logistic company founded in Turkey. The objective of the case study is evaluating the logistic service provided by pharmaceutical companies from the point of view of hospitals, pharmacies and pharmaceutical logistics providers.

The rest of this study is organized in 6 sections. Section 2 provides a concise literature review about supplier evaluation and selection. In section 3, the basic QFD framework is presented. Section 4 briefly introduces DEA approach, and delineates the proposed decision- making framework employing DEA and QFD in section 5. In Section 6 the proposed approach is implementing using a real data set concerning supplier selection and results are thoroughly discussed. Finally, Section 7 contains the concluding remarks and future research directions.

2 LITERATURE REVIEW

In the past several decades, supplier evaluation and selection decision have received considerable attention in research literature and business perspectives (Dickson, 1966; Weber et al., 1991; De Boer et al., 2001; Ho et al., 2010; Chai et al., 2013). The problem has also been cited as *vendor selection decision* by some researchers (Talluri & Narasimhan, 2003; Chen & Huang, 2007).

Choosing the right suppliers is a complex and important facet of purchasing. As the complexity of selection process increases, it is increasingly difficult to recognize the steps prior to the final decision. To cover all phases of supplier selection process, De Boer et al. (2001) identified four critical steps as follows: (1) problem definition (2) formulation of criteria (3) qualification and (4) final selection.

Supplier evaluation and selection can be defined as the process through which suppliers are identified, evaluated, and negotiated on the basis of company' s requirements (Saen, 2007). Although the traditional purchasing is inclined to strike a bargain at single criterion (i.e. the least cost), the problem has been regarded as a multi-criterion decision making problem (Soukup, 1987; Weber et al., 1993; Seydel, 2006). The formulization of the MCDM problems is historically relied on at the end of nineteenth and the beginning of the twentieth century. The methodologies developed at that times tended to maximize their utility functions which were expressing the choices of customer and producer with respect to less contradictory criteria (Pomerol & Barba-Romero, 2000). By 1960, multi-criteria analysis is acquiring its own vocabulary and a number of methods have introduced in choosing one alternative in the presence of multiple criteria (Charnes & Cooper, 1961; Pomerol & Barba-Romero, 2000). In the supplier evaluation and selection problem, these substantial criteria are identified by a group of managers or experts in accordance with the organizational decision framework. Thereby, the supplier selection problem has become a group decision - making problem under multiple criteria (Chen et al., 2006).

Several decision factors on supplier evaluation and selection have been emphasized precisely by a number of researchers. In the mid-sixties, Dickson (1966) conducted a survey of 170 managers, to point out the critical evaluation criteria for vendor selection problem. According to 23 distinct supplier attributes (Table 2.1), Dickson (1966) concluded that quality, delivery, and performance history are the three most important criteria when choosing a supplier. In a later review by Weber et al. (1991) compiled 76 articles and considered some additional factors including geographical location, which regarded as more important than those selected by Dickson (1966). Weber et al. (1991) also addressed that 47 out of 76 researchers, in their review, used multiple criteria while developing a supplier selection methodology. Verma & Pullman (1998) investigated the importance of quality and addressed that the selection process is mostly based upon the bid price of suppliers.

Although criteria used for evaluating and selecting suppliers have been examined for decades, the recent researches have been made progress to reveal some new dimensions for particular types of problem such as environmental factors in green supplier selection (Kumar et al., 2014), imbedded uncertainty under the stochastic nature of selection (Wu, 2010), and social factors, including employment practices and local community, for sustainable supplier selection (Bai & Sarkis, 2010).

Several publications have appeared in the last decade documenting the decision techniques implemented into supplier selection problem. Ho et al. (2010) reviewed 78 articles mainly focusing on works published between years 2000 and 2008. They addressed the most popular individual and integrated approach adopted in supplier evaluation and selection problem. In a recent paper by Chai et al. (2013), the authors gathered and reviewed 123 articles published from 2008 to 2012. Their study summarized the application of 26 DM techniques and presented concluding remarks on the means of integrating these techniques for supplier selection.

Table 2.1
Evaluation criteria for supplier selection from Dickson (1966) and Weber(1991)

Evaluation Criteria	Dickson' s (1966) importance ranking	Weber' s (1991) importance	Reference quantity
Price	6	Very Important	61
Deliver on time	2	Very Important	44
Quality	1	Extremely Important	40
Equipment and Capability	5	Very Important	23
Geographic Location	20	Important	16
Technical Capability	7	Very Important	15
Management and Organization	13	Important	10
Industrial reputation	11	Important	8
Financial situation	8	Very Important	7
Historical performance	3	Very Important	7
Maintenance service	15	Important	7
Service attitude	16	Important	6
Packing ability	18	Important	3
Production control ability	14	Important	3
Training ability	22	Important	2
Procedure legality	9	Very Important	2
Employment relations	19	Important	2
Communication system	10	Very Important	2
Mutual negotiation	23	Important	2
Previous image	17	Important	2
Business relations	12	Important	1
Previous sales	21	Important	1
Guarantee and compensation	4	Very Important	0

Considering the practical complexity of final decision, the remainder of this section organized as follows. In sub-sections 2.1 and 2.2, a concise review of individual and integrated approaches for supplier selection will be presented respectively. Sub-section 2.3 provides a review of DEA model on supplier selection. Finally, sub-section 2.4 outlines the applications of QFD in supplier selection.

2.1 Individual Approaches

2.1.1 Multi-Attributed Decision Making Techniques

Multi-attributed decision making (MADM) can be referred as the methodological framework by which the decision maker is faced with making a choice among set of alternatives (also known as choice set, candidates or actions) while considering several points of view, called criteria, incorporated into decision process (Pomerol & Barba-Romero, 2000). To solve this decision problem, several researchers have proposed various techniques of MADM. As reported by Chai et al. (2013), we can classify these techniques into four categories on the basis of their principles behind decision-making: (1) multi-attribute utility methods such as AHP and ANP, (2) outranking methods such as Elimination and Choice Expressing Reality (ELECTRE) and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE); (3) compromise methods such as Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) and Multi-criteria Optimization and Compromise Solution (VIKOR), and (4) other MADM techniques such as Simple Multi-attribute Rating Technique (SMART) and Decision-Making Trial and Evaluation (DEMATEL)

2.1.1.1 AHP and ANP

Multi-attribute utility methods are essentially based on a utility function defined on the set of feasible alternatives. The decision maker wishes to assign an importance rating for each alternative through the utility values on each criterion (Martel, 1997). AHP and ANP are commonly well-known multi-attribute utility methodologies to solve the multi-criteria decision making (MCDM) problems (Pomerol & Barba-Romero, 2000).

AHP, introduced by Saaty (1977), is designed in a hierarchical structure. The hierarchical structure of AHP has a number of strategic levels containing the overall objective at the top, following by several numbers of criteria in intermediates, and at last, the lowest level of the hierarchy comprised of the choice set. Owing a large number of factors, the decision criteria are inherently decomposed into their sub-criteria that affect the final decision on alternatives. Using the pair-wise comparison matrices, the decision-maker undertakes comparison of alternatives independently for every criterion at each level. The same procedure is also applied to define the weights of each criteria (Liu & Hai, 2005). Employing multiple conflicting criteria and candidate suppliers in various levels of hierarchical design, the AHP method has individually found widespread application in supplier selection decision (Akarte et al., 2001; Muraladhiran et al., 2002; Chan 2003; Liu & Hai, 2005; Chan et al., 2007; Hou & Su, 2007; Levary 2008).

ANP was derived as a special case of AHP and can be used to deal with more sophisticated decision problems. Instead of constructing the hierarchical levels, the ANP technique spread out the decision factors on the strategic clusters in which interactions and feedbacks constitute the inner and outer dependency among the main criteria and their sub-divisions (Saaty, 1980). In ANP methodology, the decision maker uses a special variant of pair-wise comparison matrix, which is called supper matrix. Sarkis & Talluri (2002), Beyazit (2006), and Gencer & Gurpınar (2007) applied ANP models on supplier selection problem to select the most appropriate suppliers with respect to various evaluation criteria, which were classified into different kinds of clusters.

2.1.1.2 Outranking methods: ELECTRE and PROMETHE

The originality of the outranking decision process lies in the fact that the problem might not be completely known and that the comparison of alternatives are not fully compensatory (De Boer et al., 1998). An outranking relation is reflecting a partial relation S defined on the set of alternatives such that alternative x is at least as good as alternative y for a majority of criteria while there exists no criterion for which x is substantially less good than y, we can claim that '*x outranks y*' (abbreviated to $x\ S\ b$) (Pomerol & Barba-Romero, 2000). The ELECTRE method properly delineates this definition. Additionally, the PROMETHEE method includes the preference of decision makers to make a pair-wise comparison of actions.

De Boer et al. (1998) have primarily discussed the application of outranking methods in supplier selection decision. Liu and Zhang (2011) proposed an improved version of ELECTRE, called ELECTRE III, to solve the ranking problem of suppliers. Chen et al. (2011) employed the PROMETHEE technique for information system (IS) outsourcing under the application of a real case study.

2.1.1.3 Compromise methods: TOPSIS and VIKOR

The compromise solution denotes the feasible solution that is the closest to the ideal solution, and compromise means a mutual agreement established between ideal and anti-ideal. (Rao, 2007). Both TOPSIS and VIKOR is a kind of compromise technique used to identify the distance to the ideal solution. Conceptually the difference is that TOPSIS uses Euclidean distance (L_2-metric) to determine the overall performance of candidates, whereas L_p-metric normalization is used in VIKOR (Rao, 2007). As an alternative decision making tool, TOPSIS and VIKOR have received considerable attention in supplier selection researches (Chen & Wang, 2009; Chen, 2011; Shemshadi et al., 2011; Zeydan et al., 2011).

2.1.1.4 Other MADM methods: SMART and DEMATEL

SMART is one of the most practical ranking techniques that enclose the simple additive weighting method in order to obtain a composite performance score for each attribute and/or candidate. Barla (2003) discussed the SMART technique for reducing the supply base under the lean supply chain philosophy.

DEMATEL has a cause and effect structure, which uses matrices and diagrams to visualize the complicated relationships between critical factors. Buyukozkan & Ciftci (2012) used DEMATEL to determine the weights of evaluation criteria for the green supplier selection.

2.1.2 Mathematical Programming Techniques

Mathematical programming models tackle the multiple criteria decision-making problems in an objective manner, which is aiming to allocate the limited resources among comparable activities under a set of constraints imposed by the nature of problem (Degraeve et al., 2000). In order to determine the number of suppliers, optimum level of necessities, and several conflicting decisions supplier selection problem can be formulated as a mathematical programming model (Talluri & Narasminhan, 2003). MP formulations of supplier selection problem can be categorized as (i) Linear Programming (LP), (ii) Nonlinear Programming (NLP) (iii) Multiobjective Programming (MOP), (iv) Goal Programming (GP), and (v) Stochastic Programming (Chai et al., 2013). DEA is also included in MP techniques, and it will particularly be reviewed in sub-section 2.3.

2.1.2.1 Linear Programming (LP)

Linear programming models demonstrate the planning of activities to obtain an optimal result among all feasible alternatives. Linear programming demands that the objective function and constraints involve linear expressions (Hillier & Lieberman, 2005).

Several variants of linear programming model have provided satisfactory representations of supplier selection problem. Talluri & Narasminhan (2003,2005) developed two linear programming models to evaluate the worst and best performances of potential suppliers with respect to evaluation criteria of existing supply base. Ng (2008) proposed a weighted linear programming model for supplier selection. In some practical supplier selection problem, the decision units actually make sense only if they have integer values.

Hong et al. (2005) formulated a mixed-integer linear programming model in order to determine optimal order quantity as well as optimal number of suppliers in respect of changing customer needs over time periods.

2.1.2.2 Nonlinear Programming (NLP)

In contrast of LP, a key assumption of nonlinear programming is that some of the constraints or objective functions are nonlinear. There are many types of decision problem, depending on the characteristics of the nonlinear functions. Different NLP algorithms were used for the different types of supplier selection problem. For certain types of NLP models, the functions may take a simple form (Hsu et. al., 2010), on the other hand, for some types using integer variables, solving even small problems has become a real challenge (Ghodsypour & O'Brien, 2001). In a recent approach, Ventura et al. (2013) reformulated a MINLP model as integer LP problem model for the multi-period lot sizing and supplier selection problem.

2.1.2.3 Multi-objective Programming (MOP)

MOP technique has the ability to incorporate multiple objective functions over a set of feasible solutions. Relying on the multi-criterion nature of supplier selection problem, Narasminhan et al. (2006) developed MOP model in which five objective functions were aiming to determine optimal number of suppliers and order quantities regarding the cost, delivery, quality and complexity dimensions of decision process. Wadhwa & Ravindran (2007) applied MOP technique to vendor selection problem, in which three objective functions were used to minimize the quality (in terms of percentage of rejected items), lead time, and total cost of purchasing.

2.1.2.4 Goal Programming (GP)

Goal programming can be conceived as an extension of MOP. To acquire an optimal size of supply base, the targets of GP are assigned to different performance characteristics where the decision maker is interested in minimizing the set of deviations from these targets (Demirtas & Ustun, 2009). Karpak et al. (2001) presented a GP approach to evaluate and select suppliers in hydraulic pomp industry. Their model aimed to determine the trade-offs amongst three goals, including cost, quality, and delivery reliability while allocating optimal order quantity to the selected suppliers.

2.1.2.5 Stochastic Programming (SP)

SP is a strategic approach for decision problems characterized by uncertainty. The frameworks of SP models are delineated by the data, which are known or estimated by unknown parameters. Li & Zabinsky (2011) applied a two-phased stochastic programming model to determine the number of suppliers and optimal order quantities in order to deal with the uncertainty in customer demands. Kara (2011) employed a two-stage SP model to select suppliers and determine the flow amounts of goods under the uncertain demand conditions.

2.1.3 Artificial Intelligence Techniques

Computer methodology has attended various amounts of conductions to multi-criteria decision problems almost since the beginning (Pomerol & Barba-Romero, 2000). As the requirements and complexity of decision problems are increased, the existed methodologies may not perform the required calculations rapidly. To handle with this situation, AI can represent some sufficient numerical calculations to cope with the waste of time and lack of attention. Neural Networks (NN), Genetic Algorithm (GA), and Case-based Reasoning (CBR) are some of the well-known AI methodologies to tackle the supplier selection problems in which multitudinous transactions need to be concerned. Neural network and case-based reasoning analyze the decision process from a web site or a server such that the customer feedbacks constitute the requirements of an organization when monitoring the suppliers (Choy et al., 2003). Genetic algorithm is a heuristic method regarding that it cannot guarantee the optimal solutions. However, some type of supplier selection problems, which include integer variables and nonlinear objective functions, may need a limited solution time even if the optimality condition does not properly match (Aliabadi et al., 2013).

2.2 Integrated Approaches

Over the past decade, the decision-making techniques for supplier selection have gained a considerable amount of attention in research literature and business perspectives (Ho et al., 2010; Chai et al., 2013). The selection process has mainly involved evaluation of different suppliers based on a number of regenerated criteria (Onut et al., 2009). This has led the researchers to combine and explore some contemporary decision techniques with respect to new emerging criteria. It was noticed that there have been various integrated approaches for supplier selection.

Ho et al. (2010) reported that the integrated multiattribute utility methods, including AHP and ANP, have dominated other techniques due to their simplicity and effectiveness in ranking and task choice.

Cebi & Bayraktar (2003), for instance, proposed AHP-GP integration for supplier selection. Initially, A four-leveled AHP method was used to weight the supplier performances. Thereafter, the supplier ratings are employed in a GP model to select the best suppliers and determine the order quantities.

Kull & Talluri (2008) used a hybrid of AHP and GP to evaluate and select the suppliers with respect to risk factors and life cycle considerations. In the proposed model, AHP generated a risk score for each supplier within the fourteen potential risk sources. The GP model accommodated a set of multiple risk measures subjected several hard constraints in order to evaluate potential suppliers.

Ordoobadi (2010) developed a hybrid decision model that used AHP to determine the weight of criteria and Taguchi loss function to rank the suppliers.

In the integrated model of Demirtas & Ustun (2009), ANP was used to measure the relative importance ratings of suppliers with respect to fourteen evaluation criteria, whereas GP model is used for the optimization of quantity orders and supply base.

Another approach to solve the problem is artificial intelligence integrations. Choy et al. (2003) integrated neural network and case-based reasoning for supplier selection. Neural network was responsible for benchmarking the potential suppliers. After that, case based reasoning was used to analyze appropriate suppliers based on the previous experiences.

Apart from the formulated supplier selection problem under deterministic conditions, current studies address practical problems towards different types of uncertainties. Since fuzzy logic deals with intrinsic qualitative nature of selection, it can produce effective solutions while integrating it with powerful decision making techniques.

Kahraman et al. (2003) developed a fuzzy AHP model to evaluate and select the most suitable suppliers in a Turkish white goods manufacturing company.

Likewise Kahraman et al. (2003), Chan & Kumar (2007) used fuzzy AHP to select the best suppliers. Triangular fuzzy numbers demonstrated the linguistic assessments of decision makers.

Amid et al. (2009) provided a hybrid of fuzzy MOP model for supplier selection. The proposed decision model attempted to determine optimal order quantity for selected suppliers by considering the imprecision of the weighting issues.

Arikan (2013) developed a hybrid MOP method that considers cost minimization, quality and on time delivery maximization with fuzzy aspiration levels respectively.

Buyukozkan & Ciftci (2012) integrated three MADM techniques with fuzzy formulations: DEMATEL, TOPSIS and ANP for green supplier selection.

Kilic (2013) applied fuzzy TOPSIS to evaluate the importance weights of suppliers, and substantially, these weights are employed in a MOP model to determine the best suppliers and their order quantities.

Kannan et al. (2013) combined fuzzy AHP, fuzzy TOPSIS and MOP techniques to determine ranking of suppliers and allocate the optimum order quantity among the selected suppliers.

Masi et al. (2013) examined nine different approaches, including lowest price scoring model (SM), categorical methods (CMs), AHP, ANP, DEA, total cost of ownership (TCO), fuzzy set theory (FST), and MP in order to find an optimal selection technique with respect to the complexity of problem.

2.3 Data Envelopment Analysis for Supplier Selection

A review of supplier evaluation and selection literature reveals that DEA is one of the most popular approaches in supplier evaluation (Ho et al., 2010). DEA has been actively used in supplier selection due to its capability of handling multiple conflicting factors without the need of eliciting subjective importance weights from decision-makers.

Weber & Ellram (1992), Weber & Desai (1996), and Weber et al.(1998) have primarily discussed the applications of DEA in supplier selection.

Liu et al. (2000) presented the application of DEA for evaluating the overall performance of suppliers in a manufacturing firm.

Forker & Mendez (2001) implemented DEA to measure the comparative efficiencies of suppliers, and calculated cross-efficiencies to find the best peer suppliers.

Narasminhan et al (2001) proposed a framework based on DEA to evaluate alternative suppliers for a multinational corporation in the telecommunication industry.

Talluri & Sarkis (2002) presented a methodological extension of DEA by improving the discriminatory power of an existing variable returns to sclae model for the supplier performance evaluation and monitoring process.

Likewise Narasminhan et al. (2001), Talluri & Narasminhan (2004) employed DEA to measure the performance of suppliers. The only difference was that simple efficiency scores were used in the analysis.

Ross et al.(2006) used DEA to evaluate the supplier performance with respect to both buyer and supplier performance attributes.

Seydel (2006) modified DEA to incorporate weight constraints and used this approach to rank the available suppliers.

Saen (2006) implemented DEA for selecting the best supplier in the presence of both cardinal and ordinal data.

Saen (2008) developed a so-called imprecise DEA to evaluate the performance of suppliers. Further, in the context of same problem, Saen (2010) considered the undesirable outputs to interpret their uneconomic effects on the total efficiency.

Wu & Blackhurst (2009) introduced a weight restricted DEA model to reduce the chance of inappropriate input/output correspondence.

Toloo & Nalchigar (2011) proposed a different variant of DEA model for selecting the suppliers in conditions that both cardinal and ordinal data are deployed. Their approach, however, includes a binary variable set aiming to select the "best efficient" supplier, and thus, this contradicts the notion of production possibility set in DEA (Cooper et al., 2000).

In a recent approach, Falagario et al. (2012) applied cross efficiency DEA model on the problem of public procurement in which they regarded objectivity as more important than subjective judgments.

More recently, Kumar et al. (2014) developed a special variant of DEA model to evaluate the suppliers considering the dual role factors for green supplier selection.

Throughout supplier evaluation and selection process, DEA can be integrated with different kinds of methodologies to deal with the lacking input/output features of DMUs.

Weber et al (2000) integrated MOP and DEA to measure the efficiencies of suppliers as well as determine the optimal order quantities.

Ramanathan (2007), Saen (2007) and Sevkli et al. (2007) developed hybrid decision models which use AHP to derive the relative weights of criteria and DEA was deployed to calculate efficiency scores of suppliers.

Syedel (2005) applied SMART, which involves decision-maker preferences, and then evaluated the suppliers using DEA.

Garfamy (2006) compared suppliers based on DEA and total cost of ownership (TCO) concept.

Azadeh & Alem (2010) applied deterministic, fuzzy, and stochastic kinds of DEA model in order to observe the efficient suppliers under certain, uncertain and probabilistic decision environments.

Chen (2011) presented a hybrid model for supplier selection problem using DEA and TOPSIS methods. Instead of choosing suppliers, DEA was applied to qualify efficient supplier set.

Zeydan et al. (2011) used an approach integrating fuzzy ANP, fuzzy TOPSIS and DEA to select the efficient suppliers for an automobile company founded in Turkey.

Wu & Olson (2008a, 2008b) developed stochastic variants of DEA and discussed the conflicting criteria such as uncertainty, risk, and imbedded uncertainty in the supplier selection process.

2.4 Quality Function Deployment for Supplier Selection

Although QFD is not a novel method in the field of operations management, it has been recently used for supplier evaluation.

Bevilacqua et al. (2006) evaluated the potential suppliers against the relevant supplier assessment criteria using fuzzy QFD approach.

Ni et al. (2007) used a hybridization of QFD and data mining algorithm to understand the customer requirements in supplier selection process..

Bhattacharya et al. (2010) proposed an integrated AHP-QFD methodology to rank and subsequently select the candidate suppliers under multiple, conflicting nature of criteria environment.

Ho et al. (2011) developed a combined QFD and AHP approach to measure the performance of suppliers.

More recently, Dursun & Karsak (2013) implemented fuzzy set theory and QFD integration considering the vagueness of information in supplier selection problem. In their model, the information design related to evaluation criteria and candidate suppliers are represented through iterative HOQ matrices. The importance ratings of criteria and the supplier performance scores were evaluated by using fuzzy weighted average method. Further, a fuzzy number ranking method enabling to inconsistencies was applied to find the final rank of suppliers.

3 QUALITY FUNCTION DEPLOYMENT

Organizations have been focusing on pursuing higher quality for their products and services to maintain their competitive positions in global marketplace. Since Japanese manufacturers have changed the way of thinking about the development of new or improved products in a revolutionary way, companies operating in diverse industries have emphasized the importance of quality and customer demands in order to sharpen their competitive edges (Hauser & Clausing, 1988). Quality function deployment (QFD) plays an important role to link the customer requirements with engineering, manufacturing, service and other related functions of the company.

Quality Function Deployment (QFD) is the systematic translation of the "voice of the customer" (Griffin & Hauser, 1992) into activities of engineering characteristics, and subsequently part characteristics, process plans, and production requirements. In order to set up these relationships QFD usually requires four matrices each corresponding to a stage of the product development cycle. These are product planning, part deployment, process planning, and production/operation planning matrices respectively. The product-planning matrix, also called the house of quality (HOQ), can be named as the basic tool of QFD. This basic matrix can be expanded to provide additional insight to the companies and suppliers, and cascaded to identify process parameters that must be controlled to meet the customer requirements. There are many varieties of QFD, and many variations of the charts used. Figure 3.1 depicts an illustration of the nine elements of HOQ matrix structure (Karsak et al., 2003).

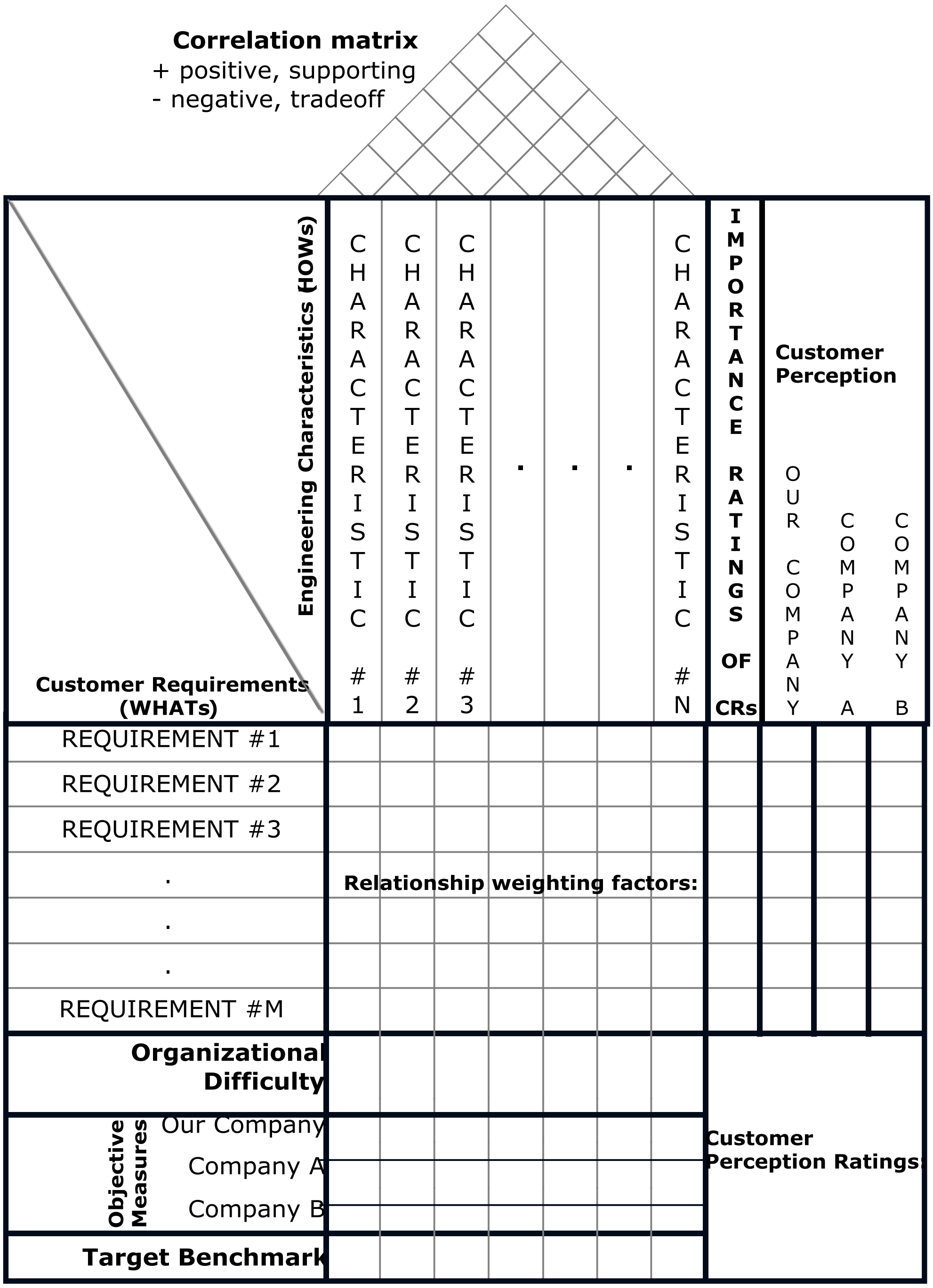


Figure 3.1 The initial structure of HOQ

Customer Requirements (WHATs): The building of the HOQ initially begins with the identification of the customer requirements (CRs). The customer requirements are generally reproduced in the customers' own words, and also known as "*voice of* *customer*" (Hauser & Clausing, 1988). As the initial input they highlight the engineering characteristics that should be taken into consideration.

Relative importance of the customer requirements: The decision-makers have to trade-off among different benefits of a product to supply customer more desirable finished goods. Project team members experience or survey with customers to relatively measure and weight the importance level of each customer requirement. At the product development stage, customer's voice is perceived in these *Importance Weights (IWs)* and can guide decision-makers to define the precedence of each benefit of a product.

Customer Perception: Companies principally want to know where they stand relative to their competitors. So on the right hand side of the house, the customer evaluations of the competitive companies are listed. This section of the house of quality provides a natural link from product concept to a company's strategic vision (Hauser & Clausing, 1988).

Engineering Characteristics (HOWs): To translate the customer requirements (WHATs) into the company's technical language, engineering characteristics are listed on the upper side of the HOQ. Engineering characteristics are also known as technical capabilities or design requirements. They describe the product in the language of engineer, and thus, are sometimes referred as the "*voice of company*" (Karsak et al., 2003). They are used to how well the company satisfies the customer requirements.

The relationship between each WHAT and HOW: The relationship matrix is established in the centre of the HOQ. The *Relationship Matrix* indicates that how much each engineering characteristic affects to each customer requirement. The relationships are specified by the judgments or the intuitions of the team members. The team uses symbols or numbers to establish the strength of these relationships. This step is crucial as it is used to make the transition from customer requirements into customer requirements.

Inner-dependence among engineering characteristics: *The Correlation Matrix* is established in the roof of the House of Quality, shows which EC affects each other by what direction. If there is a positive correlations between ECs, that means the ECs support each other whereas the negative correlations show that the ECs adversely affect each other. Again, a project team analyzes these positive/negative correlations by judging the success of the products in technical measurements.

Organizational Difficulty: Some users may impute the relative complexity to the engineering characteristics. They will establish that some technical procedure to accomplish an engineering characteristic is roughly difficult to consider another one.

Objective Measures: Once the team has identified the voice of customer and linked it to engineering characteristics, the objective measurements for the *overall priorities (OPs)* of engineering characteristics can be calculated. If customer evaluations of CRs do not correspond to objective measures of ECs then perhaps the measures are faulty or the product is suffering from a problem that is skewing customer perception (Hauser & Clausing, 1988).

Target Benchmark: When the team members calculate the overall priorities of ECs they will eventually move to establish target values to achieve an improvement. In setting targets, the team emphasizes the customer satisfaction values and not tolerance levels (Hauser & Clausing, 1988).

In this study, we speak of "voice of customer" because its measurement by QFD is drawing the individual departments of company together to understand clearly the customer's needs, and then to monitor the engineering characteristics of company on meeting those needs. Besides its ability to overcome obstacles in translating the customer requirements into product or service capabilities, QFD optionally involves constructing additional matrices which further guide the decisions that must be made throughout the product or service development process (Cohen, 1995). Once the House of Quality has been constructed, additional matrices can be connected to express the detailed decision that the development team has to make. The construction of the next matrix is started by placing all or the most important HOWs of the House of Quality on the left-hand side of the next matrix and their weights besides them. In this way the HOWs of the preceding matrix become the WHATs of the successor matrix and the weights of the HOWs from previous one become the importance degrees for the WHATs subsequently. Every matrix in the chain contains more detailed information concerning the product or service. Figure 3.2 illustrates the iterative procedure between two HOQ frameworks (Cohen, 1995).

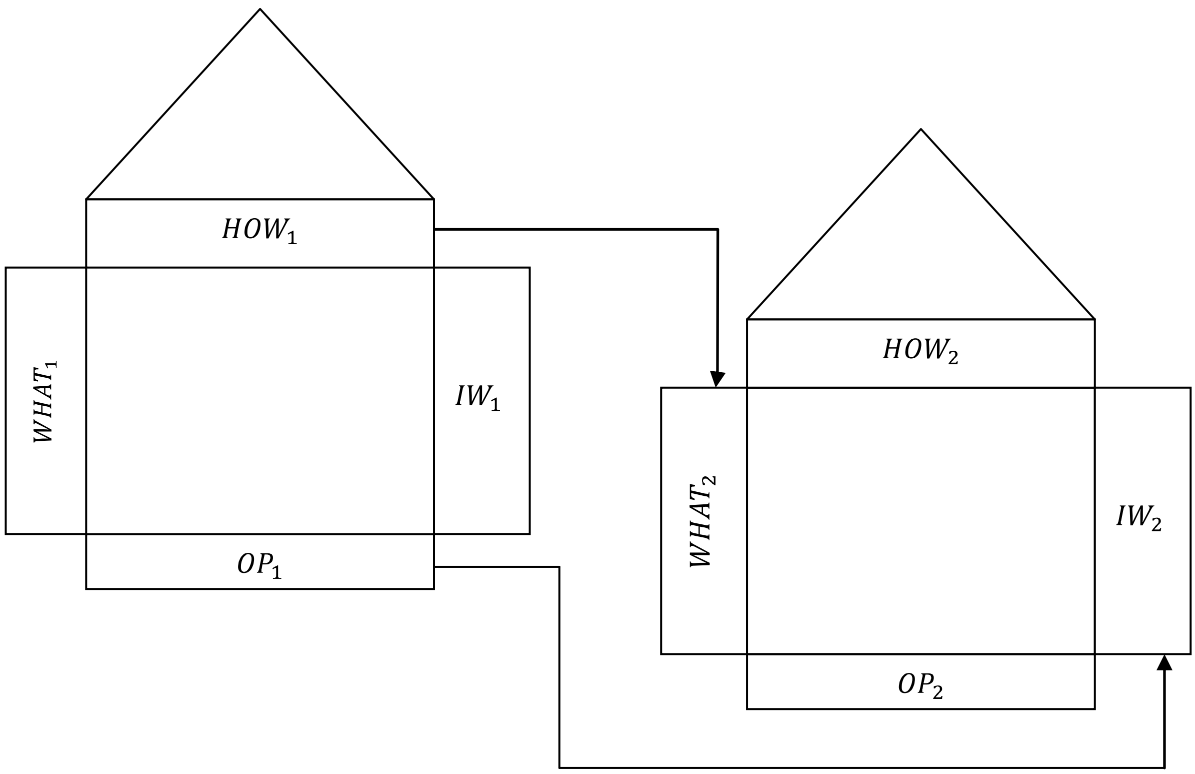


Figure 3.2 The iterative procedure between two HOQ frameworks

In a general QFD data survey, relative importance of WHATs are determined by decision-makers' linguistic expressions (eg. weak, average, strong). Then, these linguistic assessments scaled into crisp values (e.g. 1, 3, 5) or marked as different shapes or colors. However, the crisp values neglected the imprecision or vagueness of the linguistic types of expressions. Fuzzy set theory appears as a useful tool for quantifying linguistic terms such as 'around', 'approximately between', etc. that are commonly used in conveying the estimations of experts in the QFD team. Fuzzy set theory (Zadeh, 1978) is a powerful tool to help decision-makers to select proper alternatives in an imprecise environment. The key concept behind this definition is that of "membership": each element in a set is associated with a value indicating to what degree the element is a member of the set. This value comes within the range [0, 1], where 0 and 1, respectively, indicate the minimum and maximum degree of membership, while all the intermediate values indicate degrees of ‘‘partial’’ membership.

The symmetrical triangular fuzzy numbers are useful and computationally effective to quantify the verbal assessments of decision-makers. In this study, decision-makers use different verbal assessments to identify the relative importance of WHATs, and relationships between WHATs and HOWs in the HOQ matrices. Throughout each iterative HOQ matrix the linguistic judgments of decision-makers are transformed to symmetrical triangular fuzzy numbers. The triangular fuzzy numbers represented $\tilde{Q} = (q_1, q_2, q_3)$ with membership function given below:

$$\mu_{\tilde{Q}}(y) = \begin{cases} 0, & y < q_1 \\ \frac{y-q_1}{q_2-q_1}, & q_1 \leq y \leq q_2 \\ \\ \frac{q_3-y}{q_3-q_2}, & q_2 \leq y \leq q_3 \\ 0, & x \geq q_3 \end{cases} \tag{3.1}$$

When the symmetrical triangular fuzzy numbers are considered the ratios $\frac{y-q_1}{q_2-q_1}$, and $\frac{q_3-y}{q_3-q_2}$ become equal to each other. That means, the membership function value of $y \in [q_1, q_2]$ is same as $y \in [q_2, q_3]$. Therefore, the membership functions of symmetrical triangular fuzzy numbers are drawn as isosceles triangles (Figure 3.3).

More specifically, let U= (VL; L; M; H; VH) be a linguistic set used to express opinions on a group of attributes (VL=very low, L=low, M=medium, H=high, VH=very high). The linguistic variables of U can be quantified using symmetrical triangular fuzzy numbers as follows (Bevilacqua et al., 2006) :

VL=(0, 1, 2); L=(2, 3, 4); M=(4, 5, 6); H=(6, 7, 8); VH=(8, 9, 10).

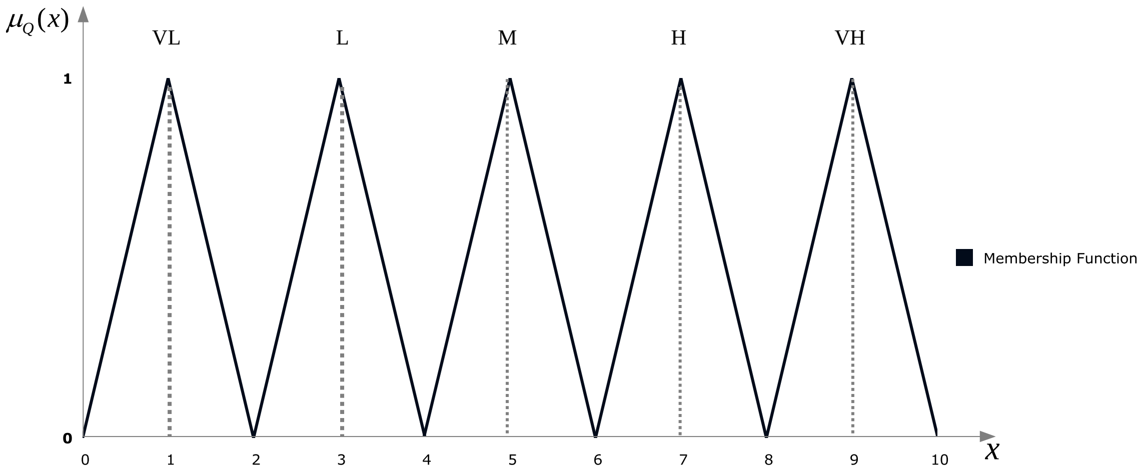


Figure 3.3 Membership function for triangular fuzzy numbers

If a decision-maker validates a criteria with linguistic assessment high (H), it represent as a symmetrical triangular fuzzy number with the pessimistic value $y^a = 6$, the optimistic value $y^c = 8$ and the most probabilistic value$y^b = 7$. To combine all the decision-makers' assessments on the same criteria, the method, proposed by Facchinetti et al. (1998), is applied. This method is described as follows by using the following fuzzy algebra operations:

Let $\tilde{A}_1 = (a_1, b_1, c_1)$ and $\tilde{A}_2 = (a_2, b_2, c_2)$ be 2 triangular fuzzy numbers: the equation (3.2) that describes the addition operator is as follows:

$$\tilde{A}_1 \oplus \tilde{A}_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \tag{3.2}$$

where a_1, b_1, c_1 and a_2, b_2, c_2 are real numbers. Let $\tilde{A}_i = (a_i, b_i, c_i)$ are to be triangular fuzzy numbers and $k \in R$ is a constant, where a_i, b_i, c_i are all positive real numbers for

i=1,…,n. Then the following equation represents the multiplication of a triangular fuzzy number with a constant:

$$k \otimes (\tilde{A}_1 \oplus \tilde{A}_2 \oplus \tilde{A}_3 \oplus \dots \dots \dots \oplus \tilde{A}_n) = \left(\sum_{i=1}^{n} ka_i , \sum_{i=1}^{n} kb_i , \sum_{i=1}^{n} kc_i \right) \tag{3.3}$$

Each decision-maker validates the level of relevance of the "WHATs" with different linguistic variable, i.e. very low, low, medium, high, very high (VL=very low, L=low, M=medium, H=high, VH=very high). The linguistic variables are translated to triangular fuzzy numbers by defining appropriate fitness functions:

The decision-makers' validations are combined using the average operator:

$WEIGHTS_{WHAT} = \{\widetilde{w_r}, where\ r = 1, \dots, s\}$,

$$\widetilde{w_r} = \frac{1}{z} \otimes (w_{r1} \oplus w_{r2} \oplus \dots \oplus w_{rz}) \tag{3.4}$$

Where s is the number of *WHATs* and z is the number of decision-makers. Here $\widetilde{w_r}$ denotes the weightings of $WHAT_r$ and represented as a triangular fuzzy number $\widetilde{w_r} = (w_{ra}, w_{rb}, w_{rc})$.

There must be some cohesion between HOWs and WHATs to analyze customer requirements according to company attributes. HOW-WHAT relation matrix is determined by decision-makers to visualize how company responds to customer requirements. Each decision-maker defines the importance level of the relationships WHATs and HOWs by assessing with linguistic variables. The members of relationship matrix are obtained from each decision-maker evaluation and expressed as a triangular fuzzy number as follows:

$RATING_{WHAT \times HOW} = \{\widetilde{y_{rj}}, where\ r = 1, \dots, s\ and\ j = 1, \dots, n\}$

$$\widetilde{y_{rj}} = \frac{1}{z} \otimes (y_{rj1} \oplus y_{rj2} \oplus \dots \oplus y_{rjz}) \tag{3.5}$$

Where s is the number of *WHATs*, n is the number of *HOWs* and z is the number of decision-makers. Here $\widetilde{y_{rj}}$ denotes the overall evaluation rating of HOW_j with respect to $WHAT_r$, and represented again as a triangular fuzzy number $\widetilde{y_{rj}} = \left(y_{rja}, y_{rjb}, y_{rjc}\right)$.

4 DATA ENVELOPMENT ANALYSIS

DEA is a mathematical programming technique proposed by Charnes et al. (1974) to relatively measure the performance of decision making units (DMUs) in the presence of multiple inputs and outputs. DMU implies that the unit of assessment transforming the resources into outcomes (Cooper et al., 2000). In DEA, inputs are referred as the resources that DMU utilize and outputs are the outcomes produced by DMU. The ratio of the outputs to input represents the performance indicator pertaining the unit being assessed and called the efficiency of DMU. DEA is a non-parametric approach, which avoids hypothesizing a functional dependency linking inputs and outputs while observing the unit of assessments (Braglia & Petroni, 2000). The basic idea underlying DEA is the production possibility set that contains all the input-output correspondences, which are feasible in assumption.

4.1 The Basic DEA Structure

DEA evaluates the relative efficiencies of DMUs with reference to some set of units being compared. The relative efficiency of a DMU is defined as the ratio of its total weighted output to the total weighted input. In mathematical programming terms, the objective function, which subjects to set of normalizing constraints, aims to maximize this weighted output-input ratio of the DMU being evaluated. The resulting fractional programming model is represented as follows:

$$Max\ E_{j_0} = \frac{\sum_r u_r y_{rj_0}}{\sum_i v_i x_{ij_0}}$$

subject to

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \leq 1, \qquad j = 1, \dots, n$$

$$u_r, v_i \geq \varepsilon > 0, \qquad r = 1, \dots, s\ ; i = 1, \dots, m. \tag{4.1.1}$$

where there are *n* number of DMUs, *m* inputs and *s* outputs totally. E_{j_0} is the efficiency score of the evaluated DMU_{j0} , u_r is the weight assigned to output *r*, v_i is the weight assigned to input *i*, y_{rj} represents the amount of output *r* produced by the DMU_j whereas x_{ij} denotes the amount of input *i* consumed by the j_{th} DMU, and ε is an infinitestimal positive number.

The objective function maximizes DMU_{j0}'s output input ratio by assigning u_r and v_i weights effectively. A relative efficiency score of DMU_{j0} is equal to one, means DMU_{j0} is efficient whereas less than one, means it is an inefficient DMU according to given input and output parameters. The normalization constraint ensures that all the optimal weights for the DMU in the objective function do not denote an efficiency score greater than unity either for the DMU itself or for the other DMUs, and the last constraints ensure the non-negativity of the output and input weights.

The fractional program is not preferable to compute the efficiency scores of DMUs due to the non-linear and non-convex properties (Charnes et al., 1978). Instead, it is reformulated as a linear programming program given below that is calculated separately for each DMU, generating *n* set of optimal weights.

$$Max\ E_{j_0} = \sum_r u_r y_{rj_0}$$

Subject to

$$\sum_i v_i x_{ij_0} = 1,$$

$$\sum_r u_r y_{rj} - \sum_i v_i x_{ij} \leq 0, \qquad j = 1, \dots, n$$

$$u_r, v_i \geq \varepsilon > 0, \qquad r = 1, \dots, s\ ; i = 1, \dots, m \tag{4.1.2}$$

The maximization of the discrimination among consecutive rank positions can be assured by using the maximum feasible value for ε, which can be determined by maximizing ε subject to the constraint set of formulation (4.1.2) for *j=1,..., n*, and then by defining $\varepsilon_{max} = min_j(\varepsilon_j)$.

4.2 DEA Model to Cope with Crisp and Fuzzy Data

The traditional DEA models evaluate the performance of decision making units by employing exact (i.e. *crisp*) input/output data. However, real-world problems can require trade-offs among multiple inputs and outputs that involve both qualitative and quantitative factors. This subsection presents a special variant of DEA model (Karsak, 2008) to deal with the decision problems which are in need of exact and imprecise information in their nature. Karsak (2008) extended imprecise DEA model of Despotis & Smirlis (2002) and this method described as follows:

Different types of fuzzy numbers have been employed to express the imprecise nature of the decision problem, but triangular fuzzy numbers are more explicative and practical in such circumstances that wide range of evaluation criteria and calculations are needed (Azadeh & Alem, 2010).

Let $x_{ij} = (x_{ij_a}, x_{ij_b}, x_{ij_c})$, for $0 \leq x_{ij_a} \leq x_{ij_b} \leq x_{ij_c}$, denote the triangular fuzzy input parameter i, used by DMU_j, and $y_{rj} = (y_{rj_a}, y_{rj_b}, y_{rj_c})$, for $0 \leq y_{rj_a} \leq y_{rj_b} \leq y_{rj_c}$, denote the triangular fuzzy output number r, produced by DMU_j, Let

$$(x_{ij})_\alpha^L = x_{ij_a} + \alpha_i(x_{ij_b} - x_{ij_a}), \alpha_i \in [0,1],$$

$$(x_{ij})_\alpha^U = x_{ij_c} - \alpha_i(x_{ij_c} - x_{ij_b}), \alpha_i \in [0,1],$$

$$(y_{rj})_\alpha^L = y_{rj_a} + \alpha_r(y_{rj_b} - y_{rj_a}), \alpha_r \in [0,1],$$

$$(y_{rj})_\alpha^U = y_{rj_c} - \alpha_r(y_{rj_c} - y_{rj_b}), \alpha_r \in [0,1],$$

Where $(x_{ij})_\alpha^L$ and $(x_{ij})_\alpha^U$ represent the lower and upper bounds of the α-cut of the membership function of $\tilde{x}_{ij}$, and similarly, $(y_{rj})_\alpha^L$ and $(y_{rj})_\alpha^U$ represent the lower and upper bounds of the α-cut of the membership function of $\tilde{y}_{ij}$. Let $\omega_i = v_i\alpha_i$ where $0 \leq \omega_i \leq v_i$. Then,

$\sum_i v_i(x_{ij})_\alpha^L$ and $\sum_i v_i(x_{ij})_\alpha^U$ denoted as:

$$\sum_i v_i(x_{ij})_\alpha^L = \sum_i v_i[x_{ij_a} + \alpha_i(x_{ij_b} - x_{ij_a})]$$

$$= \sum_i v_i x_{ij_a} + \omega_i(x_{ij_b} - x_{ij_a})$$

and

$$\sum_i v_i(x_{ij})_\alpha^U = \sum_i v_i[x_{ic} - \alpha_i(x_{ij_c} - x_{ij_b})]$$

$$= \sum_i v_i x_{ij_c} - \omega_i (x_{ij_c} - x_{ij_b})$$

Likewise, let$\mu_r = u_r \alpha_r$, where$0 \leq \mu_r \leq u_r$. Then,

$\sum_r u_r (y_{rj})_\alpha^L$ and $\sum_{\mathrm{r}} u_r (y_{rj})_\alpha^U$ are respectively represented as follows:

$$\sum_r u_r (y_{rj})_\alpha^L = \sum_r u_r \left[y_{rj_a} + \alpha_r \left(y_{rj_b} - y_{rj_a} \right) \right]$$

$$= \sum_r u_r y_{rj_a} + \mu_r (y_{ij_b} - y_{ij_a})$$

and

$$\sum_{\mathrm{r}} u_r (y_{rj})_\alpha^U = \sum_r u_r \left[y_{rj_c} - \alpha_r \left(y_{rj_c} - y_{rb} \right) \right]$$

$$= \sum_r u_r \, y_{rc} - \mu_r (y_{ij_c} - y_{ij_b})$$

Let $(E_{j_0})^L$ and $(E_{j_0})^U$ represent the upper and lower bounds of the α-cut of the membership function of the efficiency value for theDMU_{j_0}. Substituting parameters in the formulation (4.1.2) with new fuzzy input and output parameters, the optimistic scenario for the new DEA model becomes as follows:

$$maximize\ (E_{j_0})^U = \sum_{r\in C_R} u_r\, y_{rj0} + \sum_{r\in F_R} u_r\, y_{rj_{0c}} - \mu_r\big(y_{ij_{0c}} - y_{ij_{0b}}\big)$$

Subject to

$$\sum_{i\in C_I} v_i\, x_{ij0} + \sum_{i\in F_I} v_i\, x_{ij_{0a}} + \omega_i\big(x_{ij_{0b}} - x_{ij0_a}\big) = 1$$

$$\sum_{r\in C_R} u_r\, y_{rj0} + \sum_{r\in F_R} u_r\, y_{rj0c} - \mu_r\big(y_{ij0_c} - y_{ij_{0b}}\big)$$
$$-\sum_{i\in C_I} v_i\, x_{ij0} - \sum_{i\in F_I} v_i\, x_{ij_{0a}} + \omega_i\big(x_{ij_{0b}} - x_{ij_{0a}}\big) \le 0$$
$$\sum_{r\in C_R} u_r\, y_{rj} + \sum_{r\in F_R} u_r\, y_{rj_a} + \mu_r\big(y_{ij_b} - y_{ij_a}\big)$$
$$-\sum_{i\in C_I} v_i\, x_{ij} - \sum_{i\in F_I} v_i\, x_{ij_c} - \omega_i\big(x_{ij_c} - x_{ij_b}\big) \le 0,\ \ \forall_j,\quad j \ne j_0$$

$$\mu_r - u_r \le 0,\quad r \in F_R$$
$$\omega_i - v_i \le 0,\quad i \in F_I$$
$$\mu_r \ge 0,\quad r \in F_R$$

$$\omega_i \ge 0,\quad i \in F_I$$
$$u_r \ge \varepsilon > 0,\qquad r \in F_R, r \in C_R$$
$$v_i \ge \varepsilon > 0,\qquad i \in F_I, i \in C_I \tag{4.2.1}$$

Crisp inputs and outputs are exactly the same as in model (4.1.2), In addition to formulation (2), $F_R \subseteq R$ and $F_I \subseteq I$ represents the fuzzy output and input subsets respectively where R denotes the set of outputs ($F_R \cup C_R = R$) ,and I denotes the set of inputs ($F_I \cup C_I = I$). The formulation given above represents an optimistic scenario since the inputs and the outputs of the evaluated DMU are adjusted at the lower bounds and the upper bounds of the membership functions, respectively, whereas the inputs and outputs are adjusted unfavorably for the other DMUs, i.e., the inputs are adjusted at the upper bounds and the outputs are adjusted at the lower bounds (Karsak, 2008). On the contrary, when the inputs and the outputs of the evaluated DMU are adjusted respectively at the upper bounds and the lower bounds of the membership functions, and the inputs and outputs are adjusted favorably for the other DMUs in a way that the inputs are adjusted at the lower bounds and the outputs at the upper bounds, a pessimistic scenario DEA formulation is obtained as follows:

$$maximize\ \left(E_{j_0}\right)^L = \sum_{r\in C_R} u_r\, y_{rj0} + \sum_{r\in F_R} u_r\, y_{rj_{0a}} + \mu_r\left(y_{ij_{0b}} - y_{ij_{0a}}\right)$$

Subject to

$$\sum_{i\in C_I} v_i\, x_{ij0} + \sum_{i\in F_I} v_i\, x_{ij_{0c}} - \omega_i\left(x_{ij_{0c}} - x_{ij0_b}\right) = 1$$

$$\sum_{r\in C_R} u_r\, y_{rj0} + \sum_{r\in F_R} u_r\, y_{rj0a} + \mu_r\left(y_{ij0_b} - y_{ij_{0a}}\right)$$

$$-\sum_{i\in C_I} v_i\, x_{ij0} - \sum_{i\in F_I} v_i\, x_{ij_{0c}} - \omega_i\left(x_{ij_{0c}} - x_{ij_{0b}}\right) \le 0$$

$$\sum_{r\in C_R} u_r\, y_{rj} + \sum_{r\in F_R} u_r\, y_{rj_c} - \mu_r\left(y_{ij_c} - y_{ij_b}\right)$$

$$-\sum_{i\in C_I} v_i\, x_{ij} - \sum_{i\in F_I} v_i\, x_{ij_a} + \omega_i\left(x_{ij_b} - x_{ij_a}\right) \le 0,\ \ \forall_j, j \ne j_0$$

$$\mu_r - u_r \le 0,\quad r \in F_R$$

$$\omega_i - v_i \le 0,\quad i \in F_I$$

$$\mu_r \ge 0,\quad r \in F_R$$

$$\omega_i \ge 0,\quad i \in F_I$$

$$u_r \ge \varepsilon > 0,\qquad r \in R$$

$$v_i \ge \varepsilon > 0,\qquad i \in I \tag{4.2.2}$$

5 THE PROPOSED METHODOLOGY

Several researchers have emphasized that supplier evaluation and selection assists firms in reducing the costs related to purchasing, quality, delivery and services, and leading long-term relationships for their competitive advantage. Reaching an agreement between buyer and supplier is usually regarded as a challenging process mainly due to the deep concerns about the supplier's ability to meet the specific requirements of buyer (Beil, 2009). In essence, the entire organization gravitates toward customers who dominantly dictate the term of purchasing, hence, the selection process does not only involve the buyer and supplier relationships but also the customer expectations (Pamerol & Barba-Romero, 2000). Moreover, since the voice of customer is perceived in every function of the company related to manufacturing, purchasing managers cannot solely evaluate and select the suppliers, but other interrelated departments need to take part in the decision.

The decision framework presented in this study integrates QFD with data envelopment analysis (DEA) for supplier selection problem. The DEA model employs the information from developed HOQ matrices and additional quantitative evaluation criteria related to suppliers. The proposed method is apt to incorporate information from a group of decision-makers assessed using linguistic scales. Owing the subjective human judgments, triangular fuzzy numbers are used to express qualitative factors.

5.1 QFD-DEA Integration

In this study, DEA is used in conjunction with QFD to compute the efficiency scores of DMUs. The House of Quality constructs the central information design of this study. To establish the relevant evaluation framework, we model a multi-level supply chain considering P - stages in which HOQ matrices represent the qualitative factors information. DEA models are applied to in P - stages employing the data from HOQ matrices and quantitative evaluation criteria. Since the DEA models evaluate the decision making units independently, the correlation matrix of HOQ is not established throughout designing of the integrated decision matrices. In addition, organizational difficulties, customer perception and target values (Figure 3.1) are neglected in order that the proposed approach only considers the particular supply chain relationships across a single company (Figure 5.1.1).

Let $E_{jp_0}^{L}$ and $E_{jp_0}^{U}$ represent the upper and lower bounds of the α-cut of the membership function of the efficiency value for the DMU_{j_0} at stage p (p =1,…,P). Substituting parameters in the formulation (4.2.1) with new input and output parameters, the optimistic scenario at stage p for the new DEA model becomes as follows:

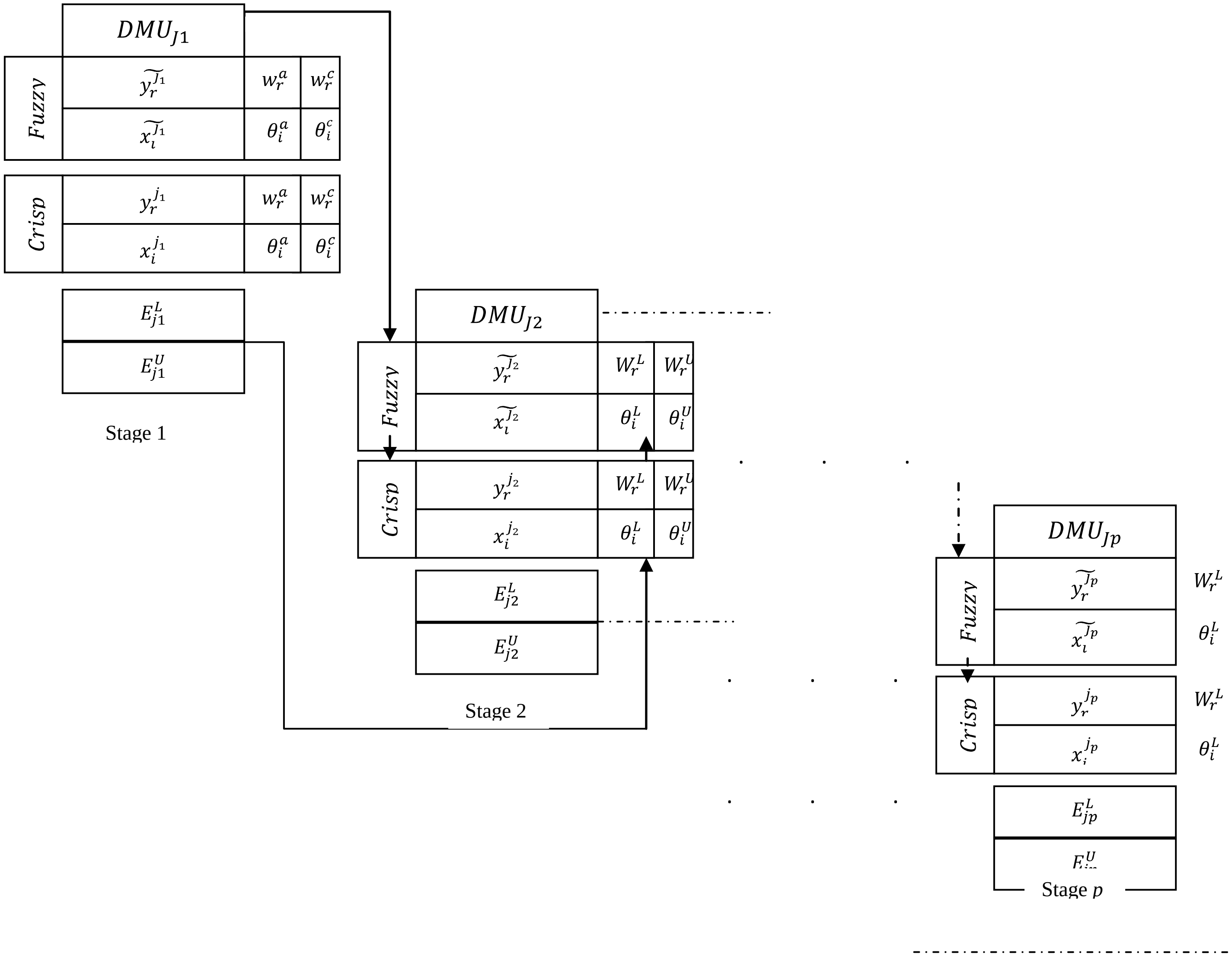


Figure 5.1.1 Information design of proposed decision framework

$$Maximize\ E^U_{j_{p0}} = \sum_{r\in C_{R_P}} u_r\, y_r^{j_{p0}} + \sum_{r\in F_{R_P}} u_r\, y_{rc}^{j_{p0}} - \mu_r\left(y_{rc}^{j_{p0}} - y_{rb}^{j_{p0}}\right)$$

Subject to

$$\sum_{i\in C_{I_P}} v_i\, x_i^{j_{p0}} + \sum_{i\in F_{I_P}} v_i\, x_{ia}^{j_{p0}} + \omega_i\left(x_{ib}^{j_{p0}} - x_{ia}^{j_{p0}}\right) = 1$$

$$\sum_{r\in C_{R_P}} u_r\, y_r^{j_{p0}} + \sum_{r\in F_{R_P}} u_r\, y_{rc}^{j_{p0}} - \mu_r\left(y_{rc}^{j_{p0}} - y_{rb}^{j_{p0}}\right)$$

$$-\sum_{i\in C_{I_P}} v_i\, x_i^{j_{p0}} - \sum_{i\in F_{I_P}} v_i\, x_{ia}^{j_{p0}} + \omega_i\left(x_{ib}^{j_{p0}} - x_{ia}^{j_{p0}}\right) \le 0$$

$$\sum_{r\in C_{R_P}} u_r\, y_r^{j_p} + \sum_{r\in F_{R_P}} u_r\, y_{ra}^{j_p} + \mu_r\left(y_{rb}^{j_p} - y_{ra}^{j_p}\right)$$

$$-\sum_{i\in C_{I_P}} v_i\, x_i^{j_p} - \sum_{i\in F_{I_P}} v_i\, x_{ic}^{j_p} - \omega_i\left(x_{ic}^{j_p} - x_{ib}^{j_p}\right) \le 0, \qquad \forall_{jp}, jp \ne jp_0$$

$$u_k w_r^L \le u_r \le u_k w_r^U, \qquad r \in R_p\ , k \in R_p \quad k \ne r$$

$$v_t \theta_i^L \le v_i \le v_t \theta_i^U, \qquad i \in I_p, t \in I_p, t \ne i$$

$$\mu_r - u_r \le 0, \quad r \in F_{R_p}$$

$$\omega_i - v_i \le 0, \quad i \in F_{I_p}$$

$$\mu_r \ge 0, \quad r \in F_{R_p}$$

$$\omega_i \ge 0, \quad i \in F_{I_p}$$

$$u_r \ge \varepsilon > 0, \qquad r \in R_p$$

$$v_i \ge \varepsilon > 0, \qquad i \in \mathrm{I_p} \qquad (5.1.1)$$

$F_{R_p} \subseteq R_p$ and $F_{I_p} \subseteq I_p$ are the qualitative evaluation sets taken from HOQ_p(p = 1,..,P) and represents the fuzzy output and input subsets in the DEA models respectively, where R_p denotes the set of outputs ($F_{R_p} \cup C_{R_p} = R_p$) ,and I_p denotes the set of inputs ($F_{I_p} \cup C_{I_p} = I_p$) for stage *p*. The DMU set J_p ($j_p = 1, \dots, N_p$)from the preceding stage p (p=1,…,P-1) will constitute the corresponding fuzzy and crisp input/output sets at the next stage ($J_p = I_{p+1} \cup R_{p+1}$). We introduce the crisp and fuzzy input vectors at stage p (p=1,…,P) by $x_i^{j_p}$ where $i \in C_{I_P}$ and $\widetilde{x_i^{j_p}} = (x_{ia}^{j_p}, x_{ib}^{j_p}, x_{ic}^{j_p})$ where $i \in$

F_{I_P} respectively. The output vectors from stage p take two forms: $y_r^{j_p}$ where $r \in C_{R_P}$ and $\widetilde{y_r^{j_p}} = (y_{ra}^{j_p}, x_{rb}^{j_p}, y_{rc}^{j_p})$ where $r \in F_{R_P}$. Fuzzy parameters are taken from the observed information through the corresponding HOQ matrix. $w_r^L, w_r^U, \theta_i^L, \theta_i^U$ are user specified constants to reflect value judgments the DM wishes to incorporate in the assessment, and are mainly introduced to prevent outputs or inputs from being over emphasized or ignored in the analysis (Thanassoulis, 2001). For stage p=1, w_r^L, w_r^U *and* θ_i^L, θ_i^U are represented by the pessimistic and optimistic values of relative importance weights of customer requirements (CRs) and by decision-makers' verbal assessments quantified as pessimistic and optimistic values of translated fuzzy numbers, namelyw_r^a, w_r^c *and* θ_i^a, θ_i^c. For stage p=2,…,P, they are equal to the corresponding pessimistic and optimistic efficiency scores of DMUs evaluated from the previous stage p - 1.

The pessimistic scenario DEA formulation for stage *p* is obtained as follows:

$$Maximize\ E^L_{j_{p0}} = \sum_{r\in C_{R_P}} u_r\, y_r^{j_{p0}} + \sum_{r\in F_{R_P}} u_r\, y_{ra}^{j_{p0}} + \mu_r\left(y_{rb}^{j_{p0}} - y_{ra}^{j_{p0}}\right)$$

Subject to

$$\sum_{i\in C_{I_P}} v_i\, x_i^{j_{p0}} + \sum_{i\in F_{I_P}} v_i\, x_{ic}^{j_{p0}} - \omega_i\left(x_{ic}^{j_{p0}} - x_{ib}^{j_{p0}}\right) = 1$$

$$\sum_{r\in C_{R_P}} u_r\, y_r^{j_{p0}} + \sum_{r\in F_{R_P}} u_r\, y_{ra}^{j_{p0}} + \mu_r\left(y_{rb}^{j_{p0}} - y_{ra}^{j_{p0}}\right)$$

$$-\sum_{i\in C_{I_P}} v_i\, x_i^{j_{p0}} - \sum_{i\in F_{I_P}} v_i\, x_{ic}^{j_{p0}} - \omega_i\left(x_{ic}^{j_{p0}} - x_{ib}^{j_{p0}}\right) \le 0$$

$$\sum_{r\in C_{R_P}} u_r\, y_r^{j_p} + \sum_{r\in F_{R_P}} u_r\, y_{rc}^{j_p} - \mu_r\left(y_{rc}^{j_p} - y_{rb}^{j_p}\right)$$

$$-\sum_{i\in C_{I_P}} v_i\, x_i^{j_p} - \sum_{i\in F_{I_P}} v_i\, x_{ia}^{j_p} + \omega_i\left(x_{ib}^{j_p} - x_{ia}^{j_p}\right) \le 0, \qquad \forall_{jp}, jp \ne jp_0$$

$$u_k w_r^L \le u_r \le u_k w_r^U, \qquad r \in R_p\ , k \in R_p \quad k \ne r$$

$$v_t \theta_i^L \le v_i \le v_t \theta_i^U, \qquad i \in I_p, t \in I_p, t \ne i$$

$$\mu_r - u_r \le 0, \quad r \in F_{R_p}$$

$$\omega_i - v_i \le 0, \quad i \in F_{I_p}$$

$$\mu_r \ge 0, \quad r \in F_{R_p}$$

$$\omega_i \ge 0, \quad i \in F_{I_p}$$

$$u_r \ge \varepsilon > 0, \qquad r \in R_p$$

$$v_i \ge \varepsilon > 0, \qquad i \in I_p \tag{5.1.2}$$

5.2 Proposed Decision Framework

The previous sub-section presented a comprehensive evaluation technique for a multi-stage process. In this sub-section, a simple supply chain considering three stages (p=1, 2, 3) is developed for the supplier selection problem. In a traditional supplier selection process, experts occasionally refer to customer requirements while exploring the decision factors. The aim of this study is to develop a supplier selection methodology by relating the supplier performances not only with the supplier characteristics (SCs) but also the technical capabilities (TCs) of the buyer firm and the customer requirements (CRs) that a customer needs to be satisfied. At the first stage, TCs are evaluated with respect to the CRs. The second stage exhibits the relationships between TCs and SCs, and aims to determine the relative importance scores of SCs. Finally, supplier performances are evaluated at the last stage.

Since the first and second stages are aiming to calculate the relative importance of decision criteria with respect to decision-makers' opinion, crisp data and fuzzy input variables are neglected throughout the development of DEA models for P=1, 2. Instead, an alternative DEA model, which employs a dummy input set that has a value of 1 for all DMUs (Ramanathan, 2007; Zeydan et al., 2011) should be used together with fuzzy outputs in order to evaluate the upper and lower importance ratings of TCs and SCs. The optimistic and pessimistic efficiency scenarios for the supplier selection stage (P=3) are same as formulations *(5.1.1) and (5.1.2).*

The decision framework of this study differs from the previous hybrid QFD applications for supplier selection in several aspects. First, the proposed method uses a mathematical programming technique to approach the problem in an optimality manner. Further, it makes interval analysis to find out the lower and upper levels of efficiency scores for supplier performances. Moreover, the previous researches did not consider both technical capabilities and customer requirements at the same time while evaluating performances of suppliers. However, since a supply chain consists of upstream and downstream transactions among suppliers, buyers and customers, this study proposes a comprehensive methodology to link the supplier attributes not only the technical capabilities of company but also the customer requirements.

The stepwise representation of the proposed decision making framework that is also depicted in Figure 5.2.1 is given below:

Step 1: Construct a decision-maker committee of *Z* experts (*z* = 1,…,*Z*). Identify the customer requirements (CRs) and technical capabilities (TCs) that will be represented in the first HOQ.

Step 2: Construct the first decision matrix where each decision-maker expresses the relative importance of CRs and the relationship between CRs and TCs using a linguistic variable. In this study, five different linguistic variable are used to express decision-makers' opinion: very low (VL), low (L), medium (M), high (H) and very high (VH) (Bevilacqua et al., 2006).

Step 3: Translate the linguistic variables to triangular fuzzy numbers through the definition of proper membership functions. Importance weight of r_{th} CR (r= 1,…,R_1) and the relationship between r_{th} CR and J_{1th} TC (J_1 = 1,…,N_1) for the zth decision maker (z = 1,…,Z) are denoted as $\widetilde{w_{rz}} = (w_{raz}, w_{rbz}, w_{rcz})$ and $\widetilde{y_{rz}^{j1}} = \left(y_{raz}^{j1}, y_{rbz}^{j1}, y_{rcz}^{j1}\right)$ respectively. Compute the aggregated weight of r_{th} CR and fuzzy assessment of relationship score between r_{th} CR and J_{1th} TC for p=1 and r= 1,…,R_1 as follows:

$$\widetilde{w_r} = \frac{1}{z} \otimes (\widetilde{w_{r1}} \oplus \widetilde{w_{r2}} \oplus \ldots \oplus \widetilde{w_{rZ}}) = (w_{ra}, w_{rb}, w_{rc}) \tag{5.2.1}$$

$$\widetilde{y_r^{jp}} = \frac{1}{z} \otimes (\widetilde{y_{r1}^{jp}} \oplus \widetilde{y_{r2}^{jp}} \oplus \ldots \oplus \widetilde{y_{rZ}^{jp}}) = \left(y_{ra}^{jp}, y_{rb}^{jp}, y_{rc}^{jp}\right) \tag{5.2.2}$$

Step 4: Normalize the data concerning importance weights of CRs and CR-TC relationships using max-value normalization to rectify the problems due to the scale differences.

Step 5: Construct the DEA models (5.1.1) and (5.1.2) for *p=1* to compute the upper and lower relative importance levels of TCs by ignoring crisp data and fuzzy inputs, and employing the dummy input set. The normalized pessimistic and optimistic values for the relative importance in formulation (7) represent the lower and upper bounds of the weight for each CR.

Step 6: Construct the second decision matrix. Identify the SCs where each decision-maker denotes the fuzzy assessment to determine the TCs-SCs relationship scores.

Step 7: Aggregate the ratings of TCs-SCs relationships using equation (5.2.2) for *p = 2*.

Step 8: Normalize the data concerning TCs using max-value normalization to rectify the problems due to the scale differences.

Step 8: Construct the DEA formulations (5.1.1) and (5.1.2) and *p=2* to compute the upper and lower relative importance levels of SCs by ignoring crisp data and fuzzy inputs, and employing the dummy input set. The pessimistic and optimistic scores for each TC calculated at *Step 5* represents the upper and lower bounds of the weight for each TC.

Step 9: Identify the subset and types of the SCs for the last stage as follows: fuzzy-input, fuzzy-output, crisp-input and crisp-output.

Step 10: Construct the third final matrix where each decision-maker denotes the ratings of each potential supplier with respect to each fuzzy subset of SC, and obtain the quantitative performance data of suppliers relevant to crisp subset of SC.

Step 11: Aggregate the ratings of suppliers with respect to fuzzy subsets of SC using Eq. (5.2.2) for *p=3.*

Step 12: Normalize the data concerning SCs using max-value normalization to rectify the problems due to the scale differences.

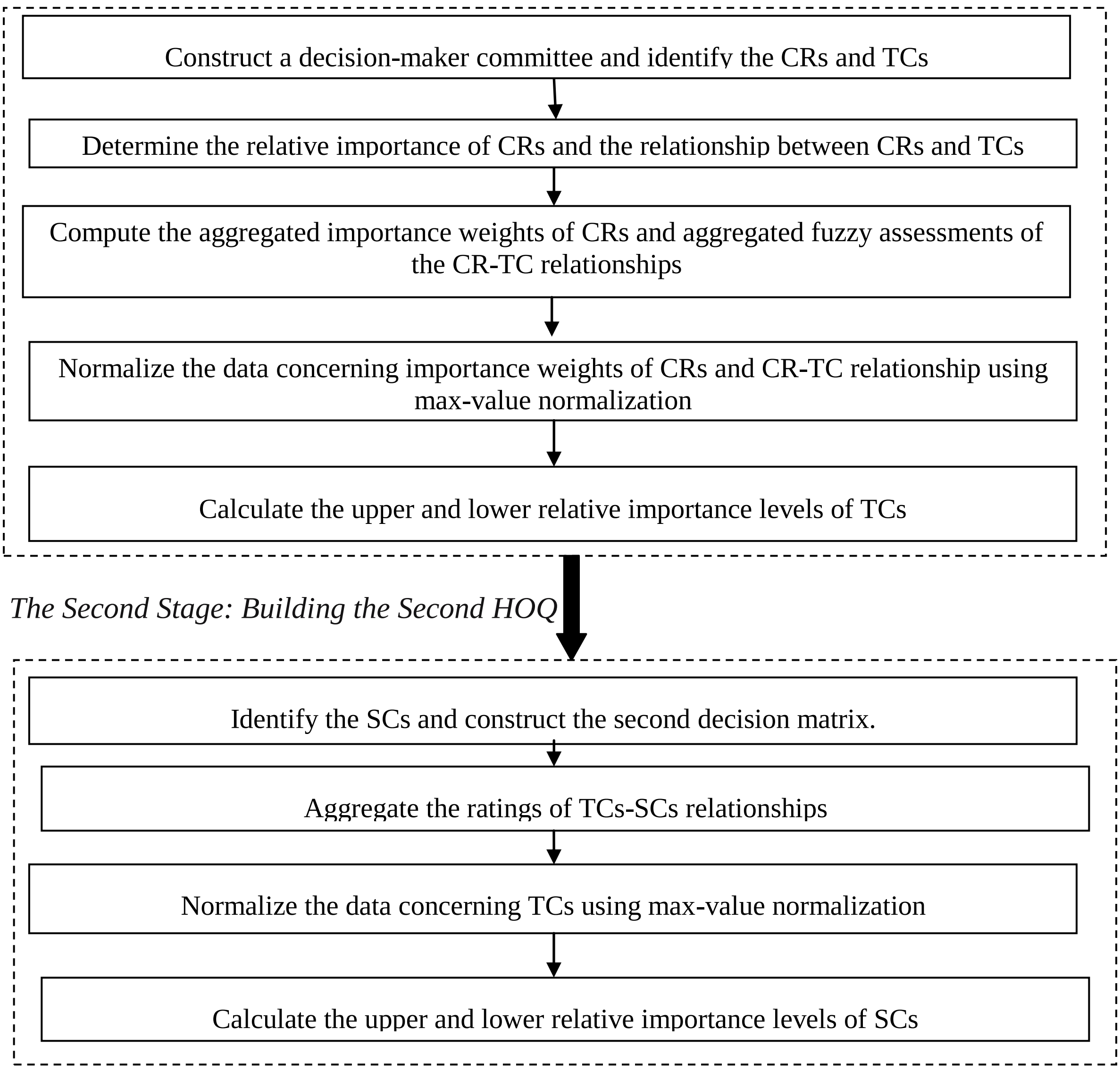
Step 13: Construct the DEA formulations (5.1.1) and (5.1.2) for *p=3*. This time, the weight for each SC is considered according to types of the data (i.e. input or output). The pessimistic and optimistic scores for each output type of SC calculated at *Step 5* represents the upper and lower bounds of the weight for each output type of SC, and same procedure is repeated for the input types of SC. The upper and lower bounds for the subsets of the same types are not determined individually.

Step 14: Rank the suppliers with respect to their pessimistic efficiency scores

.

Step 15: If there exist multiple suppliers with a pessimistic efficiency score of 1, use cross efficiency analysis (Talluri & Sarkis, 2002) to determine the best supplier.

The First Stage: Building the First HOQ



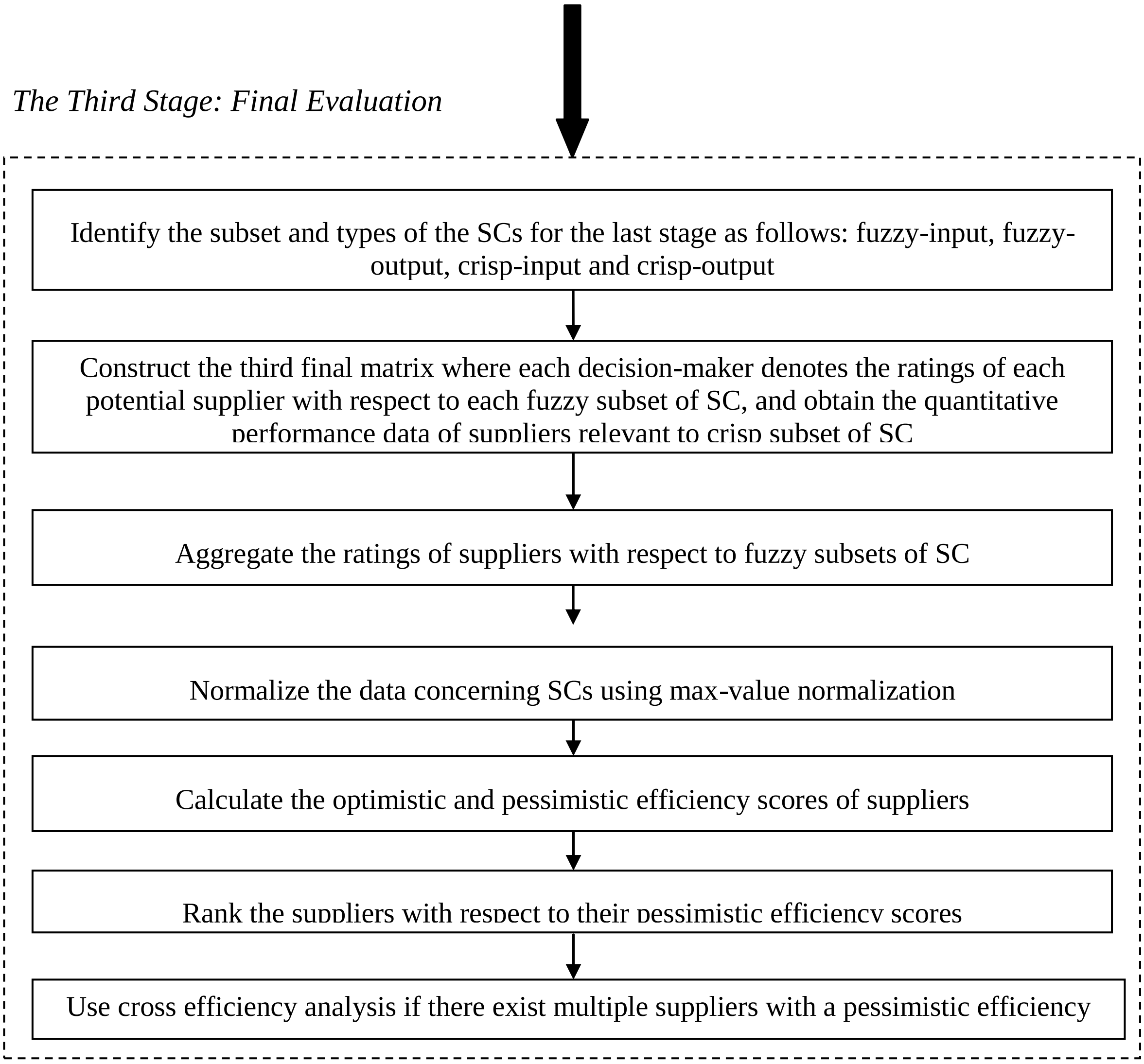


Figure 5.2.1 The proposed decision making framework

6 CASE STUDY: Pharmaceutical Supplier Evaluation Using the Proposed Decision Framework

In this section, the proposed decision-making methodology is applied to a case of pharmaceutical logistic industry in Turkey. The model is developed and validated using data from Farmalojistik A.Ş., a Turkish pharmaceutical logistics company that services more than 24 domestic destinations. Farmalojistik Pharmacy Wholesalers and Pre-Wholesalers Logistics Services Inc., founded in 2005, is a joint purchasing and logistics company established with the participation of Edak Ecza Koop., Bursa Ecza Koop., Istanbul Ecza Koop., Guney Ecza Koop. and Ankara Ecza Koop. under the guidance of TEKB (Tüm Eczacı Kooperatifler Birliği) (Farma, 2013). It undertakes a focal logistics company role which ensures that products are delivered to the affiliate cooperatives, pharmacies and hospitals by planning the needs of pharmacy cooperatives and fulfilling the task of purchasing in line with the principle of collaboration with pharmaceutical suppliers. Apart from these, it performs rapidly the basic logistics functions such as stocking, single point ordering, delivering products to the main warehouses and all branches after consolidated delivery of the products, and preparing them according to orders, quality control, withdrawal proceedings and delivery to companies (Figure 6.1).

In the past decade, Farma Lojistik has grown substantially and been recognized with a national rank of 101th in the FORTUNE TURKEY 500 list (Fortune, 2011). The system development manager Barış Tutal indicated that there are about 30 millions of drug units per month transacted through the company, and they fulfill at least 99.998-99.999% amount of orders monthly. However, besides the myriad amount of transaction, he stated that different types of failures cannot be detected during the inspection of the received products, and may not be noticed until customer will sent withdrawals back. For instance, if a supplier delivers a cracked bottle of serum or a lack of pills, it will slightly recognize while controlling the package due to the amount of total deliveries. Moreover, company may directly send this package when a hospital or pharmacy declared an emergency in order to treat some patients. Hence, company must periodically inform on failures to its suppliers and monitor the suppliers' delivery performances, so that the number of undesirable results will be reduced.

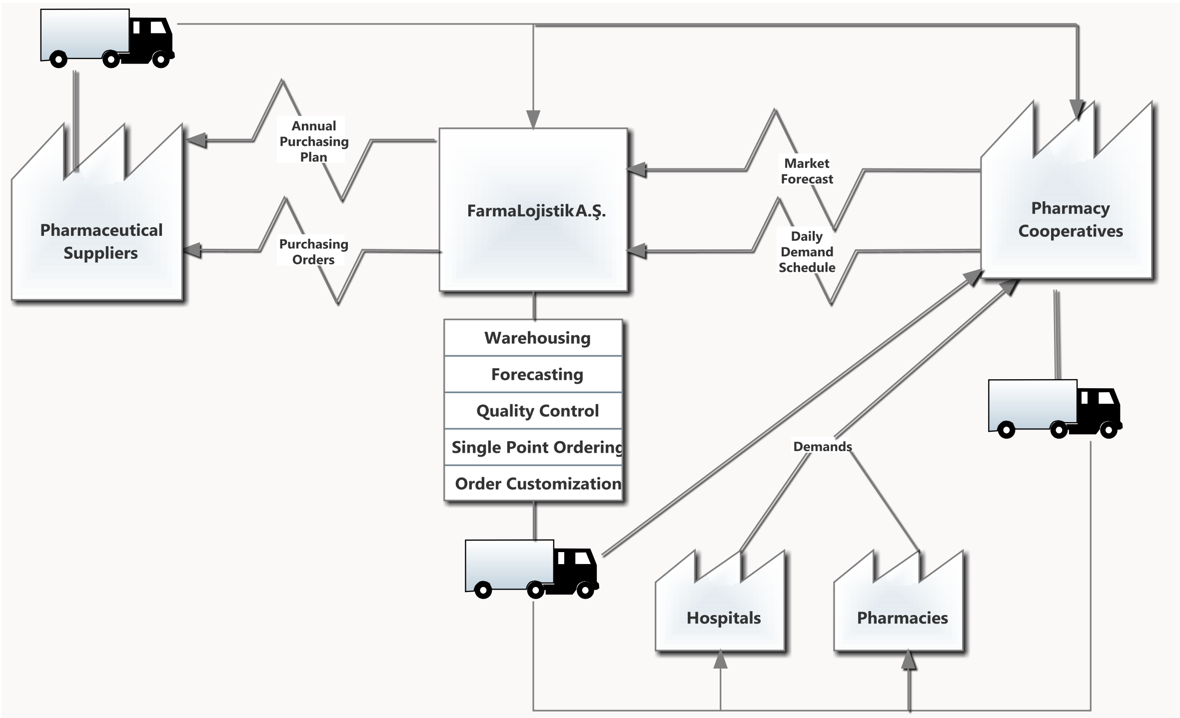


Figure 6.1 Material and information flow for the case company

In this thesis, we had conducted a field study for five months with the purpose of developing a supplier evaluation process which is supplemented by screening the previous researches considering supplier evaluation and selection, and managerial consolidation with the decision making team (DMT). The logistic manager Mehmet Songür was reporting that even though they had acquainted their suppliers with the failures over time, they would not convinced them to take corrective and proactive actions as long as the company did not present a formal evaluation system. Therefore, the main object of this study arises: how to evaluate the logistics performances of a pharmaceutical company from the hospitals and pharmacies' point of view. The supplier evaluation process is performed according to three-stage procedure mentioned in the previous section and following the steps of each stage through the implementation of proposed decision framework.

The first task in supplier evaluation is to form a team of analysts who have a rich knowledge and expertise in logistics activities (Liu & Wang, 2009). The decision-making team is constituted of an academic researcher (DM1), the logistics manager (DM2) and the system development manager (DM3). Each team member possesses a certain degree of knowledge and expertise in pharmaceutical logistics sector.

The team members agreed on the fact that one of the key points in an organization is to understand the customer requirements (CRs) in terms of the desires that must be satisfied throughout the different phases of supply chains (Liu & Wang, 2009). Customer requirements used to evaluate the logistics performances have been discussed by a vast amount of researches (Capplice & Sheffi, (1994,1995); Franchescini & Rafaele, 2000; Tonyas & Serdar, 2003; Bottani & Rizzi, 2006; Aguezol, 2012; Ho et al. 2012) After brainstorming among some cooperative managers, and reviewing previous researches, we select the following four customer requirements criteria for the subsequent evaluation process:

CR.1 Dependability: Dependability can be referred as the accurateness of planned and actual inventory, and operational performance levels. Dependability relies on information accuracy and quality consistency (Christpher, 2011).

CR.2 Cycle Time This is the elapsed time from customer order to delivery. Delivering the products at the right time can help to achieve 100% on-time delivery, and reduce the customer waiting time (Ho et al., 2012).

CR.3 Completeness: indicates that what proportion of orders do we deliver complete (i.e. no back orders or part shipment) It is the capability to deliver full orders when required. (Franchescini & Rafaele, 2000)

CR.4 Availability: Availability refers to capacity to respond the demand on time and with exact quantity. Availability is measured by out of stock frequency, order fill rate and accuracy in filling orders (Tonyaş & Serdar, 2003).

Next, the technical capabilities of company were identified based on both on a previous research considering logistics provider evaluation (Ho et al., 2012) and the firm characteristics, whose peculiarities have emerged from roundtable discussions. During the survey phase, other departments and their employees have also been interviewed about the importance of factors, in order that the number of criteria that has to be taken into consideration would have been eliminated:

TC.1 Financial Management and Logistics Cost Reductions: The company should be focused on the minimization of the total logistics costs rather than the individual costs. Total costs include transportation costs, warehousing costs, material handling costs, and packaging costs and so on.

TC.2 Lead-Time Reduction: Shorter lead time is an advantage for both customer and logistics company. Results from the lead time reductions led to identification of a competitive strategy based on speed (Treville et al.,2004).

TC.3 Quality Assurance in Logistics Activities: Special equipment, packaging, and care are essential to ensure safety condition of product delivery, and reduce the chance of malfunction and damaging.

TC.4 Flexibility: Different hospitals and pharmacy cooperatives will have various specific requirements on the logistics services. It is critical to provide flexible solutions to meet their changing needs.

TC.5 Equipment Utilizations: Both advanced hardware (e.g., a fleet of vehicles, storing and handling devices, RFID, GPS satellite tracking device) and software (ERP programs, carrier loading optimization software, data transmission and receiving systems) utilization can help to enhance the competitiveness of the logistics company.

TC.6 After-Sales Support: A logistics company should inform the customers about the features and technical requirements of products. For instance, the temperature of cold chain drugs should be tracked by RFID records until it will be delivered to hospitals.

TC.7 Efficacy: It refers to the ability of the logistic company to resolve problems and mitigate the impact of problems on the customer in an effective manner.

In this study, the HOQ designs related to CRs, TCs, SCs and suppliers are depicted in Fig 6.2 ,Table 6.7 and Table 6.12 respectively. The relative importance of the four CRs, the relationships between the four CRs and the seven TCs are all described by linguistic terms (Figure 6.2), the team members can select the appropriate linguistic terms from Figure 3.3. Next, the corresponding fuzzy numbers are calculated through appropriate membership function in Table 6.1 and Table 6.2. The normalization results are listed in Table 6.3 and Table 6.4. Dummy input for the TCs are depicted in Table 6.5. As shown in Table 6.6, for $\varepsilon= 0.268$ the lower and upper importance ratings of TCs are calculated as described below:

Technical Capabilities / Customer Requirements	*TC1*	*TC2*	*TC3*	*TC4*	*TC5*	*TC6*	*TC7*	Relative Importance Of CRs
CR1 Dependability	(H ,M ,M)	(M,H,M)	(VH,VH,VH)	(H,VH,VH)	(L,L,VL)	(M,M,M)	(H,M,H)	(H,VH,VH)
CR2 Cycle Time	(VL ,L ,VL)	(H,VH,H)	(L,M,L)	(M,H,H)	(L,M,M)	(VL,L,L)	(M,L,L)	(H,VH,H)
CR3 Completeness	(L ,L ,L)	(VL,VL,L)	(VH,H,VH)	(M,L,M)	(H,H,VH)	(VL,VL,VL)	(M,H,M)	(H,M,M)
CR4 Availability	(M ,L ,M)	(L,M,L)	(L,VL,L)	(H,VH,VH)	(VL,L,L)	(M,H,M)	(L,L,VL)	(M,L,M)

Figure 6.2 The first HOQ

Table 6.1
Importance weights of CRs

Customer Requirements	Importance
CR1 Dependability	(7.333,8.333,9.333)
CR2 Cycle Time	(6.667,7.667,8.667)
CR3 Completeness	(4.667,5.667,6.667)
CR4 Availability	(3.333,4.333,5.333)

Table 6.2
Aggregated impact of each TC on each CR

CRs	**TCs**						
	TC1	TC2	TC3	TC4	TC5	TC6	TC7
CR1Dependability	(4.667,5.667,6.667)	(4.667,5.667,6.667)	(8.000,9.000,10.000)	(7.333,8.333,9.333)	(1.333,2.333,3.333)	(4.000,5.000,6.000)	(5.333,6.333,7.333)
CR2Cycle Time	(0.667,1.667,2.667)	(6.667,7.667,8.667)	(2.667,3.667,4.667)	(5.333,6.333,7.333)	(3.333,4.333,5.333)	(1.333,2.333,3.333)	(2.667,3.667,4.667)
CR3Completeness	(2.000,3.000,4.000)	(0.667,1.667,2.667)	(7.333,8.333,9.333)	(3.333,4.333,5.333)	(6.667,7.667,8.667)	(0.000,1.000,2.000)	(4.667,5.667,6.667)
CR4Availability	(3.333,4.333,5.333)	(2.667,3.667,4.667)	(1.333,2.333,3.333)	(7.333,8.333,9.333)	(1.333,2.333,3.333)	(4.667,5.667,6.667)	(1.333,2.333,3.333)

Table 6.3
Normalized importance weights of each CR

Customer Requirements	Importance
CR1 Dependability	(0.786,0.893,1.000)
CR2 Cycle Time	(0.714,0.821,0.929)
CR3 Completeness	(0.500,0.607,0.714)
CR4 Availability	(0.357,0.464,0.571)

Table 6.4
Normalized aggregated impact of each TC on each CR

CRs	**TCs**						
	TC1	TC2	TC3	TC4	TC5	TC6	TC7
CR1Dependability	(0.467,0.567,0.667)	(0.467,0.567,0.667)	(0.800,0.900,1.000)	(0.733,0.833,0.933)	(0.133,0.233,0.333)	(0.400,0.500,0.600)	(0.533,0.633,0.733)
CR2Cycle Time	(0.077,0.192,0.308)	(0.769,0.885,1.000)	(0.308,0.423,0.538)	(0.615,0.731,0.846)	(0.385,0.500,0.615)	(0.154,0.269,0.385)	(0.308,0.423,0.538)
CR3Completeness	(0.214,0.321,0.429)	(0.071,0.179,0.286)	(0.786,0.893,1.000)	(0.357,0.464,0.571)	(0.714,0.821,0.929)	(0.000,0.107,0.214)	(0.500,0.607,0.714)
CR4Availability	(0.357,0.464,0.571)	(0.286,0.393,0.500)	(0.143,0.250,0.357)	(0.786,0.893,1.000)	(0.143,0.250,0.357)	(0.500,0.607,0.714)	(0.143,0.250,0.357)

Table 6.5 Dummy input variable for TCs evaluation

	TC1	*TC2*	*TC3*	*TC4*	*TC5*	*TC6*	*TC7*
Dummy(i)	1	1	1	1	1	1	1

Table 6.6
The lower and upper importance ratings of TCs

	LOWER	UPPER
TC1	0.541	0.813
TC2	0.716	1
TC3	0.871	1
TC4	1	1
TC5	0.564	0.89
TC6	0.516	0.772
TC7	0.669	0.996

Table 6.7
TC-SC relationships

	SCs												
TCs	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8	SC9	SC10	SC11	SC12	SC13
TC1	(M,H,H)	(L,VL,L)	(H,H,VH)	(M,L,L)	(L,M,M)	(L,M,M)	(M,L,L)	(H,M,M)	(L,L,M)	(M,L,M)	(VL,VL,L)	(L,VL,L)	(M,M,L)
TC2	(L,VL,L)	(VH,VH,H)	(M,M,L)	(VL,VL,L)	(VL,L,VL)	(H,VH,H)	(M,H,M)	(M,M,H)	(M,M,H)	(VH,VH,H)	(L,L,VL)	(VL,L,VL)	(L,M,M)
TC3	(M,L,L)	(L,L,M)	(H,VH,VH)	(M,H,M)	(H,M,M)	(M,M,L)	(M,L,M)	(VL,VL,L)	(M,M,M)	(L,M,M)	(M,L,L)	(L,L,VL)	(VL,L,VL)
TC4	(VL,L,VL)	(VH,H,H)	(L,M,M)	(L,M,L)	(M,L,L)	(H,VH,VH)	(H,M,H)	(M,M,M)	(M,H,H)	(H,VH,H)	(M,H,H)	(M,L,L)	(M,L,L)
TC5	(VL,VL,L)	(M,L,L)	(M,H,M)	(VL,L,VL)	(L,VL,L)	(VH,H,VH)	(H,VH,VH)	(VL,L,VL)	(H,H,VH)	(H,M,H)	(H,H,H)	(L,M,M)	(VL,VL,L)
TC6	(M,M,H)	(M,H,M)	(VL,L,VL)	(L,L,M)	(VL,VL,L)	(M,H,M)	(M,L,M)	(L,VL,L)	(M,L,L)	(M,M,M)	(VL,VL,L)	(M,H,H)	(H,H,M)
TC7	(L,VL,VL)	(H,H,M)	(H,M,M)	(M,M,H)	(M,H,M)	(M,M,L)	(M,L,M)	(M,L,L)	(VH,H,H)	(L,M,L)	(L,M,L)	(L,M,M)	(L,L,L)

Table 6.8
Normalized aggregated impact of each SC on each TC

	SCs												
TCs	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8	SC9	SC10	SC11	SC12	SC13
TC1	(0.615,0.731,0.846)	(0.154,0.269,0.385)	(0.769,0.885,1.000)	(0.308,0.423,0.538)	(0.385,0.500,0.615)	(0.385,0.500,0.615)	(0.308,0.423,0.538)	(0.538,0.654,0.769)	(0.308,0.423,0.538)	(0.385,0.500,0.615)	(0.077,0.192,0.308)	(0.154,0.269,0.385)	(0.385,0.500,0.615)
TC2	(0.143,0.250,0.357)	(0.786,0.893,1.000)	(0.357,0.464,0.571)	(0.071,0.179,0.286)	(0.071,0.179,0.286)	(0.714,0.821,0.929)	(0.500,0.607,0.714)	(0.500,0.607,0.714)	(0.500,0.607,0.714)	(0.786,0.893,1.000)	(0.143,0.250,0.357)	(0.071,0.179,0.286)	(0.357,0.464,0.571)
TC3	(0.286,0.393,0.500)	(0.286,0.393,0.500)	(0.786,0.893,1.000)	(0.500,0.607,0.714)	(0.500,0.607,0.714)	(0.357,0.464,0.571)	(0.357,0.464,0.571)	(0.071,0.179,0.286)	(0.429,0.536,0.643)	(0.357,0.464,0.571)	(0.286,0.393,0.500)	(0.143,0.250,0.357)	(0.071,0.179,0.286)
TC4	(0.071,0.179,0.286)	(0.714,0.821,0.929)	(0.357,0.464,0.571)	(0.286,0.393,0.500)	(0.286,0.393,0.500)	(0.786,0.893,1.000)	(0.571,0.679,0.786)	(0.429,0.536,0.643)	(0.571,0.679,0.786)	(0.714,0.821,0.929)	(0.571,0.679,0.786)	(0.286,0.393,0.500)	(0.286,0.393,0.500)
TC5	(0.071,0.179,0.286)	(0.286,0.393,0.500)	(0.500,0.607,0.714)	(0.071,0.179,0.286)	(0.143,0.250,0.357)	(0.786,0.893,1.000)	(0.786,0.893,1.000)	(0.071,0.179,0.286)	(0.714,0.821,0.929)	(0.571,0.679,0.786)	(0.643,0.750,0.857)	(0.357,0.464,0.571)	(0.071,0.179,0.286)
TC6	(0.636,0.773,0.909)	(0.636,0.773,0.909)	(0.091,0.227,0.364)	(0.364,0.500,0.636)	(0.091,0.227,0.364)	(0.636,0.773,0.909)	(0.455,0.591,0.727)	(0.182,0.318,0.455)	(0.364,0.500,0.636)	(0.545,0.682,0.818)	(0.091,0.227,0.364)	(0.727,0.864,1.000)	(0.727,0.864,1.000)
TC7	(0.077,0.192,0.308)	(0.615,0.731,0.846)	(0.538,0.654,0.769)	(0.538,0.654,0.769)	(0.538,0.654,0.769)	(0.385,0.500,0.615)	(0.385,0.500,0.615)	(0.308,0.423,0.538)	(0.769,0.885,1.000)	(0.308,0.423,0.538)	(0.308,0.423,0.538)	(0.385,0.500,0.615)	(0.231,0.346,0.462)

Table 6.9
Dummy input for SCs

	Suppliers												
	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8	SC9	SC10	SC11	SC12	SC13
Dummy (i)	1	1	1	1	1	1	1	1	1	1	1	1	1

Before introducing the next step, let us explain the inspection and reception process in Farma Lojistik so that supplier characteristic (SCs) will be understudied in a more appropriate way.

The products are entered in four different doors. Initially, it is recorded that which product is received in which door. Before checking the physical conditions, invoiced quantities are confirmed with the real amounts. If the quantities are not matched, products will be kept until the new bills are prepared. In the following step, Pharmaceutical track system (abbreviated as ITS) and packaging track system (abbreviated as PTS) information are confirmed via internet. ITS is designed to track the location of every drug unit to ensure the reliable supply of drugs to patients. Therefore, all the drugs on the market are traced by notifications in all phases from production to consumption. Thus; the sale of fraudulent drugs, drug theft and barcode scams are prevented. In addition, if required, drugs can easily be recalled due to traceability of stocks. The serialization providing the uniqueness of the units is ensured by the Data-Matrix code instead of formerly used barcode. 2.5 billion drug units per year and about 10 transactions for each drug unit is tracked and traced with the Pharmaceutical Track and Trace System (Ministery of Health, 2013). The unique ITS codes as much amount in packages are assigned under the unique PTS codes to unitarily collect the products information. Likewise, if pallets are attributed by unique numbers, the PTS information ought to be assigned to each those pallets. Suppliers should at least announced the ITS information to the ministry of health. If the ITS number are not appeared in Pharmaceutical Track and Trace System, suppliers have to be informed for notification. Packages, shrinks (wrappings) and products are controlled whether they get damaged or not, while checking the ITS information. In the case of detecting deformed products, the return invoices are prepared for sending to supplier back. After finishing inspection process without any problem, the products are assigned to appropriate shelves identified by an ERP software.

The decision-making team analyzed thirteen supplier characteristics to evaluate the performances of suppliers as listed in Table 6.10 :

Table 6.10
List of supplier characteristics

SCs	Description	Sub-set	Type
SC 1	The responsibility of correcting failures	Fuzzy	Output
SC 2	Service flexibility	Fuzzy	Output
SC 3	Frequency of delivered damaged products	Fuzzy	Input
SC 4	Ability of delivering right amount of products.	Fuzzy	Output
SC 5	Service Quality	Fuzzy	Output
SC 6	Frequency of pallet errors	Fuzzy	Input
SC 7	Frequency of packaging errors	Fuzzy	Input
SC 8	Consistency between invoiced quantities and received amounts	Fuzzy	Output
SC 9	Consistency of ITS-PTS information	Fuzzy	Output
SC 10	Lead Time (Average)	Crisp	Input
SC 11	ITS-PTS lateness (Average)	Crisp	Input
SC 12	Product Range	Crisp	Output
SC 13	Average number of deliveries per month.	Crisp	Output

The decision – makers denote the relationships between TCs and SCs using the same linguistic variables (Figure 3.3). The normalized results are listed in Table 6.8. Table 6.9 depicts the dummy input values for SCs. For $\varepsilon = 0.194$ the lower and upper importance ratings of supplier characteristics are calculated as shown in Table 6.11.

For the last stage, the decision framework involves the evaluation of the pessimistic and optimistic relative efficiency of 42 suppliers with respect to five inputs, namely "Frequency of delivered damaged products (SC3)", "Frequency of pallet errors (SC6)", "Frequency of packaging errors (SC7)", "Lead Time (SC10)", and "ITS-PTS lateness (SC11)". "Lead Time (SC10)" and "ITS-PTS lateness (SC11) that are not assessed by linguistic variables are represented by exact numbers. There are 8 output variables deployed in formulations (5.1.1) and (5.1.2). "Product Range (SC12)" and "Average number of deliveries per month (SC13)" are provided as crisp output criteria and rest of them represented as fuzzy output data for the evaluation stage.

Table 6.11
The lower and upper importance ratings of SCs

	LOWER	UPPER
SC1	0.542	0.879
SC2	0.884	1.000
SC3	0.606	0.987
SC4	0.581	0.967
SC5	0.596	0.950
SC6	0.913	1.000
SC7	0.860	1.000
SC8	1.000	1.000
SC9	0.855	1.000
SC10	0.922	1.000
SC11	0.612	0.963
SC12	0.594	0.934
SC13	0.593	0.932

There are 42 suppliers are qualified to be evaluated by the managers. Since some of these suppliers are globally known pharmaceutical companies, we cannot declare their names throughout the decision process. The ratings of suppliers with respect to each fuzzy-SC and their performance with respect to quantitative data of crisp-SCs are provided in Table 6.15 and Table 6.16 respectively. The normalized results are listed in Table 6.17 and Table 6.18. The ε value is calculated as 0.0613 by maximizing ε subject to the constraint set of pessimistic DEA model (5.1.2).The optimistic and pessimistic efficiency scores of suppliers are calculated by utilizing formulations (5.1.1) and (5.1.2) and the results are provided in Table 6.12. The ranking of suppliers with respect to pessimistic scenario is given in Table 6.13.

The 40th supplier (Sup40) is the only efficient alternative among the candidate suppliers with respect to pessimistic scenario. According to optimistic scenario, it can be also seen from the analysts that suppliers 3-4-5-8-9-18-20-22-30-34-36-38-39 and 40 are efficient with scores of 1.000. Suppliers 1-6-17-19-24-33-41 and 42 were recognized as the worst eight suppliers based on both pessimistic and optimistic efficiency scenarios. After the evaluation stage, managers individually arranged meetings with these suppliers and reported the evaluation result to take corrective actions.

For example it can be seen that supplier 1 decrease its failure rates, after informing the results of proposed study (Table 6.14).

Table 6.12 Efficiency scores of suppliers

Suppliers	Pessimistic Eff.	Optimistic Eff.
Sup1	0.2733	0.5387
Sup2	0.4895	0.927
Sup3	0.918	1
Sup4	0.7123	1
Sup5	0.6863	1
Sup6	0.2694	0.5437
Sup7	0.3041	0.5909
Sup8	0.5232	1
Sup9	0.6486	1
Sup10	0.2908	0.592
Sup11	0.3358	0.6738
Sup12	0.3055	0.6608
Sup13	0.3107	0.6618
Sup14	0.3087	0.6282
Sup15	0.3099	0.6079
Sup16	0.3086	0.6406
Sup17	0.286	0.5661
Sup18	0.5789	1
Sup19	0.2406	0.4938
Sup20	0.5072	1
Sup21	0.3139	0.6367
Sup22	0.5065	1
Sup23	0.4196	0.9037
Sup24	0.2707	0.5532
Sup25	0.329	0.6657
Sup26	0.357	0.708
Sup27	0.3132	0.6484
Sup28	0.3204	0.6516
Sup29	0.3925	0.7732
Sup30	0.5294	1
Sup31	0.369	0.7187
Sup32	0.3287	0.6605
Sup33	0.2435	0.4873
Sup34	0.6595	1
Sup35	0.3254	0.7072
Sup36	0.8772	1
Sup37	0.3764	0.7151
Sup38	0.5825	1
Sup39	0.628	1
Sup40	1	1
Sup41	0.2601	0.5065
Sup42	0.251	0.5206

Table 6.13 Ranking of suppliers

Ranking	Supplier
1	Sup40
2	Sup3
3	Sup36
4	Sup4
5	Sup5
6	Sup34
7	Sup9
8	Sup39
9	Sup38
10	Sup18
11	Sup30
12	Sup8
13	Sup20
14	Sup22
15	Sup2
16	Sup23
17	Sup29
18	Sup37
19	Sup31
20	Sup26
21	Sup11
22	Sup25
23	Sup32
24	Sup35
25	Sup28
26	Sup21
27	Sup27
28	Sup13
29	Sup15
30	Sup14
31	Sup16
32	Sup12
33	Sup7
34	Sup10
35	Sup17
36	Sup1
37	Sup24
38	Sup6
39	Sup41
40	Sup42
41	Sup33
42	Sup19

Table 6.14
Supplier 1 Error Report

	INV. DATE	DEL. DATE	SUP	INV.NO	PROD.ID	PROD.NAME	ERROR.AMOUNT	ERROR TYPE	COR. DATE
BEFORE EVALUATION	11/5/2012	11/8/2012	1	#1	139096	P1	15 UN.	INVOICE	11/13/2012
	11/15/2012	11/15/2012	1	#2	139096	P1	3 UN.	OVER	11/21/2012
	11/15/2012	11/15/2012	1	#3	139096	P1	1000 UN.	INVOICE	11/21/2012
	11/23/2012	11/25/2012	1	#4	135011	P4	15 UN.	OVER	11/28/2012
	11/23/2012	11/29/2012	1	#5	139034	P5	50 UN.	OVER	11/29/2012
	11/28/2012	11/29/2012	1	#6	139023	P6	24 UN.	LESS	12/12/2012
	11/29/2012	11/29/2012	1	#7	139111	P7	30 PAC.	PALLET	11/29/2012
	11/29/2012	11/29/2012	1	#7	139112	P8	58 PAC.	PALLET	11/29/2012
	11/29/2012	11/29/2012	1	#7	139139	P9	30 PAC.	PALLET	11/29/2012
	11/29/2012	11/29/2012	1	#8	139059	P10	80 PAC.	INVOICE	11/30/2012
	11/29/2012	11/29/2012	1	#9	139130	P11	10 PAC.	DAMAGED	11/29/2012
	11/29/2012	11/29/2012	1	#10	139115	P12	20 PAC.	PALLET	11/29/2012
	11/29/2012	11/29/2012	1	#10	139082	P13	4608 UN.	PALLET	11/29/2012
AFTER EVALUATION	11/28/2012	12/6/2012	1	#11	139122	P14	12 PAC.	PACKAGING	12/6/2012
	12/10/2012	12/11/2012	1	#12	139047	P15	1610 UN.	PALLET	12/11/2012
	12/12/2012	12/13/2012	1	#13	139091	P16	2700 UN.	PALLET	12/13/2012
	12/12/2012	12/13/2012	1	#13	139139	P9	2700 UN.	PALLET	12/13/2012

In the scope of our study, for each pharmaceutical company, these error reports are begun to be recorded by managers to inform the suppliers periodically. The first, second and the ninth columns show the invoice date, delivery date and the date which failure is corrected

respectively. The corresponding error types are founded in the eighth column. For example, supplier 1 sent 15 extra units of product P4, which were not ordered, on December 25 of which invoice was prepared on December 23, so on these exceeding units had waited in the reception area until the date 11/28/2012 without any transaction. As an instance for pallet errors, mixed pallets are not welcomed, since they need to be separated on different places. In this report, P7, P8 and P9 are the three derivations of the same product. When we glance over these products' packages, we cannot realize them since their package sizes and colors are similar to each other. The only difference is that the barcode types stick on their package. These products were delivered on the same pallets and an employee had tried to categorize them on different three pallets for three hours.

The managers arranged some meetings with the warehouse manager of supplier 1in order to enhance the quality of delivery operations. As a consequence, the warehouse managers took notice and they have become more careful after the evaluation stage.

Table 6.15
Supplier ratings with respect to fuzzy SCs

SCs		Sup1	Sup2	Sup3	Sup4	Sup5	Sup6	Sup7	Sup8	Sup9	Sup10	Sup11
		Suppliers										
Fuzzy Outputs	SC1	(L,M,M)	(L,M,L)	(H,VH,H)	(H,VH,H)	(H,VH,H)	(L,M,L)	(M,L,L)	(H,H,H)	(H,H,VH)	(M,M,L)	(H,M,H)
	SC2	(H,M,H)	(H,H,H)	(H,M,H)	(M,M,L)	(VH,H,H)	(M,L,M)	(M,M,H)	(L,M,L)	(VH,VH,H)	(VL,VL,L)	(M,H,M)
	SC4	(M,M,H)	(L,M,L)	(M,H,M)	(M,H,M)	(H,H,VH)	(L,M,L)	(H,M,M)	(M,H,M)	(VH,H,H)	(M,H,H)	(M,L,L)
	SC5	(M,L,M)	(L,M,L)	(M,L,M)	(M,M,L)	(H,H,M)	(L,L,M)	(VL,L,VL)	(M,M,L)	(L,M,M)	(L,M,M)	(H,M,H)
	SC8	(M,H,H)	(L,VL,L)	(H,M,H)	(VH,H,H)	(L,L,M)	(M,M,L)	(L,M,M)	(VH,H,VH)	(M,M,L)	(L,L,M)	(M,H,M)
	SC9	(VL,L,VL)	(M,H,H)	(VH,H,VH)	(H,H,VH)	(H,M,H)	(M,H,M)	(M,M,H)	(M,H,M)	(L,L,VL)	(M,M,H)	(L,L,L)
Fuzzy Inputs	SC3	(H,VH,H)	(M,L,M)	(L,M,L)	(L,M,L)	(L,L,M)	(M,H,H)	(L,M,L)	(L,L,VL)	(H,M,M)	(L,L,M)	(L,L,L)
	SC6	(VH,VH,H)	(H,VH,H)	(VL,VL,L)	(L,VL,VL)	(M,M,H)	(H,VH,VH)	(H,VH,H)	(L,L,M)	(L,L,M)	(M,VH,H)	(M,M,H)
	SC7	(L,M,L)	(VL,VL,L)	(L,L,VL)	(M,H,M)	(M,L,L)	(H,H,M)	(H,H,M)	(H,M,H)	(L,L,VL)	(M,H,H)	(H,VH,H)

Table 6.16
Supplier performances with respect to quantitative criteria

SCs		Sup1	Sup2	Sup3	Sup4	Sup5	Sup6	Sup7	Sup8	Sup9	Sup10	Sup11
		Suppliers										
Crisp Outputs	SC12	157	403	99	141	25	36	272	69	161	38	11
	SC13	82.333	246.333	19.333	41.000	10.333	25.000	60.000	6.333	66.333	28.000	14.000
Crisp Inputs	SC10	0.981	1.495	1.323	0.858	0.296	0.854	1.651	1.321	1.250	2.303	1.870
	SC11	2.604	1.383	0.020	0.255	0.315	0.364	1.562	0.245	0.120	0.100	0.360

Table 6.15-Cont.

SCs		Suppliers										
		Sup12	Sup13	Sup14	Sup15	Sup16	Sup17	Sup18	Sup19	Sup20	Sup21	Sup22
Fuzzy Outputs	SC1	(L,VL,L)	(VL,L,VL)	(L,M,M)	(L,L,M)	(M,M,L)	(L,VL,VL)	(H,M,H)	(M,H,M)	(M,L,L)	(H,H,M)	(H,H,H)
	SC2	(M,L,L)	(H,H,M)	(H,H,M)	(H,H,M)	(H,H,VH)	(H,H,M)	(M,M,L)	(VL,L,L)	(M,H,M)	(M,H,H)	(H,M,H)
	SC4	(M,H,M)	(M,M,L)	(H,M,L)	(H,VH,H)	(VL,VL,L)	(M,L,M)	(H,H,H)	(H,H,M)	(H,M,M)	(L,M,L)	(M,H,H)
	SC5	(VL,L,VL)	(M,H,M)	(L,VL,VL)	(M,L,M)	(H,M,H)	(M,L,L)	(L,L,M)	(VL,VL,L)	(VH,H,H)	(L,L,VL)	(L,M,L)
	SC8	(H,M,M)	(L,VL,VL)	(M,L,M)	(M,M,M)	(VL,VL,L)	(M,VL,L)	(H,H,M)	(H,M,H)	(L,M,M)	(M,L,M)	(M,H,M)
	SC9	(M,L,L)	(L,VL,L)	(M,L,M)	(VL,L,VL)	(M,L,VL)	(L,L,L)	(M,M,L)	(M,M,M)	(M,M,H)	(L,M,L)	(VH,H,H)
Fuzzy Inputs	SC3	(L,VL,L)	(L,M,L)	(M,M,M)	(M,VH,VH)	(H,VH,H)	(H,M,H)	(M,M,L)	(M,M,H)	(L,L,M)	(M,M,L)	(M,H,M)
	SC6	(H,H,VH)	(M,M,L)	(VH,H,VH)	(VH,VH,H)	(L,L,L)	(H,H,VH)	(M,L,M)	(VH,H,H)	(M,H,M)	(M,H,M)	(L,M,L)
	SC7	(H,M,M)	(H,M,H)	(M,M,L)	(VL,L,L)	(M,M,L)	(L,M,L)	(L,M,M)	(M,L,L)	(M,M,L)	(VH,VH,H)	(H,H,VH)

Table 6.16-Cont.

SCs		Suppliers										
		Sup12	Sup13	Sup14	Sup15	Sup16	Sup17	Sup18	Sup19	Sup20	Sup21	Sup22
Crisp Outputs	SC12	9	60	75	156	4	260	38	23	38	93	17
	SC13	19.667	20.667	14.333	71.000	2.333	127.667	9.000	7.000	11.333	41.330	7.667
Crisp Inputs	SC10	0.717	1.273	0.531	1.409	0.429	0.928	0.273	2.057	0.711	0.573	0.625
	SC11	0.202	0.701	1.061	1.598	2.148	2.380	0.100	1.829	0.406	0.954	0.018

Table 6.15-Cont

SCs		Suppliers										
		Sup23	Sup24	Sup25	Sup26	Sup27	Sup28	Sup29	Sup30	Sup31	Sup32	Sup33
Fuzzy Outputs	SC1	(VL,VL,L)	(L,M,L)	(M,M,L)	(H,H,M)	(H,M,M)	(M,M,L)	(H,M,M)	(M,H,M)	(H,H,M)	(L,VL,VL)	(L,VL,L)
	SC2	(H,H,H)	(L,VL,L)	(H,L,L)	(VH,H,VH)	(VH,H,H)	(L,M,M)	(H,H,VH)	(M,L,M)	(L,VL,L)	(VH,H,H)	(L,VL,VL)
	SC4	(M,L,M)	(M,H,M)	(L,M,M)	(M,H,H)	(M,L,L)	(H,VH,H)	(H,H,H)	(VH,H,VH)	(H,H,M)	(H,H,M)	(M,L,M)
	SC5	(H,L,H)	(VL,L,VL)	(H,VH,H)	(L,L,VL)	(L,VL,L)	(L,VL,L)	(VL,L,VL)	(L,M,M)	(M,L,L)	(VL,VL,L)	(L,VL,VL)
	SC8	(L,VL,L)	(H,M,M)	(L,M,L)	(M,M,H)	(M,M,H)	(H,VH,H)	(M,L,M)	(M,M,H)	(M,H,H)	(M,L,L)	(VH,H,VH)
	SC9	(M,M,L)	(M,M,H)	(M,L,M)	(VL,VL,L)	(L,L,VL)	(VL,L,VL)	(M,M,L)	(M,L,M)	(H,M,H)	(L,L,VL)	(VH,VH,H)
Fuzzy Inputs	SC3	(L,VL,VL)	(M,M,M)	(L,M,L)	(M,H,M)	(M,H,M)	(L,VL,L)	(VL,VL,L)	(L,VL,L)	(L,M,M)	(M,L,L)	(VH,VH,VH)
	SC6	(H,VH,H)	(L,L,VL)	(VH,H,H)	(H,M,H)	(M,L,M)	(H,H,H)	(M,M,M)	(L,L,VL)	(H,VH,H)	(VH,H,H)	(M,H,M)
	SC7	(M,L,M)	(VH,VH,H)	(H,M,M)	(VH,H,H)	(H,VH,H)	(VH,H,H)	(H,VH,VH)	(M,H,M)	(L,M,M)	(H,VH,H)	(L,VL,L)

Table 6.16-Cont.

SCs		Suppliers										
		Sup23	Sup24	Sup25	Sup26	Sup27	Sup28	Sup29	Sup30	Sup31	Sup32	Sup33
Crisp Outputs	SC12	33	43	55	24	6	25	182	165	162	209	300
	SC13	2.667	19.667	25.333	10.000	0.667	18.333	67.333	21.667	72.333	18.333	58.667
Crisp Inputs	SC10	0.800	2.168	1.188	0.720	0.660	1.129	0.593	1.754	2.094	0.492	3.609
	SC11	0.120	0.700	0.847	0.062	0.667	0.509	2.215	0.438	0.466	0.291	2.304

Table 6.15-Cont

SCs		Suppliers								
		Sup34	Sup35	Sup36	Sup37	Sup38	Sup39	Sup40	Sup41	Sup42
Fuzzy Outputs	SC1	(H,VH,VH)	(VL,VL,L)	(H,VH,H)	(H,H,M)	(M,M,H)	(H,H,VH)	(H,H,M)	(L,L,M)	(M,H,M)
	SC2	(M,M,H)	(H,M,H)	(VH,H,VH)	(H,M,M)	(H,VH,H)	(M,M,H)	(H,M,H)	(M,M,M)	(M,L,M)
	SC4	(H,H,H)	(M,H,H)	(H,VH,VH)	(M,L,L)	(VH,VH,H)	(H,M,M)	(L,M,M)	(VL,L,VL)	(VL,VL,L)
	SC5	(M,M,L)	(L,L,VL)	(L,M,M)	(L,L,VL)	(VL,L,L)	(M,H,M)	(M,L,M)	(L,VL,L)	(M,H,H)
	SC8	(M,L,M)	(M,L,L)	(H,M,H)	(VH,H,VH)	(H,M,M)	(H,M,M)	(H,VH,VH)	(H,H,VH)	(VL,L,VL)
	SC9	(L,M,L)	(VL,L,VL)	(H,H,M)	(L,L,VL)	(M,M,H)	(H,M,H)	(H,H,VH)	(VH,H,H)	(L,L,L)
Fuzzy Inputs	SC3	(VL,L,L)	(L,L,M)	(L,M,L)	(VH,VH,H)	(L,L,L)	(VL,L,L)	(VL,L,VL)	(VH,VH,VH)	(M,L,M)
	SC6	(L,L,VL)	(H,M,H)	(L,L,VL)	(M,L,M)	(L,M,H)	(H,M,H)	(VL,VL,L)	(M,M,M)	(L,M,L)
	SC7	(VL,L,L)	(L,M,M)	(M,H,M)	(L,M,M)	(M,H,M)	(L,VL,L)	(M,L,L)	(VH,VH,H)	(H,M,M)

Table 6.16-Cont.

SCs		Suppliers								
		Sup34	Sup35	Sup36	Sup37	Sup38	Sup39	Sup40	Sup41	Sup42
Crisp Outputs	SC12	36	16	33	292	76	13	407	113	23
	SC13	41.667	14.667	15.667	175.667	25.000	9.667	146.667	52.000	19.600
Crisp Inputs	SC10	1.346	0.886	0.099	1.076	0.538	0.919	1.146	1.997	1.975
	SC11	0.915	0.301	0.127	1.954	0.242	0.297	0.354	0.536	1.953

Table 6.17
Normalized aggregated supplier ratings with respect to fuzzy SCs

		Suppliers										
		Sup1	Sup2	Sup3	Sup4	Sup5	Sup6	Sup7	Sup8	Sup9	Sup10	Sup11
Fuzzy Outputs	SC1	(0.357,0.464,0.571)	(0.286,0.393,0.500)	(0.714,0.821,0.929)	(0.714,0.821,0.929)	(0.714,0.821,0.929)	(0.286,0.393,0.500)	(0.286,0.393,0.500)	(0.643,0.750,0.857)	(0.714,0.821,0.929)	(0.357,0.464,0.571)	(0.571,0.679,0.786)
	SC2	(0.571,0.679,0.786)	(0.643,0.750,0.857)	(0.571,0.679,0.786)	(0.357,0.464,0.571)	(0.714,0.821,0.929)	(0.357,0.464,0.571)	(0.500,0.607,0.714)	(0.286,0.393,0.500)	(0.786,0.893,1.000)	(0.071,0.179,0.286)	(0.500,0.607,0.714)
	SC4	(0.500,0.607,0.714)	(0.286,0.393,0.500)	(0.500,0.607,0.714)	(0.500,0.607,0.714)	(0.714,0.821,0.929)	(0.286,0.393,0.500)	(0.500,0.607,0.714)	(0.500,0.607,0.714)	(0.714,0.821,0.929)	(0.571,0.679,0.786)	(0.286,0.393,0.500)
	SC5	(0.385,0.500,0.615)	(0.308,0.423,0.538)	(0.385,0.500,0.615)	(0.385,0.500,0.615)	(0.615,0.731,0.846)	(0.308,0.423,0.538)	(0.077,0.192,0.308)	(0.385,0.500,0.615)	(0.385,0.500,0.615)	(0.385,0.500,0.615)	(0.615,0.731,0.846)
	SC8	(0.571,0.679,0.786)	(0.143,0.250,0.357)	(0.571,0.679,0.786)	(0.714,0.821,0.929)	(0.286,0.393,0.500)	(0.357,0.464,0.571)	(0.357,0.464,0.571)	(0.786,0.893,1.000)	(0.357,0.464,0.571)	(0.286,0.393,0.500)	(0.500,0.607,0.714)
	SC9	(0.071,0.179,0.286)	(0.571,0.679,0.786)	(0.786,0.893,1.000)	(0.714,0.821,0.929)	(0.571,0.679,0.786)	(0.500,0.607,0.714)	(0.500,0.607,0.714)	(0.500,0.607,0.714)	(0.143,0.250,0.357)	(0.500,0.607,0.714)	(0.214,0.321,0.429)
Fuzzy Inputs	SC3	(0.667,0.767,0.867)	(0.333,0.433,0.533)	(0.267,0.367,0.467)	(0.267,0.367,0.467)	(0.267,0.367,0.467)	(0.533,0.633,0.733)	(0.267,0.367,0.467)	(0.133,0.233,0.333)	(0.467,0.567,0.667)	(0.267,0.367,0.467)	(0.200,0.300,0.400)
	SC6	(0.786,0.893,1.000)	(0.714,0.821,0.929)	(0.071,0.179,0.286)	(0.071,0.179,0.286)	(0.500,0.607,0.714)	(0.786,0.893,1.000)	(0.714,0.821,0.929)	(0.286,0.393,0.500)	(0.286,0.393,0.500)	(0.643,0.750,0.857)	(0.500,0.607,0.714)
	SC7	(0.286,0.393,0.500)	(0.071,0.179,0.286)	(0.143,0.250,0.357)	(0.500,0.607,0.714)	(0.286,0.393,0.500)	(0.571,0.679,0.786)	(0.571,0.679,0.786)	(0.571,0.679,0.786)	(0.143,0.250,0.357)	(0.571,0.679,0.786)	(0.714,0.821,0.929)

Table 6.18
Normalized supplier performances with respect to quantitative criteria

		Suppliers										
SCs		Sup1	Sup2	Sup3	Sup4	Sup5	Sup6	Sup7	Sup8	Sup9	Sup10	Sup11
Crisp Outputs	SC12	0.386	0.990	0.243	0.346	0.061	0.088	0.668	0.170	0.396	0.093	0.027
	SC13	0.334	1.000	0.078	0.166	0.042	0.101	0.244	0.026	0.269	0.114	0.057
Crisp Inputs	SC10	0.272	0.414	0.367	0.238	0.082	0.237	0.457	0.366	0.346	0.638	0.518
	SC11	1.000	0.531	0.008	0.098	0.121	0.140	0.600	0.094	0.046	0.038	0.138

Table 6.17-Cont.

		Suppliers										
		Sup12	Sup13	Sup14	Sup15	Sup16	Sup17	Sup18	Sup19	Sup20	Sup21	Sup22
Fuzzy Outputs	SC1	(0.143,0.250,0.357)	(0.071,0.179,0.286)	(0.357,0.464,0.571)	(0.286,0.393,0.500)	(0.357,0.464,0.571)	(0.071,0.179,0.286)	(0.571,0.679,0.786)	(0.500,0.607,0.714)	(0.286,0.393,0.500)	(0.571,0.679,0.786)	(0.643,0.750,0.857)
	SC2	(0.286,0.393,0.500)	(0.571,0.679,0.786)	(0.571,0.679,0.786)	(0.571,0.679,0.786)	(0.714,0.821,0.929)	(0.571,0.679,0.786)	(0.357,0.464,0.571)	(0.143,0.250,0.357)	(0.500,0.607,0.714)	(0.571,0.679,0.786)	(0.571,0.679,0.786)
	SC4	(0.500,0.607,0.714)	(0.357,0.464,0.571)	(0.429,0.536,0.643)	(0.714,0.821,0.929)	(0.071,0.179,0.286)	(0.357,0.464,0.571)	(0.643,0.750,0.857)	(0.571,0.679,0.786)	(0.500,0.607,0.714)	(0.286,0.393,0.500)	(0.571,0.679,0.786)
	SC5	(0.077,0.192,0.308)	(0.538,0.654,0.769)	(0.077,0.192,0.308)	(0.385,0.500,0.615)	(0.615,0.731,0.846)	(0.308,0.423,0.538)	(0.308,0.423,0.538)	(0.077,0.192,0.308)	(0.769,0.885,1.000)	(0.154,0.269,0.385)	(0.308,0.423,0.538)
	SC8	(0.500,0.607,0.714)	(0.071,0.179,0.286)	(0.357,0.464,0.571)	(0.429,0.536,0.643)	(0.071,0.179,0.286)	(0.214,0.321,0.429)	(0.571,0.679,0.786)	(0.571,0.679,0.786)	(0.357,0.464,0.571)	(0.357,0.464,0.571)	(0.500,0.607,0.714)
	SC9	(0.214,0.321,0.429)	(0.143,0.250,0.357)	(0.357,0.464,0.571)	(0.071,0.179,0.286)	(0.214,0.321,0.429)	(0.214,0.321,0.429)	(0.357,0.464,0.571)	(0.429,0.536,0.643)	(0.500,0.607,0.714)	(0.286,0.393,0.500)	(0.714,0.821,0.929)
Fuzzy Inpu	SC3	(0.133,0.233,0.333)	(0.267,0.367,0.467)	(0.400,0.500,0.600)	(0.667,0.767,0.867)	(0.667,0.767,0.867)	(0.533,0.633,0.733)	(0.333,0.433,0.533)	(0.467,0.567,0.667)	(0.267,0.367,0.467)	(0.333,0.433,0.533)	(0.467,0.567,0.667)
	SC6	(0.714,0.821,0.929)	(0.357,0.464,0.571)	(0.786,0.893,1.000)	(0.786,0.893,1.000)	(0.214,0.321,0.429)	(0.714,0.821,0.929)	(0.357,0.464,0.571)	(0.714,0.821,0.929)	(0.500,0.607,0.714)	(0.500,0.607,0.714)	(0.286,0.393,0.500)
	SC7	(0.500,0.607,0.714)	(0.571,0.679,0.786)	(0.357,0.464,0.571)	(0.143,0.250,0.357)	(0.357,0.464,0.571)	(0.286,0.393,0.500)	(0.357,0.464,0.571)	(0.286,0.393,0.500)	(0.357,0.464,0.571)	(0.786,0.893,1.000)	(0.714,0.821,0.929)

Table 6.18-Cont.

		Suppliers										
SCs		Sup12	Sup13	Sup14	Sup15	Sup16	Sup17	Sup18	Sup19	Sup20	Sup21	Sup22
Crisp Outputs	SC12	0.022	0.147	0.184	0.383	0.010	0.639	0.093	0.057	0.093	0.229	0.042
	SC13	0.080	0.084	0.058	0.288	0.009	0.518	0.037	0.028	0.046	0.168	0.031
Crisp Inputs	SC10	0.199	0.353	0.147	0.390	0.119	0.257	0.076	0.570	0.197	0.159	0.173
	SC11	0.078	0.269	0.407	0.613	0.825	0.914	0.038	0.702	0.156	0.366	0.007

Table 6.17-Cont.

		Suppliers										
		Sup23	Sup24	Sup25	Sup26	Sup27	Sup28	Sup29	Sup30	Sup31	Sup32	Sup33
Fuzzy Outputs	SC1	(0.071,0.179,0.286	(0.286,0.393,0.500	(0.357,0.464,0.571)	(0.571,0.679,0.786)	(0.500,0.607,0.714)	(0.357,0.464,0.571)	(0.500,0.607,0.714)	(0.500,0.607,0.714)	(0.571,0.679,0.786)	(0.071,0.179,0.286)	(0.143,0.250,0.357)
	SC2	(0.643,0.750,0.857	(0.143,0.250,0.357	(0.357,0.464,0.571)	(0.786,0.893,1.000)	(0.714,0.821,0.929)	(0.357,0.464,0.571)	(0.714,0.821,0.929)	(0.357,0.464,0.571)	(0.143,0.250,0.357)	(0.714,0.821,0.929)	(0.071,0.179,0.286)
	SC4	(0.357,0.464,0.571	(0.500,0.607,0.714	(0.357,0.464,0.571)	(0.571,0.679,0.786)	(0.286,0.393,0.500)	(0.714,0.821,0.929)	(0.643,0.750,0.857)	(0.786,0.893,1.000)	(0.571,0.679,0.786)	(0.571,0.679,0.786)	(0.357,0.464,0.571)
	SC5	(0.538,0.654,0.769	(0.077,0.192,0.308	(0.769,0.885,1.000)	(0.154,0.269,0.385)	(0.154,0.269,0.385)	(0.154,0.269,0.385)	(0.077,0.192,0.308)	(0.385,0.500,0.615)	(0.308,0.423,0.538)	(0.077,0.192,0.308)	(0.077,0.192,0.308)
	SC8	(0.143,0.250,0.357	(0.500,0.607,0.714	(0.286,0.393,0.500)	(0.500,0.607,0.714)	(0.500,0.607,0.714)	(0.714,0.821,0.929)	(0.357,0.464,0.571)	(0.500,0.607,0.714)	(0.571,0.679,0.786)	(0.286,0.393,0.500)	(0.786,0.893,1.000)
	SC9	(0.357,0.464,0.571	(0.500,0.607,0.714	(0.357,0.464,0.571)	(0.071,0.179,0.286)	(0.143,0.250,0.357)	(0.071,0.179,0.286)	(0.357,0.464,0.571)	(0.357,0.464,0.571)	(0.571,0.679,0.786)	(0.143,0.250,0.357)	(0.786,0.893,1.000)
Fuzzy Inputs	SC3	(0.067,0.167,0.267	(0.400,0.500,0.600	(0.267,0.367,0.467)	(0.467,0.567,0.667)	(0.467,0.567,0.667)	(0.133,0.233,0.333)	(0.067,0.167,0.267)	(0.133,0.233,0.333)	(0.333,0.433,0.533)	(0.267,0.367,0.467)	(0.800,0.900,1.000)
	SC6	(0.714,0.821,0.929	(0.143,0.250,0.357	(0.714,0.821,0.929)	(0.571,0.679,0.786)	(0.357,0.464,0.571)	(0.643,0.750,0.857)	(0.429,0.536,0.643)	(0.143,0.250,0.357)	(0.714,0.821,0.929)	(0.714,0.821,0.929)	(0.500,0.607,0.714)
	SC7	(0.357,0.464,0.571	(0.786,0.893,1.000	(0.500,0.607,0.714)	(0.714,0.821,0.929)	(0.714,0.821,0.929)	(0.714,0.821,0.929)	(0.786,0.893,1.000)	(0.500,0.607,0.714)	(0.357,0.464,0.571)	(0.714,0.821,0.929)	(0.143,0.250,0.357)

Table 6.18-Cont.

		Suppliers										
SCs		Sup23	Sup24	Sup25	Sup26	Sup27	Sup28	Sup29	Sup30	Sup31	Sup32	Sup33
Crisp Outputs	SC12	0.081	0.106	0.135	0.059	0.015	0.061	0.447	0.405	0.398	0.514	0.737
	SC13	0.011	0.080	0.103	0.041	0.003	0.074	0.273	0.088	0.294	0.074	0.238
Crisp Inputs	SC10	0.222	0.601	0.329	0.200	0.183	0.313	0.164	0.486	0.580	0.136	1.000
	SC11	0.046	0.269	0.325	0.024	0.256	0.196	0.851	0.168	0.179	0.112	0.885

Table 6.17-Cont.

		Suppliers								
		Sup34	Sup35	Sup36	Sup37	Sup38	Sup39	Sup40	Sup41	Sup42
Fuzzy Outputs	SC1	(0.786,0.893,1.000)	(0.071,0.179,0.286)	(0.714,0.821,0.929)	(0.571,0.679,0.786)	(0.500,0.607,0.714)	(0.714,0.821,0.929)	(0.571,0.679,0.786)	(0.286,0.393,0.500)	(0.500,0.607,0.714)
	SC2	(0.500,0.607,0.714)	(0.571,0.679,0.786)	(0.786,0.893,1.000)	(0.500,0.607,0.714)	(0.714,0.821,0.929)	(0.500,0.607,0.714)	(0.571,0.679,0.786)	(0.429,0.536,0.643)	(0.357,0.464,0.571)
	SC4	(0.643,0.750,0.857)	(0.571,0.679,0.786)	(0.786,0.893,1.000)	(0.286,0.393,0.500)	(0.786,0.893,1.000)	(0.500,0.607,0.714)	(0.357,0.464,0.571)	(0.071,0.179,0.286)	(0.071,0.179,0.286)
	SC5	(0.385,0.500,0.615)	(0.154,0.269,0.385)	(0.385,0.500,0.615)	(0.154,0.269,0.385)	(0.154,0.269,0.385)	(0.538,0.654,0.769)	(0.385,0.500,0.615)	(0.154,0.269,0.385)	(0.615,0.731,0.846)
	SC8	(0.357,0.464,0.571)	(0.286,0.393,0.500)	(0.571,0.679,0.786)	(0.786,0.893,1.000)	(0.500,0.607,0.714)	(0.500,0.607,0.714)	(0.786,0.893,1.000)	(0.714,0.821,0.929)	(0.071,0.179,0.286)
	SC9	(0.286,0.393,0.500)	(0.071,0.179,0.286)	(0.571,0.679,0.786)	(0.143,0.250,0.357)	(0.500,0.607,0.714)	(0.571,0.679,0.786)	(0.714,0.821,0.929)	(0.714,0.821,0.929)	(0.214,0.321,0.429)
Fuzzy Inputs	SC3	(0.133,0.233,0.333)	(0.267,0.367,0.467)	(0.267,0.367,0.467)	(0.733,0.833,0.933)	(0.200,0.300,0.400)	(0.133,0.233,0.333)	(0.067,0.167,0.267)	(0.800,0.900,1.000)	(0.333,0.433,0.533)
	SC6	(0.143,0.250,0.357)	(0.571,0.679,0.786)	(0.143,0.250,0.357)	(0.357,0.464,0.571)	(0.429,0.536,0.643)	(0.571,0.679,0.786)	(0.071,0.179,0.286)	(0.429,0.536,0.643)	(0.286,0.393,0.500)
	SC7	(0.143,0.250,0.357)	(0.357,0.464,0.571)	(0.500,0.607,0.714)	(0.357,0.464,0.643)	(0.500,0.607,0.714)	(0.143,0.250,0.357)	(0.286,0.393,0.500)	(0.786,0.893,1.000)	(0.500,0.607,0.714)

Table 6.18-Cont.

		Suppliers								
SCs		Sup34	Sup35	Sup36	Sup37	Sup38	Sup39	Sup40	Sup41	Sup42
Crisp Outputs	SC12	0.08845	0.04	0.08	0.72	0.19	0.03	1	0.28	0.06
	SC13	0.16915	0.06	0.06	0.71	0.1	0.04	0.6	0.21	0.08
Crisp Inputs	SC10	0.37282	0.25	0.03	0.3	0.15	0.25	0.32	0.55	0.55
	SC11	0.35116	0.12	0.05	0.75	0.09	0.11	0.14	0.21	0.75

7 CONCLUSION and FUTURE WORKS

In this study, a decision methodology is presented that integrates QFD and DEA allowing for a tradeoff among qualitative and quantitative types of information within the supply chain. Through construction HOQs, which enable the relationships among customer requirements, technical capabilities, and supplier assessment criteria to be considered, the company can develop a supplier evaluation process to have access to suppliers that ensure a certain quality standard in terms of the characteristics of the perceived service. DEA is employed to evaluate suppliers utilizing the qualitative data from HOQ and quantitative evaluation metrics. DEA avoids the critical assumption that the performance parameters are mutually independent. Likewise, DEA disregards the possibility of selecting a suboptimal supplier.

The proposed decision-making methodology is applied to a case of pharmaceutical logistic industry in Turkey. The proposed approach is a sound and effective tool that enables qualitative as well as quantitative aspects to be taken into account, and thus improves the quality of complex supplier selection decision.

Although the proposed approach enables to systematically incorporate the qualitative factors into decision process, subjective judgment may still be required in selecting the inputs and outputs as well as interpreting the results of the analysis. Furthermore, different decision making techniques may be used in assessing the relative importance weights of CRs, TCs and SCs.

Future research will focus on applying the network variant of DEA model (N-DEA) to observe overall efficiency scores of customer-buyer-supplier networks. In conclusion, a user-friendly interface could be developed for decision-makers who are novice in mathematical programming since DEA may appear as a “black box” for decision makers who are not familiar with mathematical programming.

References

Aguezoul, A. (2012). Overview on Supplier Selection of Goods versus 3PL Selection. Journal of Logistics Management, 1(3), p.18-23.

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

Aliabadi, D.E., Kaazemi, A., Pourghannad, B. (2013). A two-level GA to solve an integrated multi-item supplier selection model. Applied Mathematics and Computation, 219(14), p.7600-7615.

Amid, A., Ghodsypour, S. H., O'Brien, C. (2009). A weighted additive fuzzy multi-objective model for the supplier selection problem under price breaks in a supply chain. International Journal of Production Economics, 121(2), p.323–332.

Arikan,F., (2013). A fuzzy solution approach for multi objective supplier selection. Expert System with Applications, 40(3), p.947-952.

Azadeh, A., Alem, S. M. (2010). A flexible deterministic, stochastic and fuzzy data envelopment analysis approach for supply chain risk and vendor selection problem: Simulation analysis. Expert Systems with Applications, 37(12), p.7438–7448.

Bai, C., Sarkis, J. (2010). Integrating sustainability into supplier selection with grey system and rough set methodologies. International Journal of Production Economics, 124(1), p. 252–264.

Barla, S.B. (2003). A case study of supplier selection for lean supply by using a mathematical model. Logistics Information Management, 16 (6), p.451–459.

Bayazit, O. (2006). Use of analytic network process in vendor selection decisions. Benchmarking: An International Journal 13 (5), p.566–579.

Bell,D.(2009).SupplierSelection.URL:
http://wwwpersonal.umich.edu/~dbeil/Supplier_Selection_Beil-EORMS.pdf

Bevilacqua, M., Ciarapica, F.E., Giacchetta, G. (2006). A fuzzy-QFD approach to supplier selection. Journal of Purchasing and Supply Management, 12 (1),14–27.

Bhattacharya, A., Geraghty, J., Young, P. (2010). Supplier selection paradigm: An integrated hierarchical QFD methodology under multiple-criteria environment. Applied

Soft Computing Journal, 10(4), p.1013–1027.

Bottani, E., Rizzi, A. (2006). Strategic management of logistics service: A fuzzy QFD approach, 103(2), p.585-599.

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

Buyukozkan, G., & Cifci, G. (2012). A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers. Expert Systems with Applications, 39(3), p.3000–3011.

Caplice, C., Sheffi, Y. (1994). A review and evaluation of logistics performance metrics. The International Journal of Logistics Management, 5(4), p. 12-28.

Caplice, C., Sheffi, Y. (1995). A review and evaluation of logistics performance measurement systems. The International Journal of Logistics Management, 6(1), p. 61-74.

Çebi, F., Bayraktar, D. (2003). An integrated approach for supplier selection. Logistics Information Management, 16 (6), p.395–400.

Chai, J., N.K. Liu, J., Ngai, E. (2013). Application of decision-making techniques in supplier selection: A systematic review of literature. Expert System with Applications 40 (10), p.3872-3885

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

Chan, F.T.S., Chan, H.K., Ip, R.W.L., Lau, H.C.W. (2007). A decision support system for supplier selection in the airline industry. Proceedings of the Institution of Mechanical Engineers Part B – Journal of Engineering Manufacture 221 (4),741–758.

Chan, F.T.S., Kumar, N. (2007). Global supplier development considering risk factors using fuzzy extended AHP-based approach. OMEGA – International Journal of Management Science 35 (4), p.417–431.

Charnes, A., Cooper, W.W. (1961). Management models and industrial applications of linear programming. New Jersey: John Wiley and Sons.

Charnes, A., Cooper, W.W., Rhodes, E. (1978). Measuring the efficiency of decision making units. European Journal of Operational Research 2(6), p. 429–444.

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 (2), p. 289–301.

Chen, Y. (2011). Structured methodology for supplier selection and evaluation in a supply chain. Information Sciences, 181(9), p.1651–1670.

Chen, Y., Wang, T., & Wu, C. (2011). Strategic decisions using the fuzzy PROMETHEE for IS outsourcing. Expert Systems with Applications, 38(10), p.13216–13222.

Chen, L. Y., & Wang, T. (2009). Optimizing partners' choice in IS/IT outsourcing projects: The strategic decision of fuzzy VIKOR. International Journal of Production Economics, 120(1), p.233–242.

Chen, Y.M., Huang, P.N. (2007). Bi-negotiation integrated AHP in suppliers selection.Benchmarking: An International Journal 14 (5), p. 575–593.

Choy, K.L., Fan, K.K.H., Lo, V. (2003). Development of an intelligent customer–supplier relationship management system: The application of case-based reasoning. Industrial Management and Data Systems 103 (4), p.263–274.

Christopher, M. (2011). Logistics and supply chain management. London: Pearson Education Limited.

Cohen, L. (1995). Quality function deployment: How to make QFD work for you. Reading, Massachusetts: Addison Wesley Longman.

Cooper, W.W., Seiford, L.M., Tone, K. (2000). Data Envelopment Analysis: A comprehensive text with models, applications, references and DEA-solver software. Boston: Kluwer Academic Publishers.

De Boer L, Van der Wegen L, Telgen J. (1998). Outranking methods in support of supplier selection. European Journal of Purchasing and Supply Management, 4(2–3):109–18.

De Boer, L., Labro, E., Morlacchi, P. (2001). A review of methods supporting supplier selection. European Journal of Purchasing and Supply Management, 7 (2), p.75–89.

De Treville, S., Shapiro, R.D., Hameri, A.P. (2004). From supply chain to demand chain: the role of lead time reduction in improving demand chain performance. Journal of Operations Management, 21(6). P. 613- 627.

Degraeve, Z., Labro, E., Roodhooft, F. (2000). An evaluation of supplier selection methods from a total cost of ownership perspective. European Journal of Operational Research 125 (1), p.34–58.

Demirtas, E.A., Üstün, Ö. (2009). Analytic network process and multi-period goal programming integration in purchasing decisions. Computer and Industrial Engineering, 56 (2), p.677–690.

Despotis, D.K., Smirlis, Y.G., (2002). Data envelopment analysis with imprecise data. European Journal of Operational Research, 140(1), p.24-36.

Dickson, G. W. (1966). An analysis of vendor selection systems and decisions. Journal of Purchasing, 2, 5–17.

Dursun, M., Karsak, E.E. (2013). A QFD – based fuzzy MCDM approach for supplier selection. Applied Mathematical Modelling, 37(8), p.5864-5875.

Falagario, M., Sciancalepore, F., Costantino, N., & Pietroforte, R. (2012). Using a DEA cross efficiency approach in public procurement tenders. European Journal of Operational Research, 218(2), p.523–529.

Farma. (2013). URL: http://www.farmalojistik.com.tr/

Facchinetti, G., Ghiselli, Ricci, R., Muzioli, S., 1998. Note on ranking fuzzy triangular numbers. International Journal of Intelligent Systems 13, 613–622.

Forker, L.B., Mendez, D. (2001). An analytical method for benchmarking best peer suppliers. International Journal of Operations and Production Management, 21 (1–2), p.195–209.

Fortune. (2011) Top 500 Turkey. URL: http://www.fortuneturkey.com/fortune500-2011/fortune500_detay.asp?ID=101

Franceschini, F., Rafele, C. (2000). Quality evaluation in logistics management. International Journal of Agile Management Systems. 2(1), p.49-53.

Garfamy, R.M. (2006). A data envelopment analysis approach based on total cost of ownership for supplier selection. Journal of Enterprise Information Management 19 (6), p.662–678.

Gencer, C., Gürpinar, D. (2007). Analytic network process in supplier selection: A case study in an electronic firm. Applied Mathematical Modeling 31 (11), p.2475– 2486.

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

Griffin A., Hauser, J. (1992). The voice of the customer, Technical report, Marketing Science Institute, Cambridge: MA working paper 92-106.

Hauser, J.R., Clausing, D. (1988). The house of quality. Harvard Business Review, p. 63–73.

Hillier, F.S., Lieberman, G.J. (2005). Introduction to Operations Research. New York: McGraw-Hill.

Ho, W., Dey, P. K., Lockström, M. (2011). Strategic sourcing: A combined QFD and AHP approach in manufacturing. Supply Chain Management, 16(6), p.446–461.

Ho, W., He, T., Lee, C.K.M., Emrouznejad, A. (2012). Strategic logistics outsourcing: An integrated QFD and fuzzy AHP approach. Expert Systems with Applications. 39(12), p. 10841-10850.

Ho, W., Xu, X., Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. European Journal of Operational Research, 202(1), p.16–24.

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

Hou, J., Su, D. (2007). EJB–MVC oriented supplier selection system for mass customization. Journal of Manufacturing Technology Management 18 (1), p.54– 71.

Hsu, B., Chiang, C., & Shu, M. (2010). Supplier selection using fuzzy quality data and their applications to touch screen. Expert Systems with Applications, 37(9), p.6192–6200.

Huang, S.H., Keska, H., 2007. Comprehensive and configurable metrics for supplier selection. International Journal of Production Economics 105 (2), p.510–523.

Kahraman, C., Cebeci, U., Ulukan, Z. (2003). Multi-criteria supplier selection using fuzzy AHP. Logistics Information Management 16 (6), p.382–394.

Kannan, D., Khodaverdi, R., Olfat L., Jafarian, A., Diabat, A., (In Press) Integrated fuzzy multi criteria decision making method and multiobjective programming approach for supplier selection and order allocation in a green supply chain. Journal of Cleaner Production.

Kara, S. S. (2011). Supplier selection with an integrated methodology in unknown environment. Expert Systems with Applications, 38(3), p.2133–2139.

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

Karsak, E.E. (2008). Using data envelopment analysis for evaluating flexible manufacturing systems in the presence of imprecise data. The International Journal of Advanced Manufacturing Technology, 35 (9-10), p.867-874

Karsak, E.E., Sozer, S., Alptekin, E. (2003). Product planning in quality function deployment using a combined analytic network process and goal programming approach. Computers & Industrial Engineering, 44 (1), p.171-190.

Kilic, H.S., (In Press). An integrated approach for supplier selection in multi-item/multi-supplier environment. Applied Mathematical Modelling.

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

Kumar,A., Jain, V., Kumar, S., (2014). A comprehensive environment friendly approach for supplier selection. Omega, 42(1), p.109-123.

Levary, R. R. (2008). Using the analytic hierarchy process to rank foreign suppliers based on supply risks. Computers and Industrial Engineering, 55(2), p.535–542.

Liu, J., Ding, F.Y., Lall, V. (2000). Using data envelopment analysis to compare suppliers for supplier selection and performance improvement. Supply Chain Management: An International Journal, 5 (3), p.143–150.

Li, L., Zabinsky, Z. B. (2011). Incorporating uncertainty into a supplier selection problem. International Journal of Production Economics, 134(2), p. 344–356.

Liu, F.H.F., Hai, H.L. (2005). The voting analytic hierarchy process method for selecting supplier. International Journal of Production Economics 97 (3), p. 308–317.

Liu, H.T., Wang, W.K. (2009). An integrated fuzzy approach for provider evaluation and selection in third-party logistics. Expert Systems with Applications, 36(3), p. 4387-4398

Liu, P., Zhang, X. (2011). Research on the supplier selection of a supply chain based on entropy weight and improved ELECTRE-III method. International Journal of Production Research, 49(3), p.637–646.

Martel, J.M. (1997). Aggregating preference: utility function and outranking approaches. In: J. Climaco (Ed.), Multicriteria Analysis (76-84). Heidelberg: Springer-Verlag.

Masi, D., Micheli J.L., Cagno, E., (2013). A meta-model for choosing a supplier selection technique within an EPC company. Journal of Purchasing and Supply Management, 19 (1), p.5-15.
Ministery of Health. (2013). URL: www.saglik.gov.tr.

Monczka, R.M., Handfield, R.B., Giunipero, L.C., Petterson, J.L. (2008). Purchasing and supply chain management. South-Western: Cengage Learning.

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

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

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

Ng, W. L. (2008). An efficient and simple model for multiple criteria supplier selection problem. European Journal of Operational Research, 186(3), p.1059–1067.

Ni, M., Xu, X., Deng, S. (2007). Extended QFD and data-mining-based methods for supplier selection in mass customization.International Journal of Computer Integrated Manufacturing, 20 (2-3), p.280-291.

Onüt, S., Kara, S. S., & Isik, E. (2009). Long term supplier selection using a combined fuzzy MCDM approach: A case study for a telecommunication company. Expert Systems with Applications, 36(2), p.3887–3895.

Ordoobadi, S. M. (2010). Application of AHP and taguchi loss functions in supply chain. Industrial Management and Data Systems, 110(8), p.1251–1269.

Pomerol, J-C., Barba-Romero, S. (2000). Multicriterion decision in management: Principles and Practice. Boston: Kluwer Academic Publishers.

Ramanathan, R. (2007). Supplier selection problem: Integrating DEA with the approaches of total cost of ownership and AHP. Supply Chain Management: An International Journal, 12 (4), p.258–261.

Rao, R.V. (2007). Decision making in the manufacturing environment: Using graph theory and fuzzy multiple attribute decision making methods. London: Springer Series in Manufacturing.

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

Saaty, T. (1977). A scaling method for priorities in hierarchical structures. Journal of Mathematical Psychology, 15 (3), p. 234–281.

Saaty, T. (1980). The analytic hierarchy process. New York: McGraw-Hill.

Saen, R.F. (2006). A decision model for selecting technology suppliers in the presence of nondiscretionary factors. Applied Mathematics and Computation, 181 (2),1609–1615.

Saen, R.F. (2007). A new mathematical approach for supplier selection: Accounting for non-homogeneity is important. Applied Mathematics and Computation, 185 (1), p.84–95.

Saen, R. F. (2008). Supplier selection by the new AR-IDEA model. International Journal of Advanced Manufacturing Technology, 39(11–12), p.1061–1070.

Sarkis, J., Talluri, S. (2002). A model for strategic supplier selection. Journal of Supply Chain Management 38 (1), p.18–28.

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

Seydel, J. (2005). Supporting the paradigm shift in vendor selection: Multi-criteria methods for sole-sourcing. Managerial Finance, 31 (3), p.49–66.

Seydel, J. (2006). Data envelopment analysis for decision support. Industrial Management and Data Systems, 106 (1), p.81–95.

Shemshadi, A., Shirazi, H., Toreihi, M., Tarokh, M. J. (2011). A fuzzy VIKOR method for supplier selection based on entropy measure for objective weighting. Expert Systems with Applications, 38(10), p.12160–12167.

Soukup, W.R. (1987). Supplier Selection Strategies. Journal of Purchasing and Materials Management, Summer, p.7-12

Talluri, S., Sarkis, J. (2002). A model for performance monitoring of suppliers. International Journal of Production Research, 40 (16), p.4257–4269.

Talluri, S., Narasimhan, R. (2003). Vendor evaluation with performance variability: A max–min approach. European Journal of Operational Research, 146 (3), p.543–552.

Talluri, S., Narasimhan, R. (2004). A methodology for strategic sourcing. European Journal of Operational Research, 154 (1), p.236–250.

Talluri, S., Narasimhan, R. (2005). A note on ‘‘a methodology for supply baseoptimization”. IEEE Transactions on Engineering Management, 52 (1), p.130–139.

Tanyas, M., Serdar, S., (2003). A comparison of quality performance criteria of logistics service providers and those of their customers. In: International Logistics Congress, June 31, July 1, Istanbul, p.1-5.

Thanassoulis, E. (2001). Introduction to Data Envelopment Analysis. Massachusetts: Kluwer Academic Publishers.

Toloo, M., Nalchigar, S. (2011). A new DEA method for supplier selection in presence of both cardinal and ordinal data. Expert Systems with Applications, 38(12), p.14726–14731.

Ventura, J.A., Valdebenito, V.A., Golany, B., (In Press). A Dynamic Inventory Model with Supplier Selection in a Serial Supply Chain Structure. European Journal of Operational Research.

Verma R, Pullman ME. (1998).An analysis of the supplier selection process. Omega 26 (6). P.739–50.

Wadhwa, V., Ravindran, A.R. (2007). Vendor selection in outsourcing. Computers and Operations Research, 34 (12), p.3725–3737.

Waters, D. (2003). Logistics: An introduction to supply chain management. New York: Palgrave Macmillan.

Weber, C.A., Current, J.R., Benton, W.C. (1991). Vendor selection criteria and methods. European Journal of Operational Research, 50 (1), p.2–18.

Weber, C.A., Ellram, L.M., 1992. Supplier selection using multi-objective programming: a decision support system approach. International Journal of Physical Distribution& Logistics Management 23 (2), p.3}14.

Weber, C.A., Desai, A., 1996. Determination of paths to vendor market e$ciency using parallel co-ordinates representation: a negotiation tool for buyers. European Journal of Operational Research 90, p. 142-155.

Weber, C.A., Current, J.R., Desai, A., 1998. Non-cooperative negotiation strategies for vendor selection. European Journal of Operational Research 108, p. 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), p.90–98.

Wu, D. D. (2010). A systematic stochastic efficiency analysis model and application to international supplier performance evaluation. Expert Systems with Applications, 37(9), p. 6257–6264.

Wu, D., Olson, D. L. (2008a). A comparison of stochastic dominance and stochastic DEA for vendor evaluation. International Journal of Production Research, 46(8),2313–2327.

Wu, D., Olson, D. L. (2008b). Supply chain risk, simulation, and vendor selection. International Journal of Production Economics, 114(2), p.646–655.

Wu, T., Blackhurst, J. (2009). Supplier evaluation and selection: An augmented DEA approach. International Journal of Production Research, 47(16), p.4593–4608.

Zadeh, L.A. (1978). Fuzzy sets as a basis for a theory of possibility, Fuzzy Sets Syst. 100, p.9–34.

Zeydan, M., Çolpan, C., Çobanoglu, C. (2011). A combined methodology for supplier selection and performance evaluation. Expert Systems with Applications, 38(3), p.2741–2751.

Biographical Sketch

Melih ECE was born on June 28, 1986, in Aydin. He received the Bachelor of Industrial Systems Engineering and a Minor in Mathematics degrees from Izmir University of Economics in Izmir, in 2010. He attended Master of Science in Industrial Engineering in the Institute of Science and Engineering of Galatasaray University in 2010. His major interests are Decision Theory, Timetabling and Portfolio Optimization.