MULTI-CRITERIA DECISION MAKING APPROACHES FOR SUPPLIER SELECTION

(TEDARİKÇİ SEÇİMİ İÇİN ÇOK ÖLÇÜTLÜ KARAR VERME YAKLAŞIMLARI)

by

Mehtap DURSUN USTA, M.S.

Thesis

Submitted in Partial Fulfillment

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ABSTRACT

Supply chain is composed of a complex sequence of processing stages, ranging from raw materials supplies, parts manufacturing, components and end-products assembling, to the delivery of end products. In the context of supply chain management, supplier selection decision is considered as one of the key issues faced by operations and purchasing managers to remain competitive. Today, a significant number of manufacturers spend roughly half its revenue to purchase goods and services, which makes a company's success dependent on its interactions with suppliers. In a globally competitive environment, organizations give particular importance to the identification and selection of alternative supply sources. A well-selected set of suppliers makes a strategic difference to an organization's ability to reduce costs and improve quality of its end products. As a result, an effective supplier selection process is a crucial element in a company's quality success or failure.

Supplier selection and management can be applied to a variety of suppliers throughout a product's life cycle from initial raw material acquisition to end-of-life service providers. Thus, the breadth and diversity of suppliers make the process even more cumbersome. Supplier selection process has different phases such as problem definition, decision criteria formulation, pre-qualification of potential suppliers, and making a final choice. The quality of the final choice largely depends on the quality of all the steps involved in the selection process.

Most of the existing research on supplier selection considers only quantifiable aspects of the supplier selection decision. However, several factors such as incomplete information, qualitative criteria and imprecision preferences are not taken into account in the decision making process. These criteria are subjective factors that are difficult to quantify. The uncertainty of subjective judgment is present when carrying out a supplier selection process. Moreover, decision-making becomes more complicated

when the available information is incomplete or imprecise. The classical MCDM methods that incorporate deterministic or random processes cannot effectively tackle decision problems including subjective information. In practice, decision making in supplier selection includes a high degree of vagueness and imprecision. Fuzzy set theory sets forth a sound decision support methodology to overcome the inherent uncertainty.

The objective of this thesis is to propose fuzzy multi-criteria group decision making approaches based on the quality function deployment (QFD) concept for supplier selection. In supplier selection process, the company's primary purpose is to identify suppliers that ensure a certain quality standard regarding characteristics of the purchased products or services. Achieving these objectives depends heavily on accounting for the relationships between purchased product features and supplier assessment criteria, and also the relationships between supplier assessment criteria overruling the unrealistic independence assumption. Hence, constructing a house of quality (HOQ), which enables not only the relationships among the purchased product features and supplier assessment criteria but also inner dependence of supplier assessment criteria to be considered, is essential to determine how well each supplier characteristic succeeds in meeting the requirements established for the product being purchased.

QFD is a customer-oriented design tool for maximizing customer satisfaction. As an interdisciplinary team process, QFD is used to plan and design new or improved products or services that satisfy customer needs. The basic concept of QFD is to translate the desires of customers into technical attributes (TAs), and subsequently into parts 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, called the house of quality (HOQ) translates customer needs into engineering characteristics, ant it is the most frequently employed matrix in QFD.

In traditional QFD applications, the company has to identify its customers' expectations and their relative importance to determine the design characteristics for which resources should be allocated. On the other hand, when the HOQ is used in supplier selection, the company starts with the features that the outsourced product/service must possess to meet certain requirements that the company has established, and then tries to identify which of the suppliers' attributes have the greatest impact on the achievement of its established objectives.

The procedures used in this thesis consider the QFD planning as a fuzzy multi-criteria group decision tool and construct two interrelated HOQ matrices to compute the weights of supplier selection criteria and the ratings of suppliers. The first and second developed approaches employ fuzzy weighted average (FWA) method to calculate the upper and lower bounds of the weights of supplier selection criteria and the ratings of the suppliers. Then, a ranking method that is reported to be more efficient and accurate than its predecessors is employed to rank the suppliers. The third proposed multi-criteria decision making (MCDM) approach utilizes the fusion of fuzzy information and the 2-tuple linguistic representation model, which enable decision-makers to tackle the problems of multi-granularity and loss of information.

In order to illustrate the application of the proposed decision making methods to medical supplier selection problem, a case study conducted in a private hospital in the Asian side of Istanbul is presented. The hospital operates with all major departments, and also includes facilities such as clinical laboratories, emergency service, intensive care units and operating room. The first two of the proposed methods yield the same ranking. According to the results of the analysis, supplier 1 is determined as the most suitable supplier, which is followed by supplier 7. Suppliers 10 and 12 are ranked at the bottom due to late delivery time, inadequate experience in the sector, unsatisfactory earlier business relationships, and improper geographical location. Using the third proposed algorithm, supplier 7 is determined as the most suitable supplier, which is followed by supplier 1. Suppliers 10 and 12 are ranked at the bottom as obtained from the other two methods.

RESUME

Une chaîne d'approvisionnement se compose d'une séquence de processus complexe, allant de l'approvisionnement en matières premières, la fabrication de pièces, l'assemblage des composants et des produits finis, à la livraison des produits finis. Les fournisseurs constituent une des branches importantes de la hiérarchie de la chaîne d'approvisionnement, et les états du marché et les demandes de client changeant rapides exigent l'intégration des sociétés avec leurs fournisseurs. Dans les environnements de production fortement concurrentiels d'aujourd'hui, les organisations donnent une importance particulière à l'identification et la sélection des fournisseurs. Des fournisseurs qui sont bien choisis font une différence stratégique sur la capacité d'une organisation à réduire les coûts et améliorer la qualité de ses produits finis. Le processus de sélection des fournisseurs a différentes phases telles que la définition des problèmes, la formulation des critères de décision, pré-qualification des fournisseurs, et faire un choix définitif. La qualité du choix final dépend largement de la qualité de toutes les étapes du processus.

La plupart des recherches sur la sélection des fournisseurs ne considère que les aspects quantifiables de la décision de sélection des fournisseurs. Cependant, plusieurs facteurs tels que les informations incomplets, les critères qualitatifs et l'imprécision des préférences ne sont pas prises en compte dans le processus de décision. Ces critères sont subjectifs qui sont difficiles à quantifier. En outre, la prise de décision devient plus compliquée lorsque l'information disponible est incomplète ou imprécise. Les méthodes d'aide à la décision multicritère classiques qui tiennent compte des processus déterministes ou aléatoires ne peut pas traiter efficacement les problèmes de décisions avec des informations subjectives. En pratique, la décision dans le choix du fournisseur comprend un haut degré d'imprécision. La théorie des ensembles flous apparait comme une méthode efficace pour mesurer les données qualitatives.

Le but de cette thèse est de proposer des approches d'aide à la décision multicritère floue basé sur le déploiement de la fonction qualité (DFQ) pour la sélection des fournisseurs. Dans le processus de sélection des fournisseurs, le premier but de l'entreprise est de déterminer les fournisseurs qui garantissent un certain niveau de qualité en termes de caractéristiques des produits ou services achetés. La réalisation de ces objectifs dépend sur la considération des relations entre les caractéristiques des produits achetés et les critères d'évaluation des fournisseurs, ainsi que les relations entre les critères d'évaluation des fournisseurs sans tenir compte de l'hypothèse d'indépendance irréaliste. Ainsi, la construction d'une maison de qualité, qui permet de considérer les relations entre les caractéristiques des produits achetés et les critères d'évaluation des fournisseurs ainsi que la dépendance intérieure de critères d'évaluation des fournisseurs, est importante pour déterminer dans quelle mesure chaque critère d'évaluation des fournisseurs réussit à répondre aux spécifications établies pour le produit acheté.

Le DFQ est une méthode de développement de produit visée sur les besoins du client. La méthode consiste à déployer les attributs d'un produit ou d'un service exiges par le client dans chaque étape de la production. Le DFQ est basé sur la traduction des besoins du client aux caractéristiques techniques de l'ingénierie. Comme les besoins du client sont considères dès la première étape de la planification, le DFQ empêche l'augmentation des coûts de correction. Il permet à l'entreprise de faire la production en dépensant moins de ressources.

Dans les applications traditionnelles de DFQ, l'entreprise doit identifier les attentes de ses clients et leur importance relative pour déterminer les caractéristiques de conception pour lesquels les ressources devraient être allouées. D'autre part, lorsque la maison de qualité est utilisée dans la sélection des fournisseurs, la société commence avec les caractéristiques que le produit/service externalisé doit posséder pour répondre à certaines spécifications que la société a mis en place, puis tente de déterminer lequel des attributs ont le plus grand impact sur la réalisation des objectifs qu'elle s'est fixés.

Les procédures utilisées dans cette thèse examinent la planification DFQ comme un outil d'aide à la décision multicritère et construisent deux interdépendants maison de qualité matrices pour calculer les poids des attributs de sélection des fournisseurs et des évaluations des fournisseurs. Les premier et second procédés proposés d'employer moyenne pondérée floue (MPF) pour calculer les limites supérieures et inférieures des poids des critères de sélection des fournisseurs et des évaluations des fournisseurs. Après, une méthode de rangement qui est rapporté pour être plus efficace et plus précis que ses prédécesseurs est utilisé pour ranger les fournisseur. La troisième méthode proposée utilise la fusion d'informations floues et le 2-tuple linguistique représentation modèle, qui permet de résoudre les problèmes de multi-granularité et la perte de l'information.

Afin d'illustrer les applications des méthodes proposées pour la sélection des fournisseurs médicaux, une étude de cas menée dans un hôpital privé de la rive asiatique d'Istanbul est présentée. L'hôpital fonctionne avec tous les départements principaux, et comprend également des installations telles que des laboratoires cliniques, de services d'urgence, les unités de soins intensifs et les salles d'opération. Les premier et second procédés donnent le même rangement des fournisseurs. D'après les résultats de l'analyse, le fournisseur 1 est déterminé comme étant le plus approprié fournisseur, qui est suivi par le fournisseur 7. Fournisseurs 10 et 12 sont classés dans le bas à cause du retard en temps de livraison, du manque d'expérience dans le secteur, de non satisfaisants relations d'affaires antérieures, et d'une mauvaise situation géographique. Avec le troisième algorithme proposé, le fournisseur 7 est calculée comme le plus approprié, qui est suivi par le fournisseur 1. Fournisseurs 10 et 12 sont classés en bas comme obtenues avec les premiers et seconds modèles.

ÖZET

Tedarik zinciri, hammadde temini, hammaddelerin nihai ürünlere çevrilmesi ve nihai ürünlerin müşterilere dağıtılması aşamalarını içeren süreçlerden oluşmaktadır. Günümüzde, tedarik zinciri yönetimi, endüstriyel ilişkilerin yönetimine etki eden önemli bir güç ve aynı zamanda organizasyonların rekabet avantajı elde edebilmeleri için bir odak haline gelmiştir. Sürekli artan rekabet ortamında, firmaların rekabet avantajı elde edebilmeleri için tedarik zinciri yönetimi stratejilerini çevresel etmenlere uyum sağlayacak şekilde düzenlemeleri gerekmektedir. Tedarik zincirinin amaçlarını gerçekleştirmede tedarikçi performansı önemli bir role sahiptir.

Tedarik zinciri yönetiminde, tedarikçi seçimi operasyonel ve satın alma yöneticilerinin karşılaştığı temel sorunlardan biri olarak kabul edilmektedir. Global rekabet ortamında, üreticilerin çoğunluğu gelirlerinin yarısından fazlasını ürün ve servis satın almada kullanmaktadırlar. Doğru tedarikçinin belirlenmesi satın alma maliyetlerini önemli ölçüde düşürmektedir. Bu nedenle, tedarikçi seçimi etkin bir tedarik zinciri yönetim sistemi oluşturmada en önemli olgulardan biri haline gelmiştir.

Son yıllarda yapılan çalışmalar, tedarikçi seçim sürecinde düşük maliyet ölçütünün dikkate alınmasının tek başına yeterli olmadığını, aynı zamanda kalite, teslimat süresi ve esneklik gibi ölçütlerin de değerlendirme sürecine dahil edilmesi gerektiğini belirtmektedir. Bu bağlamda, tedarikçi seçim problemi, çok ölçütlü karar verme yöntemlerinin uygulanmasını gerektiren bir yapıya sahiptir. Tedarikçi seçim sürecinde belirsizlik önemli rol oynamaktadır. Belirsiz yargıları karar verme sürecine dahil etmede bulanık küme teorisinden yararlanılabilir. Bununla birlikte, karar vericilerin, değerlendirmeleri arasındaki benzerlikleri ve farklılıkları daha açık bir şekilde ortaya koymalarına olanak sağlaması nedeniyle grup karar verme yöntemleri sıklıkla tercih edilen yöntemler arasındadır.

Bu çalışmanın amacı tedarikçi seçimi problemi için kalite fonksiyonu yayılımından (KFY) yararlanan bulanık çok ölçütlü grup karar verme algoritmaları geliştirmektir. Tedarikçi seçim sürecinde firmaların asıl amacı, satın alınacak ürünün özelliklerine uygun kalite standardını sağlamış tedarikçileri belirlemektir. Bu amacın gerçekleştirilmesi, satın alınacak ürün özellikleri ve tedarikçi seçim ölçütleri arasındaki ilişkilerin ve aynı zamanda ölçütler arası etkileşimlerin karar verme sürecine dahil edilmesi ile sağlanabilmektedir. Bu nedenle, satın alınan ürün özellikleri ve tedarikçi seçim ölçütleri arasındaki ilişkileri ve bunun yanı sıra ölçütler arası ilişkileri göz önüne alan bir kalite evi oluşturmak tedarikçi ölçütlerinin, satın alınacak ürün özelliklerini ne ölçüde karşıladığını belirlemede önemlidir.

Kalite fonksiyonu yayılımı yaklaşımında esas olan müşteri beklentilerinin teknik özelliklere dönüştürülmesidir. Bu şekilde sırasıyla teknik özellikler, parça özelliklerine, süreç planlarına ve üretim gereksinimlerine dönüştürülmektedir. Sayılan ilişkilerin tanımlanmasında kalite fonksiyonu yayılımı, her biri ürün geliştirme döngüsünün farklı bir aşamasını belirten dört matristen yararlanmaktadır. Bu dört matristen ilki Kalite Evi olarak adlandırılmakta ve kalite fonksiyonu yayılımı uygulamalarının en yaygın kullanılan matrisi olma özelliğini taşımaktadır. Kalite evi, bölümler arası planlama ve iletişime yol gösteren kavramsal bir haritadır. Müşteri beklentileri ile teknik özellikler arasındaki ilişkiler kalite evinin gövde kısmında, teknik özelliklerin kendi aralarındaki ilişkiler ise çatı matrisinde gösterilmektedir. Kalite evinin amacı müşteri memnuniyetini en büyükleyecek şekilde bir ürünün teknik özelliklerinin hedef değerlerinin belirlenmesidir.

Geleneksel kalite fonksiyonu yayılımı uygulamalarında firmalar, kaynakların atanacağı tasarım özelliklerini belirleyebilmek için müşteri beklentilerini ve bu beklentilerin göreceli önemini belirlemek zorundadır. Öte yandan, tedarikçi seçiminde kalite evi kullanıldığında, firma ilk olarak dış kaynaklı ürünün/hizmetin firmanın beklentilerini karşılamak için sahip olması gereken özellikleri belirler ve daha sonra hangi tedarikçi ölçütünün bu beklentiler üzerinde daha fazla etkisi olduğunu tespit eder.

Bu tez kapsamında önerilen algoritmalar KFY'yi çok ölçütlü karar verme aracı olarak kullanmakta ve tedarikçi seçim ölçütlerinin ve tedarikçilerin değerlendirmelerinin alt ve üst sınırlarını belirleyebilmek için ilişkili iki kalite evi oluşturmaktadır. Birinci ve ikinci yöntemde tedarikçi seçim ölçütlerinin ve tedarikçi değerlendirmelerinin alt ve üst sınırları bulanık ağırlıklandırılmış ortalama yöntemi kullanılarak hesaplanmaktadır. Tedarikçilerin sıralama değerleri, alan ölçümü temelli bir bulanık sayı sıralama yöntemi kullanılarak hesaplanmaktadır. Üçüncü yaklaşım ise bulanık verilerin birleştirilmesi ve ikili sözel gösterim yöntemlerini kullanmaktadır.

Geliştirilen yaklaşımların uygulanması amacıyla tıbbi malzeme tedarik problemi seçilmiş ve İstanbul'da bulunan özel bir hastaneden veri temin edilmiştir. Yapılan analiz sonucunda ilk iki yöntem aynı sıralamayı vermektedir. Buna göre tedarikçi 1 en uygun tedarikçi olarak belirlenmiştir. Tedarikçi 7 ise ikinci sırada yer almaktadır. Tedarikçi 10 ve 12, geç teslim zamanı, deneyimsizlik ve uygun olmayan coğrafi konum gibi nedenlerden dolayı son sıralarda yer almıştır. Üçüncü algoritma kullanıldığında tedarikçi 7'nin ilk sırada, tedarikçi 1'in ise ikinci sırada yer aldığı görülmektedir. Tedarikçi 10 ve 12, ilk iki yöntemde elde edildiği gibi yine en alt sıralarda bulunmaktadır.

1 INTRODUCTION

Supply chain management has become a key aspect that has implications for effective and efficient management of industrial relations. It has also become an important focus for firms and organizations to obtain a competitive advantage (Carrera & Mayorga, 2008). A supply chain is composed of a complex sequence of processing stages, ranging from raw materials supplies, parts manufacturing, components and end-products assembling, to the delivery of end products (Wu & Olson, 2008). The short-term objective of supply chain management is primarily to increase productivity and reduce the entire inventory and the total cycle time, while the long-term objective is to increase customer satisfaction, market share, and profits for all organizations in the supply chain. To accomplish these objectives, tight coordination among the organizations in supply chains is needed (Lee et al., 2001).

In the context of supply chain management, supplier selection decision is considered as one of the key issues faced by operations and purchasing managers to remain competitive. Supplier selection and management can be applied to a variety of suppliers throughout a product's life cycle from initial raw material acquisition to end-of-life service providers. Thus, the breadth and diversity of suppliers make the process even more cumbersome (Bai & Sarkis 2010).

In facing an ever-increasingly competitive and rapidly changing environment, firms need to reorganize their supply chain management strategy to harmonize with external environments by integrating the organizational resources, information, and activities so as to maintain competitive advantages (Lang et al., 2009). The importance of purchasing and materials management expands as firms outsource some fabrication and assembly activities in order to focus on their core competencies. These efforts cause firms to rely more heavily on their suppliers for the design and production of certain component parts and subassemblies. Thus, the performance of an organization depends largely on the actions of suppliers. As organizations continue to seek performance improvement, they reorganize their supplier base and manage it as an extension of the firm's manufacturing system (Vonderembse & Tracey, 1999).

Supplier's performance has a key role on cost, quality, delivery and service in achieving the objectives of a supply chain. Hence, supplier selection is considered as one of the most critical activities of purchasing management in a supply chain. Selecting the right suppliers significantly reduces the purchasing cost and improves corporate competitiveness (Ghodsypour & O'Brien, 2001). With the increased emphasis on manufacturing and organizational philosophies such as total quality management and just in time, all companies are faced with quality assurance issues in design, manufacturing, purchasing, and delivery. The performance of suppliers effects the responsiveness of the company, and it has become a key element in a company's quality success or failure. The overall objective of the supplier selection process is to reduce purchase risk, maximize overall value to the purchaser, and build the closeness and long-term relationships between buyers and suppliers (Chen et al., 2006).

In recent years, there has been a shift in manufacturing companies from vertical integration towards smaller, leaner operations. Organizations have downsized and attempted to achieve competitive advantage by leveraging their suppliers' capabilities and technologies (Kannan & Tan, 2002). Recent business trends, such as shortened product life cycles, increased rates of technological change and foreign sourcing, have caused a shift from single sourcing to multiple sourcing. The reduced supplier base enables organizations to establish closer relationships with its suppliers that significantly reduce costs and constantly improve quality. With the trend towards closer relationships and fewer suppliers, it is highly important that sellers fully understand buyers' decision processes. These recent developments imply that the supplier selection decision has become even more critical. Suppliers can also be involved in product design at an earlier stage, and in doing so, they generate more cost effective design choices, develop alternative conceptual solutions, select the best components and technologies, and assist in design assessment (Monczka et al., 1993).

Greater dependence on suppliers increases the need to effectively manage suppliers. Three dimensions such as effective supplier selection, innovative supplier development strategies, and meaningful supplier performance assessment mechanism underlie supplier management (Kannan & Tan, 2002). While the supplier selection is one of the most fundamental decisions a company makes, it is also the most critical due to the increased levels of complexity involved in considering supplier performance and relationship factors. At the beginning of the 1980s, Evans (1981) found price to be the most important attribute in the purchase of routine products. However, recent studies have determined a shift away from price as a primary determinant of supplier selection. Organizations, which practice the latest innovations in supply chain management, no longer accept commodity partnerships that are exclusively based on price. Other important factors such as quality, delivery time and flexibility are included in managing these inter-organizational relationships. There is a continuing need for robust evaluation models that effectively incorporate several supplier criteria. With its need to trade-off multiple criteria exhibiting vagueness and imprecision, supplier selection is a highly important multi-criteria decision making (MCDM) problem.

As firms become involved in strategic partnerships with their suppliers, a new set of supplier selection criteria, termed as *soft* criteria, need to be considered. Soft factors cover issues including management compatibility, goal congruence and the strategic direction of the supplier firm (Ellram, 1990). These criteria are subjective factors that are difficult to quantify. The uncertainty of subjective judgment is present when the supplier selection process is carried out. Also, decision-making becomes difficult when the available information is incomplete or imprecise. Another procedural problem in the use of formal procedure supporting the supplier selection decision making process refers to the heterogeneous nature of the criteria considered (numerical versus categorical, and quantitative versus qualitative variables) (Bevilacqua & Petroni, 2002). The classical MCDM methods that consider deterministic or random processes cannot effectively address decision problems including imprecise and linguistic information. In practice, decision making in supplier selection includes a high degree of vagueness and imprecision. Fuzzy set theory is one of the effective tools to deal with uncertainty and vagueness.

Group decision making is an important concern in MCDM methods. Multiple decision-makers are often preferred to prevent the bias and minimize the partiality in the decision process. For group decision making problems, consensus is an important indication of group agreement or reliability. In order to fully reflect the real behavior of the group, a final decision should be made on significant level of consensus. Therefore, aggregation of expert opinions is crucial to properly conduct the evaluation process.

The objective of this thesis is to propose fuzzy multi-criteria group decision making approaches based on the quality function deployment (QFD) concept for supplier selection. In supplier selection process, the company's primary aim is to determine suppliers that ensure a certain quality standard in terms of the characteristics of the purchased products or services. Achieving these objectives depends largely on considering the relationships between purchased product features and supplier assessment criteria, and also the relationships between supplier assessment criteria disregarding the unrealistic independence assumption. Thus, constructing a house of quality (HOQ), which enables the relationships among the purchased product features and supplier assessment criteria as well as inner dependence of supplier assessment criteria to be considered, is key to identify how well each supplier characteristic succeeds in meeting the requirements established for the product being purchased.

The remaining parts of this thesis are organized as follows: The following section presents a taxonomy and review of analytical methods for supplier selection. In Section 3, a concise treatment of the basic concepts of QFD is presented. The preliminaries of fuzzy sets are given in Section 4. Section 5 outlines fuzzy weighted average. Section 6 and Section 7 delineate the fusion of fuzzy information approach and 2-tuple fuzzy linguistic representation model, respectively. Section 8 presents the developed decision making approaches and provides their stepwise representations. The implementations of the proposed frameworks for evaluating medical suppliers of a private hospital in Istanbul are provided in Section 9. Finally, concluding observations and directions for future research are given in the last section.

2 REVIEW OF ANALYTICAL METHODS FOR SUPPLIER SELECTION

Lately, increasing number of factors in global markets has motivated organizations to search for competitive advantages considering their entire supply chain. The purchasing function is increasingly seen as a strategic issue in supply chain hierarchy. Among the various activities involved in supply chain management, supplier selection is regarded as one of the most important decisions because it enables organizations to reduce costs, and thus, increase profits. Suppliers can also be involved in product design at an earlier stage, and in doing so, generate more cost effective design choices, develop alternative conceptual solutions, select the best components and technologies, and assist in design assessment (Monczka et al. 1993).

Earlier studies on supplier selection focused on identifying the criteria used to select suppliers. Dickson (1966) conducted one of the earliest works on supplier selection and identified 23 supplier attributes that managers consider when choosing a supplier. The study concluded that quality, on-time delivery, and performance history were the three most important criteria in supplier evaluation. Several studies emphasized the relative importance of various supplier criteria such as price, quality, on-time delivery, and performance (Lehmann & O'Shaughnessy, 1974; Wilson 1994; Kannan & Tan 2002). Involvement of diverse criteria in decision making process has further complicated supplier evaluation and selection decisions.

The aim of this section is to present a detailed review on supplier selection models, and identify the most popular criteria considered by the decision-makers for evaluating the potential suppliers. Various methods have been developed to date, which address the requirements of supplier selection process. Although there are different classifications for models developed for supplier selection in the literature, this thesis limits its focus on analytical methods such as optimization techniques, multi-attribute decision making (MADM) methods, and metaheuristic methods. According to a literature search using major electronic databases, there are six journal articles reviewing the literature regarding supplier evaluation and selection models (Weber et al., 1991; Degraeve et al., 2000; De Boer et al., 2001; Aissaoui et al., 2007; Jain et al., 2009; Ho et al., 2010). Since these research studies reviewed the literature up to 2008, this thesis extends them and provides an up-to-date version by surveying supplier evaluation and selection methods from 2000 to 2011. This thesis presents a taxonomy of the supplier selection methods by classifying the published supplier selection articles into three prime categories, namely deterministic approaches, non-deterministic approaches, and integrated approaches. Then, these categories are divided into sub-categories. 171 articles were analyzed as a result of search using six major electronic databases, namely EBSCO, Emerald, IEEE Xplore, ProQuest, ScienceDirect, SpringerLink, and Taylor & Francis. This thesis covers only the journal articles, whereas proceeding papers, theses and other manuscripts are not included. The distribution of 171 articles with respect to the years and journals are summarized in Table 2.1 and Table 2.2, respectively. There is a significant growth in the number of articles published between 2006 and 2011. Expert Systems with Applications published 38 articles (22.22%), International Journal of Production Research published 20 articles (11.70%), and International Journal of Production Economics published 18 articles (10.53%) throughout the 12-year period. In 50% of cases, journals published just one article concerning supplier selection during this time interval.

Table 2.1 Distribution of the articles according to the years

Years	Number of Articles
2000	2
2001	7
2002	5
2003	6
2004	2
2005	5
2006	16
2007	14
2008	19
2009	26
2010	33
2011	36

Table 2.2 Distribution of the articles according to the journals

Journal	Number of Articles
Expert Systems with Applications	38
International Journal of Production Research	20
International Journal of Production Economics	18
International Journal of Advanced Manufacturing Technology	9
Computers & Industrial Engineering	6
Applied Mathematical Modelling	5
Supply Chain Management: An International Journal	5
European Journal of Operational Research	4
Omega	4
Computers & Operations Research	3
IEEE Transactions on Engineering Management	3
Industrial Management & Data Systems	3
Mathematical and Computer Modelling	3
Production Planning & Control	3
Advances in Engineering Software	2
Annals of Operations Research	2
Applied Mathematics and Computation	2
Applied Soft Computing	2
Information Sciences	2
International Journal of Computer Integrated Manufacturing	2
International Journal of Physical Distribution & Logistics Management	2
International Transactions in Operational Research	2
Journal of Purchasing & Supply Management	2
Journal of the Operational Research Society	2
The Journal of Supply Chain Management: A Global Review of Purchasing and Supply	2
Computers and Mathematics with Applications	1
Cost Management	1
European Journal of Purchasing & Supply Management	1
Flexible Services and Manufacturing Journal	1
IEEE Transactions on Fuzzy Systems	1

Table 2.2 Distribution of the articles according to the journals (cont.)

Journal	Number of Articles
IEEE Transactions on Industrial Informatics	1
Industrial Management	1
International Business Research	1
International Journal of Information Technology & Decision Making	1
International Journal of Logistics Research and Applications	1
International Journal of Manufacturing Technology and Management	1
International Journal of Operations & Production Management	1
International Journal of Sustainable Engineering	1
Journal of Advances in Management Research	1
Journal of Business Logistics	1
Journal of Cleaner Production	1
Journal of Enterprise Information Management	1
Journal of the Franklin Institute	1
Journal of Intelligent Manufacturing	1
Kybernetes	1
Opsearch	1
OR Insight	1
OR Spectrum	1
Quality & Quantity	1
Transportation Research Part B	1

In the following Sub-section the supplier selection process is described. Sub-sections 2.2, 2.3, and 2.4 present the deterministic approaches, non-deterministic approaches, and integrated approaches for supplier selection, respectively. Finally, observations and discussions are presented in Sub-section 2.5.

2.1 Supplier Selection Process

As reported in De Boer et al. (2001), supplier selection process has different phases such as problem definition, decision criteria formulation, pre-qualification of potential suppliers, and making a final choice. The quality of the final choice largely depends on the quality of all the steps involved in the selection process. In this Sub-section, the key objectives and features of each step are exposed in a general way and a review of the criteria used between 2000 and 2011 is provided to identify the most popular criteria considered by decision-makers for evaluating the potential suppliers.

2.1.1 Problem Definition

Due to shortened product life cycles, the search for new suppliers is a continuous priority for companies in order to upgrade the variety and typology of their products range. Decision- makers are facing a wide variety of purchasing situations that lead to different decisions (Aissaoui et al., 2007). Thus, the first step in supplier selection process involves determining the ultimate problem and finding out exactly what we want to achieve by selecting a supplier.

2.1.2 Decision Criteria Formulation

Supplier selection decisions are complicated by the fact that various criteria must be considered in decision making process. The analysis of supplier selection criteria has been the focus of many research works since the 1960's. Dickson (1966) presented a study, which is a reference for the majority of papers dealing with supplier selection problem. The study identified 23 supplier attributes that managers consider when choosing a supplier. Among these quality, on-time delivery, and performance history were the most significant criteria.

Another study conducted by Lehmann and O'Shaughnessy (1974) found that the key criteria generally claimed to affect supplier selection decisions were price, reputation of supplier, reliability, and delivery.

Weber et al. (1991) classified the articles published since 1966 according to the considered criteria. Based on 74 papers, they observed that price, delivery, quality, and production facility and location are the most frequently employed criteria.

The 23 criteria presented by Dickson still cover the majority of the criteria presented in the literature. Table 2.3 summarizes the criteria used for supplier selection between 2000 and 2011. The most popular criterion is ‘cost’, followed by ‘quality’ and ‘delivery’. 148 papers considered ‘cost’ in the supplier selection process, whereas 147 studies considered ‘quality’, and 106 papers accounted for ‘delivery’.

Table 2.3 Summary of the criteria used for supplier selection

Criteria	**No. of articles**
Price/Cost	148
Quality	147
Delivery	106
Technical capability (Technology)	46
Production facilities and capacity	43
Service	38
Relationship	26
Flexibility	23
Management and organization	22
Amount of past business	21
Financial position	20
Geographical location	19
Lead time	18
Research and development	18
Reliability	16
Warranties and claim policies	18
Product/service design	13
Risk	13
Environmental issues	12
Performance history	11
Training aids	9
Manufacturing capability	5
Profitability	4

2.1.3 Pre-qualification of Potential Suppliers

Today's logistics environment requires a low number of suppliers as it is very difficult to manage a high number (Aissaoui et al., 2007). Pre-qualification of potential suppliers is the process of reducing the set of all suppliers to a smaller set of acceptable suppliers. Therefore, pre-qualification is a sorting process rather than a ranking process (De Boer et al., 2001).

2.1.4 Final Choice

Most of the research studies in the area of supplier selection have focused on determining the best supplier to supply all needed items. At this stage, the ultimate supplier is identified while considering the system's constraints and taking into account various quantitative and/or qualitative criteria (Aissaoui et al., 2007). In order to implement this procedural aspect, numerous formal techniques that are analyzed in Sub-sections 2.2-2.4 have been developed in the literature based on particular conceptual approaches.

2.2 Deterministic Approaches

43 articles (25.15%) have focused on the use of deterministic analytical methods including mathematical programming, and multi-attribute decision making (MADM) approaches. Advantages and limitations of mathematical programming and MADM approaches to supplier selection are discussed in the respective tables.

2.2.1 Mathematical Programming

Among 171 articles, 28 papers (16.38%) shown in Table 4 formulated the supplier selection problem as various types of mathematical programming models. These models include data envelopment analysis (DEA), integer programming, linear programming, goal programming, and multi-objective programming.

Table 2.4 Advantages and limitations of mathematical programming approaches

Methods	References	Advantages	Limitations
DEA	Braglia and Petroni (2000), Liu et al. (2000), Forker and Mendez (2001), Narasimhan et al. (2001), Talluri and Sarkis (2002), Garfamy (2006), Ross et al. (2006), Saen (2006a), Saen (2006b), Seydel (2006), Saen (2007), Saen (2008a), Ross and Buffa (2009), Wu and Blackhurst (2009), Saen (2010b), Shirouyehzad et al. (2011), Toloo and Nalchigar (2011)	• Completely objective for it does not require specifying either the form of the production function or the weights for the different inputs and outputs chosen. • Defines a non-parametric best practice frontier that can be used as a reference for efficiency measures, and allows determining inefficient alternatives. • Disregards the possibility of selecting a sub-optimal supplier. • Identifies not only how efficient a particular decision making unit (DMU) may be, but also provides a benchmark on the non-inferior frontier, where the DMU would be efficient. This benchmark can then be used as a value for negotiation with inefficient DMUs and necessary improvement.	• Dichotomizes alternatives as efficient and inefficient. • Does not provide a complete ranking of alternatives in most cases. • Can be used only when decision making units are comparable, meaning they use the same set of inputs to produce the same set of outputs. • Assumes that the collected data accurately reflects all relevant input and output variables that describe the evaluation process, and also assumes that the observations refer to reasonably homogenous DMUs whose performances are comparable in the sense that they share a common production possibility set. • As the number of input and output variables increases, more DMUs tend to lie on or close to the efficient frontier. • Unable to handle risk, uncertainty and imprecision.

Table 2.4 Advantages and limitations of mathematical programming approaches (cont.)

Methods	References	Advantages	Limitations
Linear programming	Talluri and Narasimhan (2003), Talluri and Narasimhan (2005), Hassini (2008), Ng (2008)	• Determines the optimal solution. • Helps to make the best possible use of available productive resources. • Highlighting bottlenecks. • Provides practical solutions. • Fast and easy to use with commercial solvers.	• Applicable only to problems where the objective function and constraints are linear. • Unable to handle risk, uncertainty and imprecision. • Assumes complete independence. • Considers only a single objective. • Assumes that decision variables can take fractional values.
Integer programming	Cakravastia et al. (2002), Hong et al. (2005), Stadtler (2007), Hammami et al. (2011)	• Determines the optimal solution. • Fractional solutions cannot be realistic for majority of problems. • Nonlinear functions can be represented by integer-programming formulations.	• Performance of any particular solution technique appears to be highly problem-dependent. • Unable to handle risk, uncertainty and imprecision. • Considers only a single objective. • Increase in computational complexity with the increase in integer decision variables.

Table 2.4 Advantages and limitations of mathematical programming approaches (cont.)

Methods	**References**	**Advantages**	**Limitations**
Non-linear programming	Kheljani et al. (2009)	• Avoids linearity assumption for objective function and constraints. • Enables realistic modeling.	• Performance of any particular solution technique appears to be highly problem-dependent. • Most algorithms cannot guarantee convergence to the global optimum. • Considers only a single objective. • Unable to handle risk, uncertainty and imprecision.
Goal programming	Karpak et al. (2001)	• Allows for multiple objectives.	• Complexity of the "overall objective". • Must elicit goal values (aspiration levels) from decision-maker. • Oftentimes weights also need to be elicited. • Must find a way to homogenize information. • Unable to handle risk, uncertainty and imprecision.

Table 2.4 Advantages and limitations of mathematical programming approaches (cont.)

Methods	**References**	**Advantages**	**Limitations**
Multi-objective programming	Wadhwa and Ravindran (2007)	• Considers multiple objectives.	• Problem with selecting an appropriate weighting scheme aggravates when three or more criteria are considered. • Unable to handle risk, uncertainty and imprecision. • Difficult to solve.

2.2.1.1 Data Envelopment Analysis

Braglia and Petroni (2000) developed a methodology based on the use of cross-efficiency in DEA for ranking the suppliers. Liu et al. (2000) demonstrated the application of DEA for evaluating the overall performance of suppliers in a manufacturing firm. Forker and Mendez (2001) applied DEA to measure the comparative efficiencies of suppliers. Similar to Braglia and Petroni (2000), the cross-efficiencies were calculated to find the best peer suppliers. Narasimhan et al. (2001) proposed a framework based on DEA to evaluate alternative suppliers for a multinational corporation in the telecommunication industry. Talluri and Sarkis (2002) presented a methodological extension of DEA by improving the discriminatory power of an existing variable returns to scale model for the supplier performance evaluation and monitoring process.

There is an upsurge in the use of DEA as a decision making methodology for supplier selection from 2006 onwards. Garfamy (2006) employed DEA to measure the overall performances of suppliers based on total cost of ownership concept. Ross et al. (2006) utilized DEA to evaluate the supplier performance with respect to both buyer and supplier performance attributes. Saen (2006a) proposed DEA for selecting technology suppliers in the presence of nondiscretionary factors from supplier's perspective. Saen (2006b) employed DEA for ranking technology suppliers in the presence of nondiscretionary factors. Seydel (2006) modified DEA to incorporate weight constraints and used this approach to rank the available suppliers. Saen (2007) used DEA for selecting the best supplier in the presence of both cardinal and ordinal data. Saen (2008a) introduced a decision making approach based on super-efficiency analysis DEA model to rank suppliers in the presence of volume discount offers. Ross and Buffa (2009) used DEA to investigate the effects of buyer performance on supplier performance. Wu and Blackhurst (2009) developed a supplier evaluation and selection methodology based on an extension of DEA. Saen (2010b) examined the supplier selection process through a DEA model enabling the incorporation of decision-maker's preferences, and considered multiple factors which simultaneously play both input and output roles. Lately, Shirouyehzad et al. (2011) used DEA modeling for measuring suppliers' performance in multiple criteria relative to other vendors competing in the same marketplace. In a recent work, Toloo and Nalchigar (2011) proposed a new DEA model which is able to identify the most efficient supplier in presence of both cardinal and ordinal data.

2.2.1.2 Linear Programming

Talluri and Narasimhan (2003) incorporated performance variability measures into the supplier evaluation process. They developed two linear programming models to maximize and minimize the performance of a supplier against the best target measures. Later, Talluri and Narasimhan (2005) proposed a linear programming model to evaluate and select potential suppliers with respect to the strengths of existing suppliers. Hassini (2008) formulated a linear programming model for a single product, multi-period order lot sizing and supplier selection problem with price discounts. Ng (2008) presented a weighted linear programming model for the supplier selection problem.

2.2.1.3 Integer Programming

Cakravastia et al. (2002) presented a mixed integer programming model for supplier selection in developing a supply chain network. Hong et al. (2005) suggested a mixed integer programming model for supplier selection that maintains a continuous supply relationship with suppliers. Stadtler (2007) developed a mixed integer programming model formulation for the generalized quantity discount and supplier selection problem. Recently, Hammami et al. (2011) developed a mixed integer programming model for supplier selection.

2.2.1.4 Non-linear Programming

Kheljani et al. (2009) developed a mixed-integer non-linear programming model for supplier selection and order allocation to minimize the average total cost incurred in supply chain. They generated a model to coordinate decisions between buyers and suppliers in a supplier selection process.

2.2.1.5 Goal Programming

Karpak et al. (2001) considered goal programming to evaluate alternative suppliers and allocate orders among them. Cost, quality, and delivery reliability were considered as goals of the model.

2.2.1.6 Multi-objective Programming

Wadhwa and Ravindran (2007) modeled supplier selection problem as a multi-objective optimization problem, where one or more buyers order multiple products from different suppliers in a multiple sourcing network. Weighted objective, goal programming and compromise programming methods were employed to solve the supplier selection problem, and the results were presented in a comparative way.

2.2.2 Multi-attribute Decision Making Approaches

15 out of 171 papers (8.77%) employed deterministic MADM techniques to select the most appropriate supplier. These papers are listed in Table 2.5. Deterministic MADM techniques for supplier selection include analytic hierarchy process (AHP), analytic network process (ANP), and multi-attribute utility theory (MAUT), where AHP and ANP are the most prevalently used methods.

Table 2.5 Advantages and limitations of deterministic MADM approaches

Methods	References	Advantages	Limitations
AHP	Akarte et al. (2001), Lee et al. (2001), Tam and Tummala (2001), Chan (2003), Hemaida and Schmits (2006), Levary (2008), Chan and Chan (2010), Labib (2011)	• Ability to structure a complex, multi-person, and multi-attribute problem hierarchically. • Hierarchical representation of a system can be used to describe how changes in priority at upper levels affect the priority of criteria in lower levels. • Employs multiple paired comparisons of criteria to rank order alternatives. • Stable and flexible. • User friendly, and supported by commercial software, which also provides sensitivity analysis of results. • Measures the consistency in the decision makers' judgments.	• Assumes mutual independence of attributes. • Rank reversal problem. • Obtaining pairwise comparisons is a time-consuming task. • Does not allow for integrating dynamic modeling of the environment. • Unable to handle uncertainty and imprecision. • Justification of nominal 9-point scale, which is interpreted as a ratio is anecdotal and has been questioned. • Encourages users to assess importance weights in isolation from the specific ranges of options available.

Table 2.5 Advantages and limitations of deterministic MADM approaches (cont.)

Methods	References	Advantages	Limitations
ANP	Sarkis and Talluri (2002), Chen and Lee (2006), Gencer and Gürpinar (2007), Hsu and Hu (2009), Chakraborty et al. (2010), Zhu et al. (2010)	• Considers interdependencies among and within levels of attributes. • Ability to incorporate feedbacks. • Ability to structure a complex, multi-person, and multi-attribute problem hierarchically. • User friendly, and supported by commercial software. • Enables to integrate dynamic modeling of the environment. • More accurate in complex situations due to its capability of modeling complex structure and the way in which comparisons are performed.	• Becomes quite complex as the number of attributes and relationships increases. • Unable to handle uncertainty and imprecision.
MAUT	Shaik and Abdul-Kader (2011)	• Enables the decision-maker to structure a complex problem in the form of a simple hierarchy. • Simple to use and interpret. • Transforming multiple attributes which normally cannot be compared due to incompatible scales into value utility scales, which can be compared and analyzed. • Always allows for obtaining a complete rank order of the alternatives.	• Assumption of linear utility functions. • Needs all the variables in the decision matrix to be measures of the utility each option leads to with respect to each attribute. • Unable to handle uncertainty and imprecision.

2.2.2.1 Analytic Hierarchy Process

Akarte et al. (2001) designed a decision support system using AHP for supplier evaluation. Lee et al. (2001) employed AHP for supplier selection process considering also the managerial criteria. Tam and Tummala (2001) investigated the feasibility of applying AHP in supplier selection of a telecommunications system for a telecom company. Chan (2003) proposed an AHP based approach, which considers the interactions among the supplier selection criteria. Chain of interaction was developed to determine the relative interactions. Hemaida and Schmits (2006) employed AHP to select supplier for tank fabrication. Levary (2008) demonstrated the use of AHP for supplier selection. A case study in which a manufacturer evaluates and ranks its current foreign supplier against two other potential foreign suppliers was presented. Chan and Chan (2010) employed AHP to solve the supplier selection problem in the apparel industry. Lately, Labib (2011) tackled the study conducted by Ordoobadi (2009), which developed a supplier selection model using fuzzy logic, and employed AHP to the same supplier selection problem using Saaty's 9-point scale.

2.2.2.2 Analytic Network Process

Sarkis and Talluri (2002) illustrated the use of ANP for supplier selection. Later, Chen and Lee (2006) employed ANP to construct the supplier selection system of a manufacturing company. Gencer and Gürpinar (2007) used ANP for supplier selection in an electronic company. Hsu and Hu (2009) presented ANP approach to incorporate the issue of hazardous substance management into supplier selection. Chakraborty et al. (2010) applied ANP to select supplier of a light engineering industry. Zhu et al. (2010) developed a methodology to evaluate suppliers using portfolio analysis based on ANP and environmental factors.

2.2.2.3 Multi-attribute Utility Theory

Shaik and Abdul-Kader (2011) presented a framework for green supplier selection integrating environmental, green, and organizational criteria. A hierarchy was constructed to facilitate the evaluation of the importance of the selected criteria and alternatives of green suppliers. Afterwards, MAUT was applied to solve the problem.

2.3 Non-deterministic Approaches

Non-deterministic analytical methods such as stochastic methods, fuzzy MADM methods, metaheuristic methods, process capability indices based approaches, and case-based reasoning were also employed for supplier selection. 53 articles (30.99%) have focused on the use of non-deterministic analytical methods. Advantages and limitations of the related non-deterministic approaches to supplier selection are denoted in the respective tables.

2.3.1 Non-deterministic Optimization Methods

22 out of 171 articles (12.87%) presented in Table 2.6 applied non-deterministic optimization techniques such as imprecise DEA, stochastic/fuzzy integer programming, non-linear programming, and stochastic/fuzzy multi-objective programming for the supplier selection process.

Table 2.6 Advantages and limitations of non-deterministic optimization approaches

Methods	References	Advantages	Limitations
Imprecise DEA	Wu et al. (2007), Saen (2008b), Wu and Olson (2008a), Saen (2009a), Saen (2009b), Azadeh and Alem (2010), Saen (2010a), Wu (2010), Azadi and Saen (2011)	• Completely objective for it does not require specifying either the form of the production function or the weights for the different inputs and outputs chosen. • Defines a non-parametric best practice frontier that can be used as a reference for efficiency measures, and allows determining inefficient alternatives. • Disregards the possibility of selecting a sub-optimal supplier. • Identifies not only how efficient a particular decision making unit (DMU) may be, but also provides a benchmark on the non-inferior frontier, where the DMU would be efficient. This benchmark can then be used as a value for negotiation with inefficient DMUs and necessary improvement. • Considers risk, uncertainty and imprecision.	• Dichotomizes alternatives as efficient and inefficient. • Does not provide a complete ranking of alternatives in most cases. • Can be used only when decision making units are comparable, meaning they use the same set of inputs to produce the same set of outputs. • Assumes that the collected data accurately reflects all relevant input and output variables that describe the evaluation process, and also assumes that the observations refer to reasonably homogenous DMUs whose performances are comparable in the sense that they share a common production possibility set. • As the number of input and output variables increases, more DMUs tend to lie on or close to the efficient frontier.

Table 2.6 Advantages and limitations of non-deterministic optimization approaches (cont.)

Methods	**References**	**Advantages**	**Limitations**
Stochastic/ fuzzy integer programming	Feng et al. (2001), Chen (2009), Talluri and Lee (2010), Sawik (2011), Zhang and Zhang (2011)	• Determines the optimal solution. • Fractional solutions cannot be realistic for majority of problems. • Nonlinear functions can be represented by integer-programming formulations. • Considers risk, uncertainty and imprecision.	• Performance of any particular solution technique appears to be highly problem-dependent. • Considers only a single objective. • Increase in computational complexity with the increase in integer decision variables.
Non-linear programming	Yang et al. (2007)	• Avoids linearity assumption for objective function and constraints. • Considers risk uncertainty and imprecision. • Enables realistic modeling.	• Performance of any particular solution technique appears to be highly problem-dependent. • Most algorithms cannot guarantee convergence to the global minimum. • Considers only a single objective.
Stochastic/ fuzzy multi-objective programming	Kumar et al. (2006), Liao and Rittscher (2007), Amid et al. (2009), Díaz-Madroñero et al. (2010), Sawik (2010), Wu et al. (2010), Yücel and Güneri (2011)	• Considers multiple objectives. • Considers risk, uncertainty and imprecision.	• Problem with selecting an appropriate weighting scheme aggravates when three or more criteria are considered. • Difficult to solve.

2.3.1.1 Imprecise Data Envelopment Analysis

Imprecise DEA, which includes stochastic DEA, fuzzy DEA and DEA models with interval data, is the most widely used method among non-deterministic approaches for supplier selection. Wu et al. (2007) developed an augmented imprecise DEA (AIDEA), which can handle imprecise data such as interval data and ordinal data for the evaluation of suppliers. Saen (2008b) introduced an assurance region-imprecise data envelopment analysis (AR-IDEA) model for selecting the best supplier in the presence of both weight restrictions and imprecise data. Wu and Olson (2008a) used stochastic DEA and stochastic dominance model applied through simulation to compute vendor efficiencies. Saen (2009a) argued the use of interval DEA model for selecting non-homogeneous suppliers where there exist a few selection criteria for some suppliers that are not common. Saen (2009b) developed a DEA model for ranking suppliers in the presence of weight restrictions, nondiscretionary factors, and cardinal and ordinal data. Azadeh and Alem (2010) presented a decision making scheme to choose appropriate method among DEA, fuzzy DEA, and chance constraint DEA for supplier selection under certainty, uncertainty and probabilistic conditions. Saen (2010a) proposed a DEA methodology that considers both undesirable outputs and imprecise data simultaneously for supplier selection. Wu (2010) extended the classical stochastic DEA model to measure international supplier performance by taking into account risk and uncertainty associated with supplier performance on multiple measures in multiple categorical suppliers. Recently, Azadi and Saen (2011) formulated a worst practice frontier Charnes-Cooper-Rhodes stochastic model for supplier selection.

2.3.1.2 Stochastic/Fuzzy Integer Programming

Feng et al. (2001) presented a stochastic integer programming approach for simultaneous selection of tolerances and suppliers based on the quality loss function and process capability indices. Chen (2009) employed a fuzzy mixed integer programming approach to account for multiple criteria and vagueness within the supplier selection decisions in the rebuy purchasing situation. Talluri and Lee (2010) provided a methodology for optimal supplier selection based on a mixed integer programming approach in the presence of market price uncertainty, supplier discounts, investment costs, and supplier capacity restrictions. Sawik (2011) enhanced the approach presented in Sawik (2010) to consider a single-period supplier selection and order allocation in the make-to-order environment in the presence of supply chain delay risk. The problem of optimal allocation of orders for parts among a set of approved suppliers under conditions of risk was modeled as a stochastic mixed integer program. Lately, Zhang and Zhang (2011) addressed the supplier selection and purchase problem with fixed selection cost and limitation on minimum and maximum order sizes under stochastic demand. The problem was modeled as a mixed integer program, and a branch and bound algorithm was proposed for the solution.

2.3.1.3. Non-linear Programming

Yang et al. (2007) studied a supplier selection problem with stochastic demand to determine order quantities from a set of suppliers with different yields and prices. They provided the mathematical formulation for the buyer's profit maximization problem and proposed a solution method based on Newton search procedure.

2.3.1.4 Stochastic/Fuzzy Multi-objective Programming

Kumar et al. (2006) treated supplier selection problem as a fuzzy multi-objective integer programming formulation that incorporates cost minimization, quality maximization, and on time delivery maximization. Liao and Rittscher (2007) formulated a multi-objective supplier selection model under stochastic demand conditions with simultaneous consideration of cost, quality, delivery, and flexibility, involving constraints of demand satisfaction and capacity. Amid et al. (2009) developed a fuzzy multi-objective model for supplier selection. Díaz-Madroñero et al. (2010) considered the supplier selection problem with fuzzy goals. A multi-objective model, which attempts to minimize the total order costs, the number of rejected items and the number of late delivered items simultaneously, was developed. Sawik (2010) proposed mixed integer programming approaches for single or multiple objective supplier selection in make-to-order manufacturing under conditions of operational risk associated with uncertain quality and reliability of supplies. Wu et al. (2010) presented a fuzzy multi-objective programming supplier selection model for supply chain outsourcing risk management. More recently, Yücel and Güneri (2011) proposed a fuzzy multi-objective linear model to tackle supplier selection problem.

2.3.2 Non-deterministic Multi-attribute Decision Making Approaches

19 out of 171 studies (11.11%) recommended the use of non-deterministic MADM techniques to select the most appropriate supplier. These studies are shown in Table 2.7. Non-deterministic MADM techniques for supplier selection include fuzzy AHP, fuzzy ANP, fuzzy TOPSIS (technique for order preference by similarity to ideal solution), fuzzy multi-criteria optimization and compromise solution (VIKOR), fuzzy ELECTRE (ELimination Et Choix Traduisant la REalité), 2-tuple linguistic representation model, fuzzy balancing and ranking, and fuzzy data mining methods.

Table 2.7 Advantages and limitations of non-deterministic MADM approaches

Methods	**References**	**Advantages**	**Limitations**
Fuzzy AHP	Bottani and Rizzi (2005), Haq and Kannan (2006a), Chan and Kumar (2007), Chan et al. (2008), Kilincci and Onal (2011)	• Ability to structure a complex, multi-person, and multi-attribute problem hierarchically. • Hierarchical representation of a system can be used to describe how changes in priority at upper levels affect the priority of criteria in lower levels. • Employs multiple paired comparisons of criteria to rank order alternatives. • Stable and flexible. • Measures the consistency in the decision makers' judgments.	• Assumes mutual independence of attributes. • Defuzzification may cause loss of information. • Uncertainty in the AHP is successfully remedied by using intermediate values in the 1–9 scale combined with the verbal scale and that seems to work better to obtain accurate results than using fuzziness to change the numbers for convenience and rather arbitrarily. • Rank reversal problem. • Obtaining pairwise comparisons is a time-consuming task. • Does not allow for integrating dynamic modeling of the environment.

Table 2.7 Advantages and limitations of non-deterministic MADM approaches (cont.)

Methods	**References**	**Advantages**	**Limitations**
Fuzzy ANP	Kang et al. (2011), Vinodh et al. (2011)	• Considers the interdependencies among and within levels of attributes. • Ability to incorporate feedbacks. • Ability to structure a complex, multi-person, and multi-attribute problem hierarchically. • Enables to integrate dynamic modeling of the environment. • More accurate in complex situations due to its capability of modeling complex structure and the way in which comparisons are performed. • Considers risk, uncertainty and imprecision.	• Becomes quite complex as the number of attributes and relationships increases. • Defuzzification may cause loss of information.

Table 2.7 Advantages and limitations of non-deterministic MADM approaches (cont.)

Methods	**References**	**Advantages**	**Limitations**
Fuzzy TOPSIS	Chen et al. (2006), Boran et al. (2009), Wang et al. (2009), Awasthi et al. (2010)	• Easy to use and understand. • Can be programmed using a spreadsheet. • Provides a compromise solution from a set of alternatives. • A sound logic that embodies the rational of human choice. • Considers the distance from the ideal solution as well as the anti-ideal solution. • Allows the use of data with different units of measure. • Considers risk, uncertainty and imprecision.	• Assumes mutual independence of attributes. • Does not consider the relative importance of the distances to ideal and anti-ideal solutions. • Subjectivity of weight coefficients. • Defuzzification may cause loss of information.
Fuzzy VIKOR	Chen and Wang (2009), Sanayei et al. (2010), Shemshadi et al. (2011)	• Provides a compromise solution from a set of alternatives. • Considers the distance from the ideal solution. • The best alternative is preferred by maximizing group utility and minimizing group regret. • Allows the use of variables with different units of measure. • Considers risk, uncertainty and imprecision.	• Assumes mutual independence of attributes. • Defuzzification may cause loss of information.

Table 2.7 Advantages and limitations of non-deterministic MADM approaches (cont.)

Methods	**References**	**Advantages**	**Limitations**
Fuzzy ELECTRE	Sevkli (2010)	• Does not assume that the criteria are mutually independent. • Considers risk, uncertainty and imprecision.	• Valuable when the number of alternatives is small (6 or less). • Has no justification for the values chosen for concordance and discordance thresholds. • Defuzzification may cause loss of information.
2-Tuple linguistic representation model	Wang (2008b), Wang (2010)	• The linguistic domain can be treated as continuous. • Enables dealing with multi-granular linguistic information. • Minimizes the loss of information. • Disregards the troublesome fuzzy number ranking process, which may yield inconsistent results for different ranking methods. • High accuracy and consistency.	• Does not possess a well-defined procedure to determine the linguistic scales.
Fuzzy balancing and ranking	Vahdani and Zandieh (2010)	• Does not require possessing the weights of effective decision criteria. • Considers risk, uncertainty and imprecision.	• Becomes quite complex as the number of alternatives increase.

Table 2.7 Advantages and limitations of non-deterministic MADM approaches (cont.)

Methods	References	Advantages	Limitations
Fuzzy data mining	Jain et al. (2007)	• Fuzzy association rules described by the natural languages are well-suited for the thinking of human subjects. • Increases the flexibility for supporting users in making decisions. • The goal of knowledge acquisition is achieved for users by checking fuzzy classification rules.	• Needs for the refinement of membership functions of linguistic variables by using various machine learning techniques.

2.3.2.1 Fuzzy Analytic Hierarchy Process

Bottani and Rizzi (2005) addressed the problem of supplier selection in an e-procurement environment. Fuzzy AHP was employed to determine the most viable supplier. Haq and Kannan (2006a) compared the results obtained by employing fuzzy AHP and AHP to the supplier selection process of a tire manufacturing company. Chan and Kumar (2007) identified the decision criteria including risk factors for the development of an efficient system for global supplier selection. Fuzzy extended AHP based methodology was used in the selection procedure. Chan et al. (2008) used a fuzzy modified AHP approach to select the best global supplier. In a recent work, Kilincci and Onal (2011) investigated supplier selection problem of a well-known washing machine manufacturer in Turkey, and employed a fuzzy AHP based methodology to select the best supplier firm.

2.3.2.2 Fuzzy Analytic Network Process

Kang et al. (2011) proposed fuzzy ANP to solve the supplier selection problem. The model was implemented in an integrated circuit packaging company. Vinodh et al. (2011) used fuzzy ANP for the supplier selection process, and presented a case study in an electronics switches manufacturing company.

2.3.2.3 Fuzzy TOPSIS

Chen et al. (2006) extended TOPSIS to develop a methodology for solving supplier selection problems in fuzzy environment. Boran et al. (2009) proposed intuitionistic fuzzy TOPSIS to select appropriate supplier in group decision making environment. Wang et al. (2009) proposed fuzzy hierarchical TOPSIS for supplier selection process. More recently, Awasthi et al. (2010) used fuzzy TOPSIS for evaluating environmental performance of suppliers.

2.3.2.4 Fuzzy VIKOR

Chen and Wang (2009) provided an integrated VIKOR framework under fuzzy environment for determining the most appropriate supplier and compromise solution from a number of potential suppliers in information system/information technology outsourcing project. Sanayei et al. (2010) proposed fuzzy VIKOR method to select the suitable supplier in a supply chain system. Lately, Shemshadi et al. (2011) tackled supplier selection as a multiple criteria group decision making problem and developed a fuzzy VIKOR method to solve this problem.

2.3.2.5 Fuzzy ELECTRE

Sevkli (2010) proposed a fuzzy ELECTRE method for supplier selection, and compared the results of crisp and fuzzy ELECTRE methods.

2.3.2.6 2-Tuple Linguistic Representation Model

Wang (2008b) used 2-tuple fuzzy linguistic representation model to determine the overall supplier performance with dynamic supply behaviors. More recently, Wang (2010) developed a model based on 2-tuple fuzzy linguistic representation model to evaluate the supplier performance.

2.3.2.7 Fuzzy Balancing and Ranking

Vahdani and Zandieh (2010) developed a novel MCDM method known as fuzzy balancing and ranking. In order to demonstrate the procedural implementation of the proposed algorithm, a case study regarding supplier selection was considered.

2.3.2.8 Fuzzy Data Mining

Jain et al. (2007) proposed an approach based on fuzzy association rule mining to support the decision-makers by enhancing the flexibility in making decisions for evaluating potential suppliers with both tangible and intangible attributes.

2.3.3 Metaheuristic Methods

Seven articles shown in Table 2.8, which consist 4.09% of the considered 171 articles, used metaheuristic methods for supplier evaluation and selection. These methods include genetic algorithms and ant colony optimization.

Table 2.8 Advantages and limitations of metaheuristic methods

Method	**References**	**Advantages**	**Limitations**
Genetic algorithms	Ding et al. (2005), Wang and Che (2007), Che and Wang (2008), Wang (2008), Che (2010a), Yang (2010)	• Works with a coding of the parameter set, not the parameters themselves. • Can solve every optimization problem which can be described with the chromosome encoding. • Uses information of the fitness function rather than derivatives or other auxiliary knowledge. • Uses probabilistic transitions rules rather than deterministic rules. • Solves multi-dimensional, non-differential, non-continuous, and even non-parametrical problems. • Often finds good solutions (near optimal) in relatively short search period.	• There is no absolute assurance that a genetic algorithm will find a global optimum. • Cannot assure constant optimization response times. • Certain optimization problems (they are called variant problems) cannot be solved by means of genetic algorithms. This occurs due to poorly known fitness functions which generate bad chromosome blocks in spite of the fact that only good chromosome blocks cross-over.

Table 2.8 Advantages and limitations of metaheuristic methods (cont.)

Method	References	Advantages	Limitations
Ant colony optimization	Tsai et al. (2010)	• Inherent parallelism. • Positive feedback accounts for rapid discovery of good solutions. • Can be used in dynamic applications.	• Theoretical analysis is difficult. • Probability distribution changes by iteration. • Research is experimental rather than theoretical. • Uncertain time to convergence. • Has slower convergence than other heuristics. • There is no centralized processor to guide the ant system towards good solutions.

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2.3.3.1 Genetic Algorithms

Ding et al. (2005) proposed a genetic algorithm (GA) based optimization approach for supplier selection. Wang and Che (2007) developed an innovative optimization algorithm for supplier selection in a configuration change. The proposed optimization algorithm adopted the optimization concept of genetic algorithms and was capable of considering cost and quality attributes with uncertainty values in determining an optimal solution. Che and Wang (2008) emphasized supplier selection and supply quantity allocation problems to identify the fundamental purchasing configuration. A GA based approach was proposed to analyze the product part configuration and to establish the supplier assessment and quantity allocation model. Wang (2008a) suggested a method based on GA for appraisal and selection of part suppliers in case of replacing parts and helped to swiftly modify the configuration of engineering products under fuzzy environment. Che (2010a) developed a hybrid genetic algorithm model for multi-period supplier evaluation. Yang (2010) proposed a hybrid GA model that demonstrates the linkages between evaluating supplier performance and improvement planning to sustain competitive advantages.

2.3.3.2 Ant Colony Optimization

Tsai et al. (2010) presented an approach based on ant colony optimization to model development and analysis of the supplier selection problem. The proposed approach implemented a framework to help buyers to choose the most appropriate suppliers in a dynamic environment.

2.3.4 Process Capability Indices Based Approaches

2 out of 171 papers (1.17%) implemented process capability indices based approaches for supplier selection. These studies are listed in Table 2.9.

Table 2.9 Advantages and limitations of process capability indices based approaches

Method	References	Advantages	Limitations
Process capability indices	Chen and Chen (2006), Wu et al. (2008)	• Effective and convenient tool for evaluating quality performance. • Provides a numerical and unitless measure of whether a process can produce the required quality specified by the product designer.	• Measures the production process of manufacturers, rather than exterior suppliers. • Considers only manufacturing capability and production quality factors.

Chen and Chen (2006) used process incapability index to develop an evaluation model that assesses the quality performance of suppliers. Wu et al. (2008) developed a practical procedure based on process capability indices to make supplier selection decisions between two given suppliers.

2.3.5 Case-based Reasoning

Three papers (1.75%) listed in Table 2.10 employed case-based reasoning (CBR) for supplier selection process.

Table 2.10 Advantages and limitations of case-based reasoning

Method	References	Advantages	Limitations
Case-based reasoning	Choy et al. (2002a), Choy et al. (2003a), Choy et al. (2003c),	• Complete expression of data. • Exact simulation of visualizing thinking. • Easy to get knowledge.	• Bottleneck problem.

Choy et al. (2002a) presented an intelligent customer–supplier relationship management system using CBR to select potential suppliers. Choy et al. (2003a) developed an intelligent customer-supplier relationship management system utilizing CBR to help solving supplier selection problem. Choy et al. (2003c) set forth an intelligent supplier relationship management system integrating a company's customer relationship management system, supplier rating system and product coding system through CBR to determine preferred suppliers during new product development process.

2.4 Integrated Approaches

Integrated approaches combined different analytical methods to deal with supplier selection problems. 75 papers (43.86%) employed integrated techniques, which point out a wider acceptability and use of these methods compared to deterministic and non-deterministic approaches. Integrated approaches are developed to overcome the limitations of the deterministic and non-deterministic approaches listed in Tables 4-10.

2.4.1 Optimization Based Integrated Approaches

20 out of 171 articles (11.70%) implemented optimization based integrated models. These studies are listed in Table 2.11.

Table 2.11 Optimization based integrated approaches

Year	Author(s)	Journal	Method(s)
2007	R. Ramanathan	Supply Chain Management: An International Journal	DEA, AHP, Total cost of ownership
2007	M. Sevkli, S.C.L. Koh, S. Zaim, M. Demirbağ, E. Tatoglu	International Journal of Production Research	DEA, AHP
2008	D. Çelebi, D. Bayraktar	Expert Systems with Applications	DEA, Neural network
2008	J. Rezaei, M. Davoodi	Applied Mathematical Modelling	Mixed integer programming, GA
2008b	D. Wu, D.L. Olson	International Journal of Production Economics	DEA, Multi-objective programming, Chance constrained programming
2009	R.M. Ebrahim, J. Razmi, H. Haleh	Advances in Engineering Software	Integer programming, Scatter search algorithm
2009	T.Y. Wang, Y.H. Yang	Expert Systems with Applications	Multi-objective programming, AHP, Fuzzy Compromise programming
2009	D. Wu	Expert Systems with Applications	DEA, Decision tree, Neural network
2010	Z.H. Che, C.J. Chiang	Advances in Engineering Software	Multi-objective programming, GA
2010	B.B. Keskin, H. Üster, S. Çetinkaya	Computers & Operations Research	Mixed-integer non-linear programming, Generalized benders decomposition
2010	R.J. Kuo, L.Y. Lee, T.L. Hu	Production Planning & Control	Fuzzy DEA, Fuzzy AHP
2011	A. Amid, S.H. Ghodsypour, C. O’Brien	International Journal of Production Economics	Weighted max–min fuzzy multi-objective programming, ANP
2011	R.U. Bilsel, A. Ravindran	Transportation Research Part B	Stochastic multi-objective programming
2011	Y.J. Chen	Information Sciences	DEA, TOPSIS

Table 2.11 Optimization based integrated approaches (cont.)

Year	Author(s)	Journal	Method(s)
2011	B. Feng, Z.P. Fan, Y. Li	International Journal of Production Economics	Multi-objective programming, Tabu search
2011	R. Jazemi, S.H. Ghodsypour, J. Gheidar-Kheljani	IEEE Transactions on Industrial Informatics	Multi-objective mixed integer programming, Additive weighted method
2011	L. Li, Z.B. Zebinsky	International Journal of Production Economics	Multi-objective stochastic programming, Multi-objective chance-constrained programming
2011	X.G. Luo, C.K. Kwong, J.F. Tang, S.F. Deng, J. Gong	International Journal of Production Research	Non-linear programming, GA, Tabu search
2011	J. Rezaei, M. Davoodi	International Journal of Production Research	Multi-objective mixed integer programming, GA
2011	M.J. Songhori, M. Tavana, A. Azadeh, M.H. Khakbaz	International Journal of Advanced Manufacturing Technology	DEA, Multi-objective programming

2.4.1.1 DEA Based Integrated Approaches

Ramanathan (2007) combined objective and subjective information obtained from the total cost of ownership and AHP approaches with DEA to select the best supplier. Sevkli et al. (2007) applied data envelopment analytic hierarchy process methodology developed by Ramanathan (2006) to a Turkish company operating in the appliance industry. Çelebi and Bayraktar (2008) explored a novel integration of neural networks (NN) and data envelopment analysis for evaluation of suppliers under incomplete information of evaluation criteria. Wu and Olson (2008b) considered chance constrained programming, DEA, and multi-objective programming models for supplier selection problem. Wu (2009) presented a hybrid model using DEA, decision trees, and neural networks to assess supplier performance. Kuo et al. (2010) developed a performance evaluation method, which integrates fuzzy AHP and fuzzy DEA for assisting organizations in supplier selection decision making. Chen (2011) used DEA and TOPSIS to filter out and evaluate potential suppliers. Songhori et al. (2011) presented a framework for solving the supplier evaluation and order allocation problem. DEA was used to determine the relative efficiency of suppliers. Then, a multi-objective mixed integer programming with two objectives as for minimizing the total costs and maximizing the overall efficiencies was developed for order allocation.

2.4.1.2 Integer Programming Based Integrated Approaches

Razaei and Davoodi (2008) introduced imperfect items and storage capacity in the lot sizing with supplier selection problem and formulated the problem as a mixed integer programming model. The model was solved employing a genetic algorithm. Ebrahim et al. (2009) proposed an integer programming model for supplier selection process. Scatter search algorithm was presented for the solution.

2.4.1.3 Non-linear Programming Based Integrated Approaches

Keskin et al. (2010) presented a mixed-integer non-linear program for supplier selection and inventory optimization problem, and developed a solution approach based on Generalized Benders Decomposition. Later, Luo et al. (2011) established an optimization model integrating components selection problem for product family design with supplier selection problem. A mixed-integer non-linear programming model with the objective of maximizing the total product family profit was formulated, and a genetic algorithm and a tabu search algorithm were proposed to solve the model.

2.4.1.4 Multi-objective Programming Based Integrated Approaches

Wang and Yang (2009) utilized fuzzy compromise programming to obtain compromise solution for allocating order quantities to each supplier offering a quantity discount rate. The weights of the criteria were determined using AHP. Che and Chiang (2010) derived a multi-objective mathematical model for built to order supply chain problems that integrates supplier selection, product assembly, and logistic distribution system of the supply chain in order to meet market demands. A genetic algorithm was applied to effectively solve the multi-objective optimization problem.

In 2011, there is a notable upsurge in the number of research articles implementing multi-objective programming based integrated approaches for supplier selection. Amid et al. (2011) developed a weighted max–min fuzzy multi-objective model for supplier selection. The relative weights of criteria were obtained using ANP. Bilsel and Ravindran (2011) proposed a stochastic sequential supplier allocation model to deal with supplier selection under uncertainty. Demand for products, capacities at suppliers as well as transportation and other variable costs were considered as the main sources of uncertainty, and were modeled using probability distributions. Feng et al. (2011) built a multi-objective 0–1 programming model involving three objectives, namely collaborative utility, service outsourcing cost and service waiting time, for supplier selection in multi-service outsourcing. Tabu search was employed to solve the multi-objective model. Jazemi et al. (2011) proposed a fuzzy multi-objective mixed integer model for supplier selection problem. Additive weighted model was employed to determine the importance levels of objectives, and a heuristic method was used to solve the problem. Li and Zebinsky (2011) presented a multi-objective two stage stochastic programming model and a multi-objective chance-constrained programming model for supplier selection problem with business volume discounts to determine a minimal set of suppliers and optimal order quantities. Rezaei and Davoodi (2011) formulated a multi-objective mixed integer programming model for supplier selection and applied genetic algorithm to solve the model and produce Pareto-optimal solutions.

2.4.2 Multi-attribute Decision Making Based Integrated Approaches

38 articles (22.22%) that are listed in Table 2.12 proposed MADM based integrated approaches to select the most appropriate supplier.

Table 2.12 MADM based integrated approaches

Year	Author(s)	Journal	Method(s)
2004	G. Wang, S.H. Huang, J.P. Dismukes	International Journal of Production Economics	AHP, GP
2005	F.H.F. Liu, H.L. Hai	International Journal of Production Economics	AHP, DEA
2006b	A.N. Haq, G. Kannan	International Journal of Production Research	Fuzzy AHP, GA
2006	W.N. Pi, C. Low	International Journal of Advanced Manufacturing Technology	AHP, Taguchi loss function
2006	H.J. Shyur, H.S. Shih	Mathematical and Computer Modelling	TOPSIS, ANP
2007	W. Xia, Z. Wu	Omega	AHP, Multi-objective programming
2008	E. Bottani, A. Rizzi	International Journal of Production Economics	AHP, Cluster analysis
2008	T.J. Kull, S. Talluri	IEEE Transactions on Engineering Management	GP, AHP
2008	A. Sanayei, S.F. Mousavi, M.R. Abdi, A. Mohaghar	Journal of the Franklin Institute	MAUT, Linear programming
2008	S.C. Ting, D.I. Cho	Supply Chain Management: An International Journal	AHP, Multi-objective programming
2008	J.L. Yang, H.N. Chiu, G.H. Tzeng, R.H. Yeh	Information Sciences	Fuzzy integral, Fuzzy AHP
2009	T.M. Lang, J.H. Chiang, L.W. Lan	Computers & Industrial Engineering	Choquet integral, ANP
2009	A.H.I. Lee	Expert Systems with Applications	AHP, BOCR
2009a	A.H.I. Lee, H.Y. Kang, C.T. Chang	Expert Systems with Applications	GP, Fuzzy AHP
2009b	A.H.I., Lee, H.Y. Kang, C.F. Hsu, H.C. Hung	Expert Systems with Applications	AHP, Delphi method
2009	R.H. Lin	Applied Mathematical Modelling	Fuzzy ANP, Multi-objective programming

Table 2.12 MADM based integrated approaches (cont.)

Year	Author(s)	Journal	Method(s)
2009	S. Önüt, S.S. Kara, E. Işik	Expert Systems with Applications	TOPSIS, ANP
2009a	J. Razmi, H. Rafiei, M. Hashemi	Computers & Industrial Engineering	ANP, Non-linear programming
2009b	J. Razmi, M.J. Songhori, M.H. Khakbaz	International Journal of Advanced Manufacturing Technology	TOPSIS, Multi-objective programming
2009	W.Y. Wu, B.M. Sukoco, C.Y. Li, S.H Chen	Expert Systems with Applications	ANP, Mixed integer programming
2010	H.Y. Kang, A.H.I. Lee	Kybernetes	AHP, DEA
2010	P. Kaur, R. Verma, N.C. Mahanti	Opsearch	AHP, Fuzzy preference programming
2010	C.Y. Ku, C.T. Chang, H.P. Ho	Quality & Quantity	Fuzzy GP, Fuzzy AHP
2010	C.N. Liao, H.P. Kao	Computers & Industrial Engineering	GP, AHP, Taguchi loss function
2010	Y.T. Lin, C.L. Lin, H.C. Yu, G.H. Tzeng	Expert Systems with Applications	ANP, Interpretive structural modeling
2010	S.M. Ordoobadi	Industrial Management & Data Systems	AHP, Taguchi loss function
2010	A.R. Ravindran, R.U. Bilsel, V. Wadhwa, T. Yang	International Journal of Production Research	AHP, GP
2010	J. Razmi, H. Rafiei	International Journal of Advanced Manufacturing Technology	ANP, Non-linear programming
2011	Z. Chen, W. Yang	Mathematical and Computer Modelling	Fuzzy TOPSIS, Fuzzy AHP
2011	D. Dalalah, M. Hayajneh, F. Batieha	Expert Systems with Applications	Fuzzy TOPSIS, Fuzzy DEMATEL

Table 2.12 MADM based integrated approaches (cont.)

Year	Author(s)	Journal	Method(s)
2011	H. Fazlollahtabar, I. Mahdavi, M.T. Ashoori, S. Kaviani, N. Mahdavi-Amiri	International Journal of Advanced Manufacturing Technology	TOPSIS, AHP, Multi-objective non-linear programming
2011	F. Jolai, S.A. Yazdian, K. Shahanaghi, M.A. Khojasteh	Journal of Purchasing & Supply Management	Fuzzy TOPSIS, GP
2011	S.S. Kara	Expert Systems with Applications	Fuzzy TOPSIS, Stochastic programming
2011	C.N. Liao, H.P. Kao	Expert Systems with Applications	Fuzzy TOPSIS, GP
2011	C.T. Lin, C.B. Chen, Y.C. Ting	Expert Systems with Applications	TOPSIS, ANP, Linear programming
2011	F. Mafakheri, M. Breton, A. Ghoniem	International Journal of Production Economics	AHP, Multi-objective programming
2011	Z. Wang, K.W. Li, J. Xu	Expert Systems with Applications	Fuzzy TOPSIS, Quadratic programming
2011	M. Zeyden, C. Çolpan, C. Çobanoğlu	Expert Systems with Applications	Fuzzy TOPSIS, Fuzzy AHP, DEA

2.4.2.1 AHP Based Integrated Approaches

Wang et al. (2004) proposed an integrated AHP and preemptive goal programming (PGP) based multi-criteria decision-making methodology that considers both qualitative and quantitative factors in supplier selection. Liu and Hai (2005) extended AHP and proposed a novel weighting procedure instead of pairwise comparison used in AHP. They employed Noguchi et al.'s (2002) ranking method, which is based on DEA, to calculate the weights of criteria and sub-criteria.

Haq and Kannan (2006b) provided an integrated supplier selection and multi-echelon distribution inventory model utilizing fuzzy AHP and GA. Pi and Low (2006) developed a supplier evaluation and selection system via Taguchi loss functions and AHP. Xia and Wu (2007) integrated AHP and multi-objective mixed integer programming to simultaneously determine the number of suppliers and the order quantity allocated to these suppliers. Bottani and Rizzi (2008) presented an approach based on AHP and cluster analysis for supplier and purchased item selection under fuzzy environment. Kull and Talluri (2008) integrated AHP and GP for supplier selection in the presence of risk measures and product life cycle considerations. Ting and Cho (2008) suggested an integrated approach to model development and analysis of the multi-sourcing supplier selection problem. A hierarchical structure for supplier selection considering both quantitative and qualitative criteria was developed using AHP to identify a set of candidate suppliers. Subsequently, a multi-objective linear programming (MOLP) model was formulated and solved to find the optimum order quantities allocated to the candidate suppliers.

The use of AHP based integrated approaches further increased over the past three years. Lee (2009) developed a fuzzy AHP model with the consideration of benefits, opportunities, costs and risks (BOCR) for supplier selection. Lee et al. (2009a) evaluated the performance of thin film transistor liquid crystal display manufacturers and allocated the purchase amount to the selected companies employing a fuzzy multi-choice goal programming approach. Fuzzy AHP was applied to obtain the weights of the evaluation criteria. Lee et al. (2009b) proposed a model for evaluating green suppliers. The Delphi method was applied first to differentiate the criteria for evaluating traditional suppliers and green suppliers. A fuzzy extended AHP based model was constructed next to evaluate green suppliers for an anonymous TFT–LCD manufacturer in Taiwan. Kang and Lee (2010) constructed a supplier performance evaluation model based on AHP and DEA. Kaur et al. (2010) proposed AHP based on fuzzy preference programming to select the most appropriate supplier. Ku et al. (2010) integrated fuzzy AHP and fuzzy GP to consider both qualitative and quantitative factors in supplier selection process. Liao and Kao (2010) combined Taguchi loss function, AHP, and multi-choice goal programming model for solving the supplier selection problem. Ordoobadi (2010) considered risk and benefit factors and provided a hybrid model for supplier selection process. Taguchi loss functions were used to measure performance of each supplier with respect to the risks and benefits. AHP was utilized to determine the relative importance of these factors. Ravindran et al. (2010) introduced two-phase multi-criteria supplier selection models incorporating supplier risk. In phase 1, initial set of supplier alternatives was reduced to a smaller set employing AHP. In phase 2, order quantities are allocated among the suppliers using a multi-objective optimization model. Recently, Mafakheri et al. (2011) developed a two-stage multiple criteria dynamic programming approach for supplier selection and order allocation. In the first stage, suppliers were ranked via AHP. In the second stage, supplier ranks were fed into an order allocation model that aims to maximize a utility function for the firm and minimize the total supply chain costs.

2.4.2.2 ANP Based Integrated Approaches

Lin (2009) combined fuzzy ANP and multi-objective linear programming to rank suppliers and allocate orders among suppliers. Razmi et al. (2009a) proposed a hybrid model based on ANP to evaluate and select suppliers under fuzzy environment. The proposed model was enhanced with a non-linear programming model to elicit weights of comparisons from comparison matrices in the ANP structure. Wu et al. (2009) integrated ANP and mixed integer programming to select suppliers with bundling strategy. Lin et al. (2010) developed an MADM method to cope with the supplier evaluation and selection problem. Using interpretive structural modeling, a relation map was constructed. ANP was then employed to derive the overall scores for each supplier based on these interrelationships. Razmi and Rafiei (2010) derived a hybrid ANP-mixed integer non-linear model for supplier selection with order allocation problem.

2.4.2.3 MAUT Based Integrated Approaches

Sanayei et al. (2008) combined MAUT and linear programming for rating and choosing the most appropriate suppliers and defining the optimum order quantities among selected suppliers in order to maximize total additive utility. MAUT unified quantitative and qualitative factors to measure desirability levels of the suppliers. The obtained levels were then used as coefficients for the objective function of the linear programming model.

2.4.2.4 TOPSIS Based Integrated Approaches

Shyur and Shih (2006) combined ANP and TOPSIS for supplier evaluation. Önüt et al. (2009) developed a supplier evaluation approach based on ANP and TOPSIS to help a telecommunication company in the GSM sector in Turkey under fuzzy environment. Razmi et al. (2009b) integrated fuzzy TOPSIS with multi-objective mixed integer programming model to solve the supplier selection and order assignment problem.

Research studies applying TOPSIS based integrated approaches have shown a considerable increase in 2011. Chen and Yang (2011) combined constrained fuzzy AHP and fuzzy TOPSIS for supplier selection. Dalalah et al. (2011) proposed a hybrid fuzzy group decision making model for supplier selection process. Fuzzy DEMATEL model was presented to deal with the relationships between evaluation criteria and to determine the weights of criteria. In addition, a modified fuzzy TOPSIS model was introduced to evaluate the alternatives. Fazlollahtabar et al. (2011) presented an integrated approach of AHP, TOPSIS, and multi objective non-linear programming in choosing the best suppliers and identifying the optimum quantities among selected suppliers. Jolai et al. (2011) suggested a two-phase approach for supplier selection and order allocation problem under fuzzy environment. In the first phase, a fuzzy MADM approach based on TOPSIS was employed to obtain the overall ratings of alternative suppliers. In the second phase, using the GP method a multi-objective mixed integer linear programming model was constructed to determine the quantity of each product that should be allocated to each supplier. Kara (2011) consolidated fuzzy TOPSIS and stochastic programming methods for supplier selection problem. Fuzzy TOPSIS was used for ranking potential suppliers considering qualitative data under fuzzy environment. Then, the ranked potential suppliers were included in a two-stage stochastic programming model for evaluation. Liao and Kao (2011) proposed an integrated fuzzy TOPSIS and multi-choice goal programming model to solve multi-sourcing supplier selection problems. Lin et al. (2011) integrated TOPSIS, ANP and linear programming for the supplier selection process. Wang et al. (2011) introduced a decision making methodology for supplier selection under the interval-valued intuitionistic fuzzy environment. The notion of relative closeness was extended to interval values, and fractional programming models were developed based on TOPSIS to determine a relative closeness interval. Zeydan et al. (2011) developed a two stage supplier evaluation methodology. In the first stage, qualitative performance evaluation was performed by using fuzzy AHP in finding criteria weights, and then fuzzy TOPSIS was utilized in determining the rank order of suppliers. In the second stage, suppliers' efficiency values were calculated via DEA using the results of fuzzy TOPSIS analysis as a quantitative output variable.

2.4.2.5 Fuzzy Integral Based Integrated Approaches

Yang et al. (2008) introduced a fuzzy MADM method for supplier selection problem. First, they used interpretive structural modeling to obtain the relationships among the sub criteria. Then, they applied fuzzy AHP to compute the relative weights for each criterion. Finally, they employed fuzzy integral to obtain the fuzzy synthetic performance and determined the rank order of alternative suppliers. Lang et al. (2009) integrated ANP with Choquet integral for supplier selection. The weights of selection criteria were obtained via ANP. Choquet integral was employed to determine the most appropriate supplier.

2.4.3 Quality Function Deployment Based Integrated Approaches

6 out of 171 papers (3.51%) implemented quality function deployment (QFD) based integrated approaches for supplier selection. These studies are listed in Table 2.13.

Table 2.13 QFD based integrated approaches

Year	Author(s)	Journal	Method(s)
2004	O.C.T. Onesime, X. Xiaofei, Z. Dechen	International Journal of Information Technology & Decision Making	QFD, AHP, GP
2006	M. Bevilacqua, F.E. Ciarapica, G. Giacchetta	Journal of Purchasing & Supply Management	Fuzzy QFD, fuzzy suitability index
2007	M. Ni, X. Xu, S. Deng	International Journal of Computer Integrated Manufacturing	QFD, Data mining
2009	S.H. Amin, J. Razmi	Expert Systems with Applications	QFD, Linear programming
2010	A. Bhattacharya, J. Geraghty, P. Young	Applied Soft Computing	QFD, AHP
2011	W. Ho, P.K. Dey, M. Lockström	Supply Chain Management: An International Journal	QFD, AHP

Onesima et al. (2004) developed a supplier selection methodology based on QFD, AHP, and preemptive goal programming. AHP was employed to measure the relative importance weights of supplier requirements and to assess the evaluation scores of candidate suppliers. Preemptive goal programming model was formulated to assign order quantities to the suppliers. Bevilacqua et al. (2006) constructed a house of quality to identify the features that the purchased product should possess in order to satisfy the customers' requirements. Then, the potential suppliers were evaluated against the relevant supplier assessment criteria. Ni et al. (2007) proposed a supplier selection methodology based on QFD and data mining techniques. Data mining techniques were utilized to find out quality requirements correlated to customer categories, product usage patterns, and frequent fault patterns in order to select the proper combination of suppliers. Amin and Razmi (2009) presented a two-phase decision model for supplier management including supplier selection, evaluation, and development. In the first phase, QFD model was integrated with a quantitative model introduced by Ng (2008) to take into account both qualitative and quantitative criteria to select the appropriate internet service providers. In the second phase, the selected internet service providers were evaluated from customer, performance, and competition perspectives. Bhattacharya et al. (2010) integrated AHP with QFD to rank and subsequently select candidate-suppliers under multiple, conflicting nature criteria environment. More recently, Ho et al. (2011) developed a combined QFD and AHP approach to measure the performance of alternative suppliers. QFD was used to translate the company stakeholder requirements into multiple evaluating factors for supplier selection. AHP was used to determine the importance of evaluating factors and preference of each supplier with respect to each selection criterion.

2.4.4 Metaheuristic Methods Based Integrated Approaches

Seven articles (4.09%) applied metaheuristic methods based integrated approaches to address supplier selection process. These papers are shown in Table 2.14.

Table 2.14 Integrated metaheuristic methods.

Year	Author(s)	Journal	Method(s)
2006	D.Y. Sha, Z.H. Che	Journal of the Operational Research Society	GA, AHP, MAUT
2009	C. Basnet, A. Weintraub	International Transactions in Operational Research	GA, Mixed-integer programming
2009	S. He, S.S. Chaudhry, Z. Lei, W. Baohua	Annals of Operations Research	GA, Chance constrained programming
2010b	Z.H. Che	International Journal of Production Research	Particle swarm optimization, Fuzzy AHP
2010	H.S. Wang, Z.H. Che, C. Wu	Expert Systems with Applications	Particle swarm optimization, AHP
2011	P.C. Huang, L.I. Tong, W.W. Chang, W.C. Yeh	Expert Systems with Applications	Particle swarm optimization, AHP
2011	P.C. Yang, H.M. Wee, S. Pai, Y.F. Tseng	Expert Systems with Applications	GA, Non-linear programming

2.4.4.1 Genetic Algorithm Based Integrated Approaches

Sha and Che (2006) proposed an approach based on GA, AHP, and multi attribute utility theory to satisfy simultaneously the preferences of the suppliers and the customers. Basnet and Weintraub (2009) modeled supplier selection problem as a mixed-integer programming model and presented a multi-population genetic algorithm for generating Pareto-optimal solutions of the problem. The performance of this algorithm was compared against mixed-integer programming solutions and Monte Carlo solutions. He et al. (2009) addressed supplier selection problem in which the quality and service factors were considered to be stochastic. A stochastic chance constrained programming model was developed for this supplier selection problem. An intelligent method based on GA was introduced to solve the problem. Recently, Yang et al. (2011) presented a non-linear programming model for stochastic demand multi-product supplier selection with service level and budget constraints, and employed GA to obtain the solution of the problem.

2.4.4.2 Particle Swarm Optimization Based Integrated Approaches

Che (2010b) integrated fuzzy AHP and particle swarm optimization (PSO) to provide a decision model to help decision-makers selecting suppliers in a balanced or defective supply chain network. Wang et al. (2010) introduced an optimized mathematical model to evaluate the suppliers and to distribute parts provided by the suppliers. In the mathematical model, AHP was proposed for formulation of factor weights and an improved PSO algorithm was developed for solving the mathematical model. Lately, Huang et al. (2011) introduced a two-phase algorithm model to deal with the issue of product part change, and supplier selection. Initially, AHP analysis was conducted to find out which module in a selected product has to be changed with top priority. Then, the results were optimized with PSO to determine the most viable supplier in line with such change.

2.4.5 CBR Based Integrated Approaches

Four articles given in Table 2.15, which consist 2.34% of the considered 171 articles, used case-based reasoning based integrated approaches for supplier evaluation and selection.

Table 2.15 Case-based reasoning based integrated approaches

Year	Author(s)	Journal	Method(s)
2002b	K.L. Choy, W.B. Lee, V. Lo	Expert Systems with Applications	CBR, Neural network
2003b	K.L. Choy, W.B. Lee, V. Lo	Expert Systems with Applications	CBR, ANN
2003	P. Humphreys, R. McIvor, F. Chan	Expert Systems with Applications	CBR, Decision support systems
2011	K. Zhao, X. Yu	Expert Systems with Applications	CBR, Neural network

Choy et al. (2002b) introduced an intelligent supplier management tool using CBR and neural network techniques to select and benchmark suppliers. Choy et al. (2003b) proposed an intelligent supplier relationship management system using hybrid CBR and artificial neural networks (ANN) techniques to select and benchmark potential suppliers. Humphreys et al. (2003) developed a knowledge-based system, which integrated environmental criteria into the supplier selection process. The system employs both CBR and decision support components including multi-attribute analysis. Lately, Zhao and Yu (2011) proposed a method based on CBR for petroleum enterprises supplier selection problem. The method weighted the attributes with information entropy, evaluated the similarities via k-prototype clustering between the original and target cases, and extracted the potential rules with back propagation neural networks.

3 QUALITY FUNCTION DEPLOYMENT

3.1 Basic Concepts

Over the past two decades, globally competitive environment and rapid technological changes have provoked a new industrial revolution. Although the early quality initiatives focused on reducing process variability in manufacturing, later efforts focused on re-engineering the upstream activities of product design and development (Cristiano et al., 2000). As a result, in order to reduce the influence of strong functional organizations of the mass production era, U.S. companies have shifted to a more concurrent engineering approach. Concurrent engineering facilitates time-based competition, however it is a strategy for failure without a critical link to customer requirements (Stalk & Webber, 1993).

One Japanese design and development methodology that helps enable quality planning throughout the concurrent engineering process is Quality Function Deployment (QFD). Unlike other quality methods, the QFD methodology was born out of total quality control activities in Japan during the 1960s. Development was motivated by two issues as how to design a new product that meets customer needs and the desire to provide process charts to manufacturing before initial production (Cristiano et al., 2000).

Quality function deployment is a strategic tool to help companies in developing products that satisfy the desires of customers. QFD is used to develop better products and services responsive to customer needs (CNs).   It employs a cross-functional team to identify the needs of customer and translate them into design characteristics to plan new or improved products. QFD ensures a higher quality level that meets customer expectations throughout each stage of product planning.

QFD allows for the company to allocate resources and to coordinate skills based on CNs, and thus, helps to decrease production costs and to reduce the cycle time. It evaluates the necessary decisions for change and development at the beginning of the product design phase and minimizes the corrections during the entire development process (Karsak et al., 2003).

QFD was originally proposed, through a well structured framework of analyzing the needs of the customer, to develop products with higher quality to meet or exceed customer expectations. Hence, the primary functions of QFD are product development, quality management, and customer needs analysis. Later, QFD's functions have been expanded to wider fields such as design, planning, decision-making, engineering, management, teamwork, timing, and costing.

QFD history began in Japon with a process assurance items chart created by Mr. Oshiumi of the Kurume Mant plant of Bridgestone Tire Corporation. This chart that contains some of the basic characteristics of QFD and the ideas of *functional deployment of business* developed by K. Ishihara formed the basis of the quality system called *hinshitsu tenkai* and conceptualized by Akao in the late 1960s in order to convert engineering characteristics of a product into quality control points in the quality control process charts prior to production startup (Chan & Wu, 2002).

Quality function deployment (QFD) was first implemented at the Kobe Shipyards of Mitsubishi Heavy Industries Ltd. in 1972. After the first implementation, Toyota and its suppliers further developed QFD in order to address design problems associated with automobile manufacturing (Iranmanesh & Thomson, 2008). Even though its applications were followed by successful implementations throughout Japan, QFD was brought to the attention of the U.S. firms ten years later. Recently, the U.S. companies have used QFD to a greater extent than Japanese companies and have reported deriving more significant product and process improvements. Management support and cross-functional involvement are also higher in the U.S. companies (Cristiano et al., 2000).

3.2 Overview

Quality function deployment is a crucial product development method dedicated to translating customer requirements into activities to develop products and services (Carnevalli & Miguel, 2008). QFD focuses on delivering value by taking into account the customer needs, and then deploying this information throughout the development process (Karsak, 2004). It attempts to reduce design risk and uncertainty, thus improving customer service and customer satisfaction levels and business processes, and resulting in increased competitiveness, customer satisfaction and profitability.

QFD allows for the company to allocate resources and to coordinate skills based on CNs, and thus, helps to decrease production costs and reduce the cycle time. It evaluates the necessary decisions for change and development at the beginning of the product design phase and minimizes the corrections during the entire development process (Karsak et al., 2003).

The basic concept of QFD is to translate the desires of customers into technical attributes (TAs), and subsequently into parts characteristics, process plans and production requirements (Karsak, 2004). 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 translates customer needs (CNs) into technical attributes (TAs); the part deployment matrix translates important TAs into product/part characteristics; the process planning matrix translates important product/part characteristics into manufacturing operations; the production/operation planning matrix translates important manufacturing operations into day-to-day operations and controls (Shillito, 1994). The four phases of QFD is summarized in Figure 3.1.

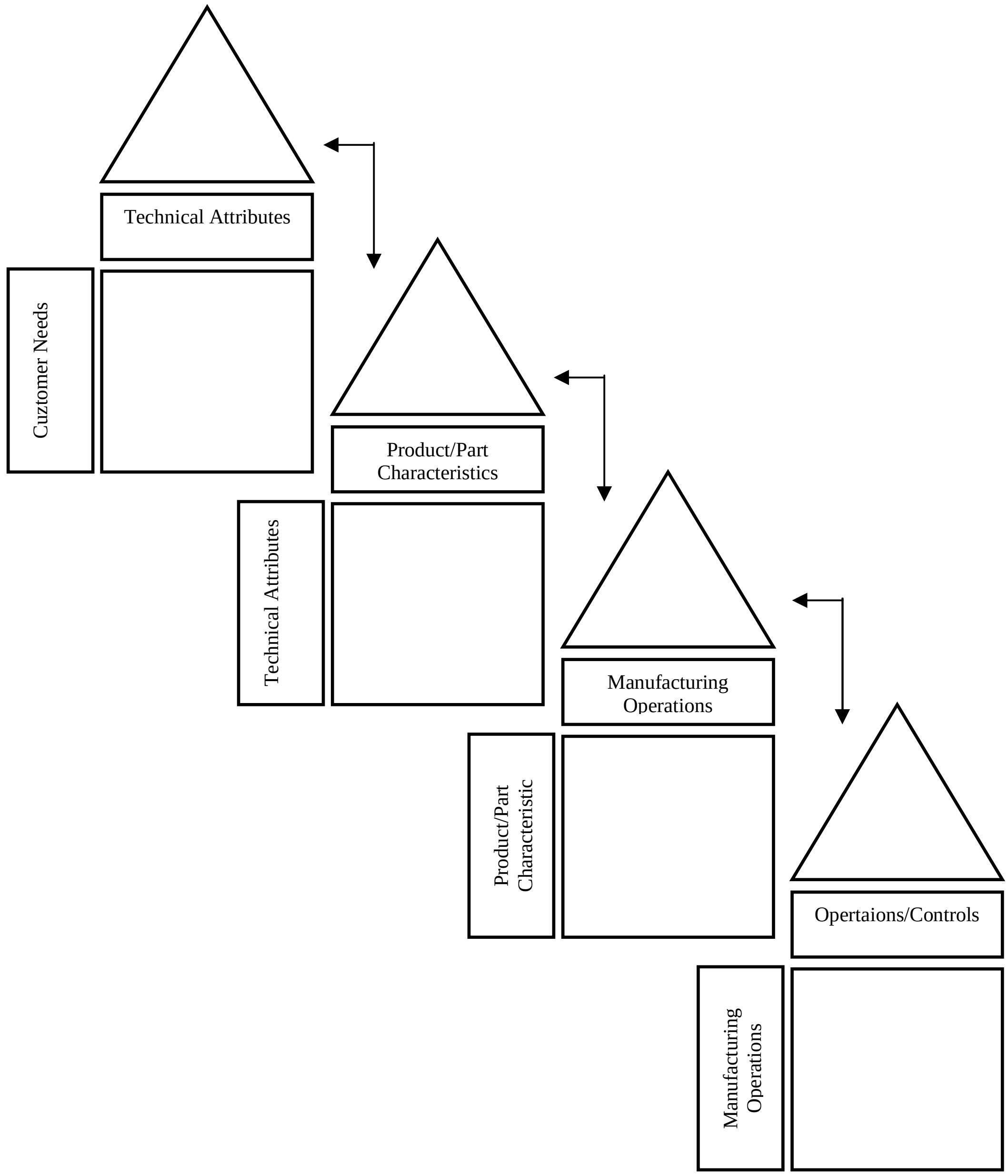


Figure 3.1 The four phases of QFD process

Ideally, these four stages combined provide a traceable link from the floor back to customer requirements that provides workers insight into how their job function impacts customer satisfaction (Cristiano et al., 2000). The first of the four matrices, also called the house of quality (HOQ), is the most frequently employed matrix in QFD. Applications begin with the HOQ, which is used by a team to understand customer needs and to translate these needs into the technical attributes.

3.3 The House of Quality

The quality chart topped with a triangular peak, created by Toyota Auto Body, was for the firs time referred by the name *house of quality* at a Japanese Society for Quality Control research presentation conference by Sawada in 1979 because of its shape (Akao, 1997).

According to Hauser and Clausing (1998), the HOQ is a kind of conceptual map that provides the means for interfunctional planning and communications. Relationships between CNs and TAs and among the TAs are defined by answering a specific question corresponding to each cell in HOQ. It contains seven elements as shown in Figure 3.2.

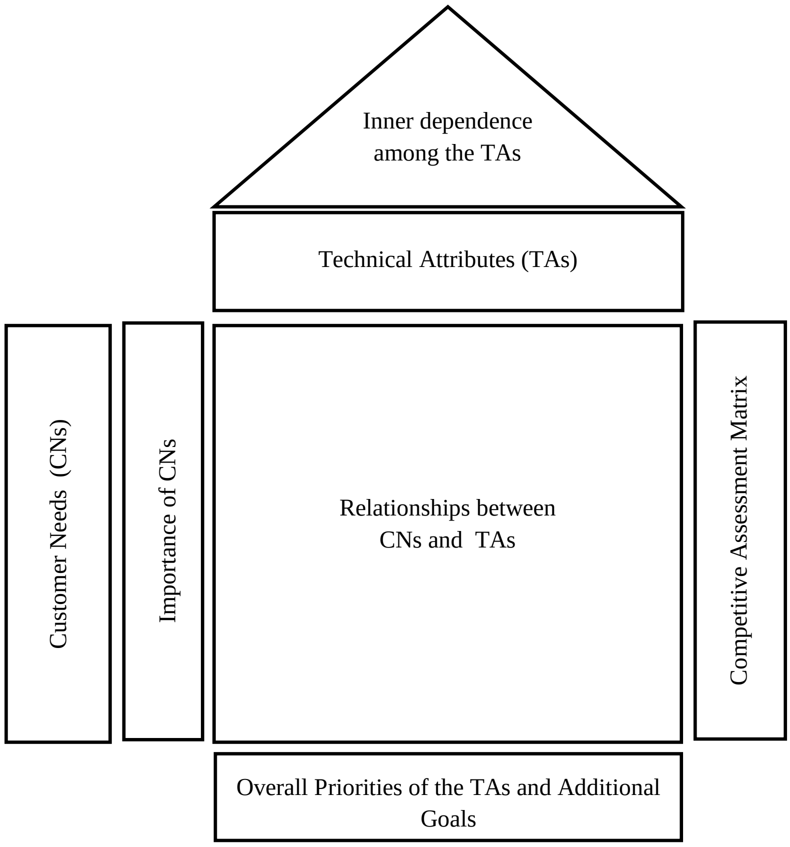


Figure 3.2 The house of quality

The seven elements of the HOQ shown in Figure 3.2 can be briefly described as follows:

1. Customer Needs (CNs): They are also known as voice of the customer, customer attributes, customer requirements or demanded quality. The process of building the HOQ begins with the collection of the needs of customers for the product or service concerned. As the initial input for the HOQ, they highlight the product characteristics that should be paid attention to. The CNs can include the requirements of retailers or the needs of vendors.
2. Technical Attributes (TAs): TAs are also named as design requirements, product features, engineering attributes, engineering characteristics or substitute quality characteristics. They are the product requirements that relate directly to the customer requirements. TAs describe the product in the language of the engineer; therefore, are sometimes referred to as the voice of the company. They are used to determine how well the company satisfies the CNs (Karsak et al., 2003).
3. Importance of CNs: Since the collected and organized data from the customers usually contain too many needs to deal with simultaneously, they must be rated. The company should trade off one benefit against another, and work on the most important needs while eliminating relatively unimportant ones (Karsak et al., 2003).
4. Relationships between CNs and TAs: The relationship matrix indicates to what extent each TA affects each CN and is placed in the body of the HOQ (Alptekin & Karsak, 2011). The relationships between CNs and TAs are generally expressed with graphic symbols, which are translated in an appropriate rating scale.
5. Competitive assessment matrix: Understanding how customers rate the competition can be a tremendous competitive advantage. The information needed can be obtained by asking the customers to rate the performance of the company's and its competitors' products for each CN using a predetermined scale.
6. Inner dependence among the TAs: The HOQ's roof matrix is used to specify the inner dependencies among TAs. This enables to account for the correlations between TAs, which in turn facilitates informed trade-offs.
7. Overall priorities of the TAs and additional goals: Here, the results obtained from preceding steps are used to calculate a final rank order of TAs.

The objective constructing the HOQ is to determine the target levels of TAs of a product to maximize customer satisfaction. The process of setting the target levels is currently accomplished in a subjective, ad hoc manner. In general, importance of CNs, degree of relationship between CNs and TAs, inner dependence among TAs cannot be assessed by either crisp values or random processes. Fuzzy set theory appears to be an effective means to represent imprecise design information (Karsak, 2004).

4 PRELIMINARIES OF FUZZY SETS

Fuzzy set theory, which was introduced by Zadeh (1965) to deal with problems in which a source of vagueness is involved, has been utilized for incorporating imprecise data into the decision framework.

A fuzzy set $\tilde{A}$ can be defined mathematically by a membership function $\mu_{\tilde{A}}(x)$, which assign each element x in the universe of discourse X a real number in the interval [0,1]. This terms the membership grade of the element with the concept represented by the fuzzy set.

In the following paragraph, we briefly review some basic definitions of the fuzzy sets (Chen, 2001). These basic definitions and notations below will be used in the following paragraphs, unless otherwise stated.

Definition 4.1 A fuzzy set $\tilde{A}$ is convex if and only if for all x_1 and $x_2 \in X$:

$$\mu_{\tilde{A}}(\lambda x_1 + (1-\lambda)x_2) \geq \min(\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2)), \quad \lambda \in [0,1] \tag{4.1}$$

Definition 4.2 A fuzzy set $\tilde{A}$ is called a normal fuzzy set implying

$$\exists\, x_i \in X, \mu_{\tilde{A}}(x_i) = 1 \tag{4.2}$$

Definition 4.3 α-cut is defined as

$$\tilde{A}_\alpha = \{x_i : \mu_{\tilde{A}}(x_i) \geq \alpha, x_i \in X\} \tag{4.3}$$

where $\alpha \in [0,1]$

$\tilde{A}_\alpha$ is a limited nonempty bounded interval contained in X and it can be noted by $\tilde{A}_\alpha = \left[\left(\tilde{A}\right)_\alpha^L, \left(\tilde{A}\right)_\alpha^U \right]$, where $\left(\tilde{A}\right)_\alpha^L$ and $\left(\tilde{A}\right)_\alpha^U$ are the lower and higher bounds of the closed interval, respectively.

A triangular fuzzy number $\tilde{A}$ can be defined by a triplet (a_1, a_2, a_3). The membership function $\mu_{\tilde{A}}(x)$ is defined as

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x - a_1}{a_2 - a_1}, & a_1 \le x \le a_2 \\ \dfrac{x - a_3}{a_2 - a_3}, & a_2 \le x \le a_3 \\ 0, & \text{otherwise} \end{cases} \tag{4.4}$$

Definition 4.4 If $\tilde{A}$ is a fuzzy number and $a_1^\alpha > 0$ for $\alpha \in [0,1]$, then $\tilde{A}$ is named as a positive fuzzy number.

Any two positive fuzzy numbers $\tilde{A}$ and $\tilde{B}$ and a positive real number *k*, the *α*-cuts of two fuzzy numbers are $\tilde{A}_\alpha = \left[\left(\tilde{A}\right)_\alpha^L, \left(\tilde{A}\right)_\alpha^U \right]$, and $\tilde{B}_\alpha = \left[\left(\tilde{B}\right)_\alpha^L, \left(\tilde{B}\right)_\alpha^U \right]$, respectively, where $(\alpha \in [0,1])$. According to the confidence interval, basic arithmetic operations of positive fuzzy numbers can be expressed as follows:

$$\left(\tilde{A}(+)\tilde{B}\right)_\alpha = \left[(A)_\alpha^L + (B)_\alpha^L, (A)_\alpha^U + (B)_\alpha^U \right] \tag{4.5}$$

$$\left(\tilde{A}(-)\tilde{B}\right)_\alpha = \left[(A)_\alpha^L - (B)_\alpha^L, (A)_\alpha^U - (B)_\alpha^U \right] \tag{4.6}$$

$$\left(\tilde{A}(*)\tilde{B}\right)_\alpha = \left[(A)_\alpha^L * (B)_\alpha^L, (A)_\alpha^U * (B)_\alpha^U\right] \quad (4.7)$$

$$\left(\tilde{A}(\div)\tilde{B}\right)_\alpha = \left[\frac{(A)_\alpha^L}{(B)_\alpha^U}, \frac{(A)_\alpha^U}{(B)_\alpha^L}\right] \quad (4.8)$$

$$\left(\tilde{A}_\alpha\right)^{-1} = \left[\frac{1}{(A)_\alpha^U}, \frac{1}{(A)_\alpha^L}\right] \quad (4.9)$$

$$\left(\tilde{A}(*)k\right)_\alpha = \left[(A)_\alpha^L * k, (B)_\alpha^U * k\right] \quad (4.10)$$

$$\left(\tilde{A}(\div)k\right)_\alpha = \left[\frac{(A)_\alpha^L}{k}, \frac{(A)_\alpha^U}{k}\right] \quad (4.11)$$

Definition 4.5 If $\tilde{A}$ is a fuzzy number and $(A)_\alpha^L > 0$, $(A)_\alpha^U \leq 1$ for $\alpha \in [0,1]$, then $\tilde{A}$ is called a normalized positive fuzzy number (Chen, 2001).

Definition 4.6 A linguistic variable is defined as a variable whose values are not numbers, but words or sentences in natural or artificial language. The concept of a linguistic variable appears as a useful means for providing approximate characterization of phenomena that are too complex or ill defined to be described in conventional quantitative terms (Zadeh, 1975).

5 FUZZY WEIGHTED AVERAGE

Consider the general fuzzy weighted average with *m* criteria. Define

$$\tilde{W}_i = \left\{ \left(w_i , \mu_{\tilde{W}_i} \left(w_i \right) \right) \middle| w_i \in W_i \right\}, \quad i = 1,2,...,m \tag{5.1}$$

and

$$\tilde{X}_{ij} = \left\{ \left(x_{ij} , \mu_{\tilde{X}_{ij}} \left(x_{ij} \right) \right) \middle| x_{ij} \in X_{ij} \right\}, \quad i = 1,2,...,m, \quad j = 1,2,...,n \tag{5.2}$$

where $\tilde{W}_i$ is the relative importance of criterion *i* and $\tilde{X}_{ij}$ denotes the rating of alternative *j* with respect to criterion *i*, W_i and X_{ij} are the crisp universal sets of the relative importance and the rating, and $\mu_{\tilde{W}_i}$ and $\mu_{\tilde{X}_{ij}}$ are the membership functions of the fuzzy numbers $\tilde{W}_i$ and $\tilde{X}_{ij}$, respectively. Then, the fuzzy weighted average can be defined as

$$\tilde{Y}_j = \sum_{i=1}^{m} \tilde{W}_i \tilde{X}_{ij} \Bigg/ \sum_{i=1}^{m} \tilde{W}_i , \quad j = 1,2,...,n \tag{5.3}$$

Since $\tilde{W}_i$ and $\tilde{X}_{ij}$ are fuzzy numbers, the weighted average $\tilde{Y}_j$ is also a fuzzy number.

When the relative weights of customer needs, the relationship measures between customer needs and technical attributes, and the inner dependencies of technical attributes are represented as fuzzy numbers in QFD applications, the computation of the overall priorities of the technical attributes falls into the category of fuzzy weighted average (Liu, 2005). There are several methods devised for calculating fuzzy weighted average (Dong, 1987; Liou & Wang, 1992; Lee & Park, 1997; Kao & Liu, 2001; Wang & Chin, 2011). In this paper, two alternative FWA methods proposed by Kao and Liu (2001) and Wang and Chin (2011) are employed. These methods are able to rate the importance of TAs and supplier assessments in fuzzy environments accurately through α-level sets.

Kao and Liu (2001) approached the problem via mathematical programming technique and developed a pair of fractional programs to find the α-cut of $\tilde{Y}_j$ based on the extension principle. The computational complexity of their method is lower compared to other methods. A brief summary of the method is given below.

Let $\tilde{W}_i$ denote the fuzzy relative weight of CN_i and $\tilde{X}_{ij}$ denote the fuzzy relationship measure between TA_j. Denote $\left[(W_i)_\alpha^L, (W_i)_\alpha^U\right]$ and $\left[(X_{ij})_\alpha^L, (X_{ij})_\alpha^U\right]$ be the α-level sets of the fuzzy relative weight and fuzzy relationships.

According to Zadeh's extension principle (1978), the membership function $\mu_{\tilde{Y}j}$ can be derived from the following equation:

$$\mu_{\tilde{Y}_j}(y_j) = \sup_{x,w} \min\left\{ \mu_{\tilde{W}i}(w_i), \mu_{\tilde{X}_{ij}}(x_{ij}), \forall i, j \,\middle|\, y_j = \sum_{i=1}^{m} w_i x_{ij} \Big/ \sum_{i=1}^{m} w_i \right\} \tag{5.4}$$

At a specific α-level of $\tilde{Y}_j$, Eq. (4.4) states that one needs $\mu_{\tilde{W}_i}(w_i) \geq \alpha$ and $\mu_{\tilde{X}_{ij}}(x_{ij}) \geq \alpha$, for $\forall i, j$, and at least one $\mu_{\tilde{W}_i}(w_i)$ or $\mu_{\tilde{X}_{ij}}(x_{ij})$ equal to α such that $y_j = \sum_{i=1}^{m} w_i x_{ij} \Big/ \sum_{i=1}^{m} w_i$ to satisfy $\mu_{\tilde{Y}_j}(y_j) = \alpha$. To find the membership function $\mu_{\tilde{Y}j}$, it suffices to find the right shape function and the left shape function of $\mu_{\tilde{Y}j}$, which is equivalent to finding the upper bound $(Y_j)_\alpha^U$ and the lower bound $(Y_j)_\alpha^L$ of $\tilde{Y}_j$ at the α-level. Since $(Y_j)_\alpha^U$ and $(Y_j)_\alpha^L$ are respectively the maximum and the minimum of $\sum_{i=1}^{m} w_i x_{ij} \Big/ \sum_{i=1}^{m} w_i$, the upper and the lower bounds of the α-cut of $\tilde{Y}_j$ can be solved as

$$
\begin{aligned}
&(Y_j)_\alpha^U = \max \sum_{i=1}^{m} w_i x_{ij} \Big/ \sum_{i=1}^{m} w_i \\
&\text{subject to} \\
&\qquad (W_i)_\alpha^L \le w_i \le (W_i)_\alpha^U, \quad i = 1,2,\ldots,m \\
&\qquad (X_{ij})_\alpha^L \le x_{ij} \le (X_{ij})_\alpha^U, \quad j = 1,2,\ldots,n, \quad i = 1,2,\ldots,m
\end{aligned}
\tag{5.5}
$$

$$
\begin{aligned}
&(Y_j)_\alpha^L = \min \sum_{i=1}^{m} w_i x_{ij} \Big/ \sum_{i=1}^{m} w_i \\
&\text{subject to} \\
&\qquad (W_i)_\alpha^L \le w_i \le (W_i)_\alpha^U, \quad i = 1,2,\ldots,m \\
&\qquad (X_{ij})_\alpha^L \le x_{ij} \le (X_{ij})_\alpha^U, \quad j = 1,2,\ldots,n, \quad i = 1,2,\ldots,m
\end{aligned}
\tag{5.6}
$$

It is obvious that the maximum of y_j must occur at $(x_{ij})_\alpha^U$ and the minimum must occur at $(x_{ij})_\alpha^L$. Thus, the variable x_{ij} in the objective function of formulations (4.5) and (4.6) can be replaced by $(x_{ij})_\alpha^U$ and $(x_{ij})_\alpha^L$, respectively. Following the variable substitution of Charnes and Cooper (1962), by letting $t^{-1} = \sum_{i=1}^{m} w_i$ and $v_i = twi$, formulations (5.5) and (5.6) can be transformed to the following linear programs:

$$\left(Y_j\right)_\alpha^U = \max \sum_{i=1}^{m} v_i \left(X_{ij}\right)_\alpha^U$$

subject to

$$t\left(W_i\right)_\alpha^L \le v_i \le t\left(W_i\right)_\alpha^U, \quad i = 1,2,\ldots,m \tag{5.7}$$

$$\sum_{i=1}^{m} v_i = 1$$

$$t, v_i \ge 0, i = 1,2,\ldots,m$$

$$\left(Y_j\right)_\alpha^L = \min \sum_{i=1}^{m} v_i \left(X_{ij}\right)_\alpha^L$$

subject to

$$t\left(W_i\right)_\alpha^L \le v_i \le t\left(W_i\right)_\alpha^U, \quad i = 1,2,\ldots,m \tag{5.8}$$

$$\sum_{i=1}^{m} v_i = 1$$

$$t, v_i \ge 0, i = 1,2,\ldots,m$$

The α-cuts of $\tilde{Y}_j$ is the crisp interval $\left[\left(Y_j\right)_\alpha^L, \left(Y_j\right)_\alpha^U\right]$ solved from formulations (5.7) and (5.8). By enumerating different α values, the membership function $\mu_{\tilde{Y}j}$ can be constructed.

Wang and Chin (2011) developed a pair of nonlinear programming models and two equivalent pairs of linear programming models to find the α-cut of $\tilde{Y}_i$. Their method produces normalized fuzzy importance ratings for TAs. The method can be summarized as follows:

Let $\tilde{W}_i$ denote the fuzzy relative weight of CN_i, $\tilde{X}_{ij}$ denote the fuzzy relationship measure between TA_j and customer need *i*, and $\tilde{r}_{kj}$ denote the degree of dependence of the *k*th TA on the *j*th TA. Denote $\left[\left(W_i\right)_\alpha^L, \left(W_i\right)_\alpha^U\right]$, $\left[\left(X_{ij}\right)_\alpha^L, \left(X_{ij}\right)_\alpha^U\right]$, $\left[\left(r_{kj}\right)_\alpha^L, \left(r_{kj}\right)_\alpha^U\right]$ be the α-level sets of the fuzzy relative weight, fuzzy relationships, and fuzzy correlations, respectively. Calculate the normalized fuzzy relationships as

$$\tilde{X}'_{ij} = \frac{\sum_{k=1}^{n} \tilde{X}_{ik} \tilde{r}_{kj}}{\sum_{\substack{l=1 \\ l \neq j}}^{n} \sum_{k=1}^{n} \tilde{X}_{ik} \tilde{r}_{kl} + \sum_{k=1}^{n} \tilde{X}_{ik} \tilde{r}_{kj}}, \quad i = 1,2,\ldots,m; \;\; j = 1,2,\ldots,n. \tag{5.9}$$

Eq. (5.9) can be characterized using α-level sets by the following pair of non-linear programming models for each i and j.

$$\left(\tilde{X}'_{ij}\right)^{L}_{\alpha} = \text{Min} \frac{\sum_{k=1}^{n} X_{ik} r_{kj}}{\sum_{\substack{l=1 \\ l \neq j}}^{n} \sum_{k=1}^{n} X_{ik} r_{kl} + \sum_{k=1}^{n} X_{ik} r_{kj}} \tag{5.10}$$

subject to

$$\left(X_{ik}\right)^{L}_{\alpha} \leq X_{ik} \leq \left(X_{ik}\right)^{U}_{\alpha}, k = 1,2,\ldots,n$$

$$\left(r_{kl}\right)^{L}_{\alpha} \leq r_{kl} \leq \left(r_{kl}\right)^{U}_{\alpha}, k = 1,2,\ldots,n; \;\; l = 1,2,\ldots,n$$

$$\left(\tilde{X}'_{ij}\right)^{U}_{\alpha} = \text{Max} \frac{\sum_{k=1}^{n} X_{ik} r_{kj}}{\sum_{\substack{l=1 \\ l \neq j}}^{n} \sum_{k=1}^{n} X_{ik} r_{kl} + \sum_{k=1}^{n} X_{ik} r_{kj}} \tag{5.11}$$

subject to

$$\left(X_{ik}\right)^{L}_{\alpha} \leq X_{ik} \leq \left(X_{ik}\right)^{U}_{\alpha}, k = 1,2,\ldots,n$$

$$\left(r_{kl}\right)^{L}_{\alpha} \leq r_{kl} \leq \left(r_{kl}\right)^{U}_{\alpha}, k = 1,2,\ldots,n; \;\; l = 1,2,\ldots,n$$

X'_{ij} is an increasing function of $r_{kj}\ (k=1,2,...,n)$ but decreased with $r_{kl}\ (k=1,2,...,n;\ l=1,2,...,n;\ l\neq j)$. Based on this conclusion, non-linear programming models (4.10) and (4.11) can be simplified as

$$\left(\tilde{X}'_{ij}\right)^L_\alpha = \text{Min}\frac{\sum_{k=1}^{n} X_{ik}\left(r_{kj}\right)^L_\alpha}{\sum_{\substack{l=1\\ l\neq j}}^{n}\sum_{k=1}^{n} X_{ik}\left(r_{kl}\right)^U_\alpha + \sum_{k=1}^{n} X_{ik}\left(r_{kj}\right)^L_\alpha}$$

subject to (5.12)

$$\left(X_{ik}\right)^L_\alpha \leq X_{ik} \leq \left(X_{ik}\right)^U_\alpha, k=1,2,...,n$$

$$\left(\tilde{X}'_{ij}\right)^U_\alpha = \text{Max}\frac{\sum_{k=1}^{n} X_{ik}\left(r_{kj}\right)^U_\alpha}{\sum_{\substack{l=1\\ l\neq j}}^{n}\sum_{k=1}^{n} X_{ik}\left(r_{kl}\right)^L_\alpha + \sum_{k=1}^{n} X_{ik}\left(r_{kj}\right)^U_\alpha}$$

subject to (5.13)

$$\left(X_{ik}\right)^L_\alpha \leq X_{ik} \leq \left(X_{ik}\right)^U_\alpha, k=1,2,...,n$$

By letting

$$t = \frac{1}{\sum_{\substack{l=1\\ l\neq j}}^{n}\sum_{k=1}^{n} X_{ik}\left(r_{kl}\right)^U_\alpha + \sum_{k=1}^{n} X_{ik}\left(r_{kj}\right)^L_\alpha} \text{ and } z_{ik} = tX_{ik}, k=1,2,...,n \tag{5.14}$$

$$s = \frac{1}{\sum_{\substack{l=1\\ l\neq j}}^{n}\sum_{k=1}^{n} X_{ik}\left(r_{kl}\right)^L_\alpha + \sum_{k=1}^{n} X_{ik}\left(r_{kj}\right)^U_\alpha} \text{ and } u_{ik} = sX_{ik}, k=1,2,...,n \tag{5.15}$$

Eqs. (5.12) and (5.13) can be converted into the following pair of linear programming models:

$$\left(\tilde{X}'_{ij}\right)^L_\alpha = \text{Min}\sum_{k=1}^{n} z_{ik}\left(r_{kj}\right)^L_\alpha$$

subject to

$$\sum_{k=1}^{n} z_{ik}\left(\left(r_{kj}\right)^L_\alpha + \sum_{\substack{l=1\\l\neq j}}^{n}\left(r_{kl}\right)^U_\alpha\right) = 1 \tag{5.16}$$

$$\left(X_{ik}\right)^L_\alpha t \le z_{ik} \le \left(X_{ik}\right)^U_\alpha t, \quad k = 1,2,\ldots,n$$

$$t > 0$$

$$\left(\tilde{X}'_{ij}\right)^U_\alpha = \text{Max}\sum_{k=1}^{n} u_{ik}\left(r_{kj}\right)^U_\alpha$$

subject to

$$\sum_{k=1}^{n} u_{ik}\left(\left(r_{kj}\right)^U_\alpha + \sum_{\substack{l=1\\l\neq j}}^{n}\left(r_{kl}\right)^L_\alpha\right) = 1 \tag{5.17}$$

$$\left(X_{ik}\right)^L_\alpha s \le u_{ik} \le \left(X_{ik}\right)^U_\alpha s, \quad k = 1,2,\ldots,n$$

$$s > 0$$

where t, s, z_{ik}, and u_{ik} are decision variables. By solving this pair of linear programming models for each α-level, the normalized fuzzy relationship matrix $\tilde{X}' = \left(\tilde{X}'_{ij}\right)_{m\times n}$ can be obtained. Once the normalized fuzzy relationships are generated, the fuzzy weighted average of the normalized fuzzy relationship can be formulated as

$$\tilde{Y}_j = \sum_{i=1}^{m}\tilde{W}_i\tilde{X}'_{ij} \Big/ \sum_{i=1}^{m}\tilde{W}_i\,, \quad j = 1,2,\ldots,n \tag{5.18}$$

and the upper and the lower bounds of the α-cut of $\tilde{Y}_j$ can be solved as

$$\left(Y_j\right)_\alpha^U = \max \sum_{i=1}^{m} w_i \left(X'_{ij}\right)_\alpha^U \Big/ \sum_{i=1}^{m} w_i$$

subject to (5.19)

$$\left(W_i\right)_\alpha^L \le w_i \le \left(W_i\right)_\alpha^U, \quad i = 1,2,\ldots,m$$

$$\left(Y_j\right)_\alpha^L = \min \sum_{i=1}^{m} w_i \left(X'_{ij}\right)_\alpha^L \Big/ \sum_{i=1}^{m} w_i$$

subject to (5.20)

$$\left(W_i\right)_\alpha^L \le w_i \le \left(W_i\right)_\alpha^U, \quad i = 1,2,\ldots,m$$

Following the variable substitution of Charnes and Cooper (1962), by letting $z^{-1} = \sum_{i=1}^{m} w_i$ and $v_i = zw_i$, formulations (5.19) and (5.20) can be transformed to the following linear programs:

$$\left(Y_j\right)_\alpha^U = \max \sum_{i=1}^{m} v_i \left(X'_{ij}\right)_\alpha^U$$

subject to

$$z\left(W_i\right)_\alpha^L \le v_i \le z\left(W_i\right)_\alpha^U, \quad i = 1,2,\ldots,m \qquad (5.21)$$

$$\sum_{i=1}^{m} v_i = 1$$

$$z, v_i \ge 0$$

$$\left(Y_j\right)_\alpha^L = \min \sum_{i=1}^{m} v_i \left(X_{ij}^{'}\right)_\alpha^L$$

subject to

$$z\left(W_i\right)_\alpha^L \le v_i \le z\left(W_i\right)_\alpha^U, \quad i = 1,2,\ldots,m \tag{5.22}$$

$$\sum_{i=1}^{m} v_i = 1$$

$$z, v_i \ge 0$$

The α-cuts of $\tilde{Y}_j$ is the crisp interval $\left[\left(Y_j\right)_\alpha^L, \left(Y_j\right)_\alpha^U\right]$ obtained from formulations (5.21) and (5.22). By enumerating different α values, the membership function $\mu_{\tilde{Y}_j}$ can be constructed.

6 FUSION OF FUZZY INFORMATION

Fusion approach of fuzzy information is proposed by Herrera et al. (2000). This approach is used to manage information assessed using different linguistic scales in a decision making problem with multiple information sources. It enables the sources that participate in the decision process express their judgments by means of non-homogeneous information according to their preferences (Herrera et al., 2000).

This approach consists of obtaining a collective performance profile on the alternatives according to the individual performance profiles. It is performed in two phases (Herrera et al., 2000):

i. Making the information uniform,
ii. Computing the collective performance values.

6.1 Making the Information Uniform

The performance values expressed using multi-granularity linguistic term sets are converted (under a transformation function) into a specific linguistic domain, which is a BLTS denoted as S_T, chosen so as not to impose useless precision to the original evaluations and to allow an appropriate discrimination of the initial performance values. The transformation function is defined as follows (Herrera et al., 2000):

Let $A = \{l_0, l_1, ..., l_p\}$ and $S_T = \{s_0, s_1, ..., s_g\}$ be two linguistic term sets, such that $g \geq p$. Then, the transformation function, τ_{AS_T}, is defined as

$$\begin{aligned}
&\tau_{AS_T} : A \rightarrow F(S_T),\\
&\tau_{AS_T}(l_i) = \{(s_k, \gamma_k^i) / k \in \{0,1,\ldots,g\}\}, \quad \forall l_i \in A,\\
&\gamma_k^i = \max_y \min\{\mu_{l_i}(y), \mu_{s_k}(y)\}
\end{aligned} \tag{6.1}$$

where $F(S_T)$ is the set of fuzzy sets defined in S_T, and $\mu_{l_i}(y)$ and $\mu_{s_k}(y)$ are the membership functions of the fuzzy sets associated with the terms l_i and s_k, respectively.

The transformation function is also appropriate to convert the standardized fuzzy assessments into a BLTS (Chuu, 2009). The max-min operation has been chosen in the definition of the transformation function since it is a classical tool to set the matching degree between fuzzy sets (Herrera et al., 2000).

6.2 Computing the Collective Performance Values

The input information, which was denoted by means of fuzzy sets, is expressed on a BLTS by the abovementioned transformation function. For each alternative, a collective performance value is obtained by means of the aggregation of the aforementioned fuzzy sets on the BLTS that represents the individual performance values assigned to the alternative according to each information source (Herrera et al., 2000). This collective performance value is a new fuzzy set defined on a BLTS.

This thesis employs ordered weighted averaging (OWA) operator, initially proposed by Yager (1988), to calculate the collective performance values. This operator provides aggregations which lie between two extreme cases of MCDM problems that lead to the use of "and" and "or" operators to combine the criteria function. OWA operator encompasses several operators since it can implement different aggregation rules by changing the order weights.

The OWA operator provides a unified framework for decision making under uncertainty, in which different decision criteria such as maximax, maximin, equally likely (Laplace) and Hurwicz criteria are characterized by different OWA operator weights. To apply the OWA operator for decision making, a crucial issue is to determine its weights, which can be accomplished as follows:

Let $A = \{a_1, a_2, ..., a_n\}$ be a set of values to be aggregated, OWA operator F is defined as

$$F(a_1, a_2, ..., a_n) = \mathbf{wb}^T = \sum_{i=1}^{n} w_i b_i \tag{6.2}$$

where $\mathbf{w} = \{w_1, w_2, ..., w_n\}$ is a weighting vector, such that $w_i \in [0,1]$ and $\sum_i w_i = 1$, and **b** is the associated ordered value vector where $b_i \in \mathbf{b}$ is the *i*th largest value in *A*.

The weights of the OWA operator are calculated using fuzzy linguistic quantifiers, which for a non-decreasing relative quantifier Q, are given by

$$w_i = Q(i/n) - Q((i-1)/n), \quad i = 1, ..., n \tag{6.3}$$

The non-decreasing relative quantifier, Q, is defined as (Herrera et al., 2000)

$$Q(y) = \begin{cases} 0 & , y < a, \\ \dfrac{y-a}{b-a} & , a \le y \le b, \\ 1 & , y > b, \end{cases} \tag{6.4}$$

with $a, b, y \in [0,1]$, and $Q(y)$ indicating the degree to which the proportion y is compatible with the meaning of the quantifier it represents. Some non-decreasing relative quantifiers are identified by terms 'most', 'at least half', and 'as many as possible', with parameters (a, b) are $(0.3, 0.8)$, $(0, 0.5)$, and $(0.5, 1)$, respectively.

7 2-TUPLE FUZZY LINGUISTIC REPRESENTATION MODEL

The 2-tuple linguistic model that was presented by Herrera and Martínez (2000a) is based on the concept of symbolic translation. It is used for representing the linguistic assessment information by means of a 2-tuple that is composed of a linguistic term and a number. It can be denoted as (s_i, α) where s_i represents the linguistic label of the predefined linguistic term set S_T, and α is a numerical value representing the symbolic translation (Fan et al., 2009). The main advantages of this representation can be summarized as the continuous treatment of the linguistic domain, and the minimization of the loss of information and thus the lack of precision.

The process of comparison between linguistic 2-tuples is carried out according to an ordinary lexicographic order as follows (Herrera & Martínez, 2001):

Let $r_1 = (s_c, \alpha_1)$ and $r_2 = (s_d, \alpha_2)$ be two linguistic variables represented by 2-tuples.

- If $c < d$ then r_1 is smaller than r_2;
- If $c = d$ then
  - If $\alpha_1 = \alpha_2$ then r_1 and r_2 represent the same information;
  - If $\alpha_1 < \alpha_2$ then r_1 is smaller than r_2;
  - If $\alpha_1 > \alpha_2$ then r_1 is bigger than r_2.

In the following, we define a computational technique to operate with the 2-tuples without loss of information:

Definition 7.1 (Herrera & Martínez, 2000b)**:** Let $L = (\gamma_0, \gamma_1, ..., \gamma_g)$ be a fuzzy set defined in S_T. A transformation function χ that transforms L into a numerical value in the interval of granularity of S_T, $[0, g]$ is defined as

$$\chi : F(S_T) \rightarrow [0, g],$$
$$\chi(F(S_T)) = \chi(\{(s_j, \gamma_j), j = 0,1,..., g\}) = \frac{\sum_{j=0}^{g} j\gamma_j}{\sum_{j=0}^{g} \gamma_j} = \beta \tag{7.1}$$

where $F(S_T)$ is the set of fuzzy sets defined in S_T.

Definition 7.2 (Herrera & Martínez, 2000a)**:** Let $S = \{s_0, s_1, ..., s_g\}$ be a linguistic term set and $\beta \in [0, g]$ a value supporting the result of a symbolic aggregation operation, then the 2-tuple that expresses the equivalent information to β is obtained with the following function:

$$\Delta : [0, g] \rightarrow S \times [-0.5, 0.5),$$
$$\Delta(\beta) = \begin{cases} s_i, & i = \text{round}(\beta) \\ \alpha = \beta - i, & \alpha \in [-0.5, 0.5) \end{cases} \tag{7.2}$$

where 'round' is the usual round operation, s_i has the closest index label to 'β' and 'α' is the value of the symbolic translation.

Proposition 7.1 (Herrera & Martínez, 2000a)**:** Let $S = \{s_0, s_1, ..., s_g\}$ be a linguistic term set and (s_i, α) be a 2-tuple. There is a Δ^{-1} function such that from a 2-tuple it returns its equivalent numerical value $\beta \in [0, g] \subset \Re$. This function is defined as

$$\Delta^{-1} : S \times [-0.5, 0.5) \rightarrow [0, g],$$
$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta \tag{7.3}$$

Definition 7.3 (Herrera-Viedma et al., 2004)**:** Let $x = \{(s_1, \alpha_1), \ldots, (s_n, \alpha_n)\}$ be a set of linguistic 2-tuples and $W = \{w_1, \ldots, w_n\}$ be their associated weights. The 2-tuple weighted average $\bar{x}^w$ is computed as

$$\bar{x}^w[(s_1, \alpha_1), \ldots, (s_n, \alpha_n)] = \Delta\left(\frac{\sum_{i=1}^{n} \Delta^{-1}(s_i, \alpha_i).w_i}{\sum_{i=1}^{n} w_i}\right) = \Delta\left(\frac{\sum_{i=1}^{n} \beta_i . w_i}{\sum_{i=1}^{n} w_i}\right) \tag{7.4}$$

Definition 7.4 (Herrera-Viedma et al., 2004; Wang, 2010)**:** Let $x = \{(s_1, \alpha_1), \ldots, (s_n, \alpha_n)\}$ be a set of linguistic 2-tuples and $W = \{(w_1, \alpha_1^w), \ldots, (w_n, \alpha_n^w)\}$ be their linguistic 2-tuple associated weights. The 2-tuple linguistic weighted average $\bar{x}_l^w$ is calculated with the following function:

$$\bar{x}_l^w\left(\left[(s_1, \alpha_1), (w_1, \alpha_1^w)\right] \ldots \left[(s_n, \alpha_n), (w_n, \alpha_n^w)\right]\right) = \Delta\left(\frac{\sum_{i=1}^{n} \beta_i . \beta_{w_i}}{\sum_{i=1}^{n} \beta_{w_i}}\right) \tag{7.5}$$

with $\beta_i = \Delta^{-1}(s_i, \alpha_i)$ and $\beta_{w_i} = \Delta^{-1}(w_i, \alpha_i^w)$.

8 MULTI-CRITERIA DECISION MAKING MODELS FOR SUPPLIER SELECTION

This section outlines the fuzzy multi-criteria group decision making algorithms that build on fuzzy QFD methodology. In traditional QFD applications, the company has to identify its customers’ expectations and their relative importance to determine the design characteristics for which resources should be allocated. On the other hand, when the HOQ is used in supplier selection, the company starts with the features that the outsourced product/service must possess to meet certain requirements that the company has established, and then tries to identify which of the suppliers’ attributes have the greatest impact on the achievement of its established objectives (Bevilacqua et al., 2006).

The developed algorithms compute the weights of supplier selection criteria and the ratings of suppliers using two interrelated HOQ matrices as depicted in Figure 8.1. Further, the proposed algorithms enable to consider the impacts of inner dependence among TAs.

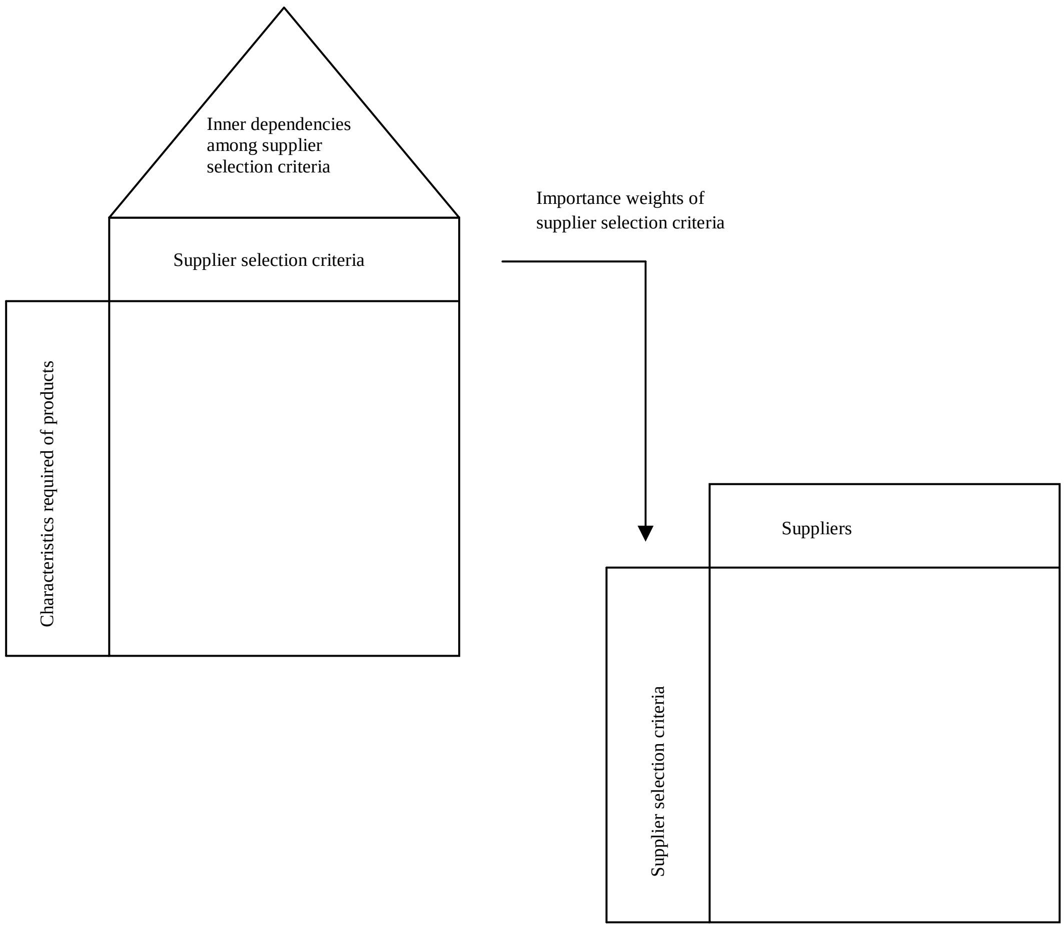


Figure 8.1 Representation of two interrelated HOQ matrices constructed to evaluate alternative suppliers

The detailed stepwise representation of the proposed fuzzy MCDM algorithms are given in the following subsections.

8.1 The First Proposed MCDM Algorithm for Supplier Selection

The proposed algorithm uses the fuzzy weighted average method proposed by Kao and Liu (2001) to calculate the upper and lower bounds of the weights of the TAs and the supplier assessments. Further, the proposed algorithm enables to consider the impacts of inner dependence among design requirements. Moreover, it employs a fuzzy number ranking method developed by Chen and Klein (1997), which is based on area measurement. This ranking method considers the loci of left and right spreads at each α-level of a group of fuzzy numbers and the horizontal-axis locations of the group of fuzzy numbers based on their common maximizing and minimizing barriers simultaneously. It combines the above techniques with the summation of interval subtractions as an area measurement to enable a more robust ranking than the other existing ranking methods. This in turn increases the ability of this method to discriminate among the numbers to be ranked, and thus yields better sensitivity (Chen & Klein, 1997).

The detailed stepwise representation of the proposed fuzzy MCDM algorithm that is also depicted in Figure 8.2 is given below.

Step 1. Construct a decision-makers' committee of Z experts ($z = 1,2,...,Z$). Identify the characteristics that the product being purchased must possess (CNs) in order to meet the company's needs and the criteria relevant to supplier assessment (TAs).

Step 2. Construct the decision matrices for each decision-maker that denote the relative importance of CNs, the fuzzy assessment to determine the CN-TA relationship scores, the degree of dependencies among TAs, and the ratings of each potential supplier with respect to each TA.

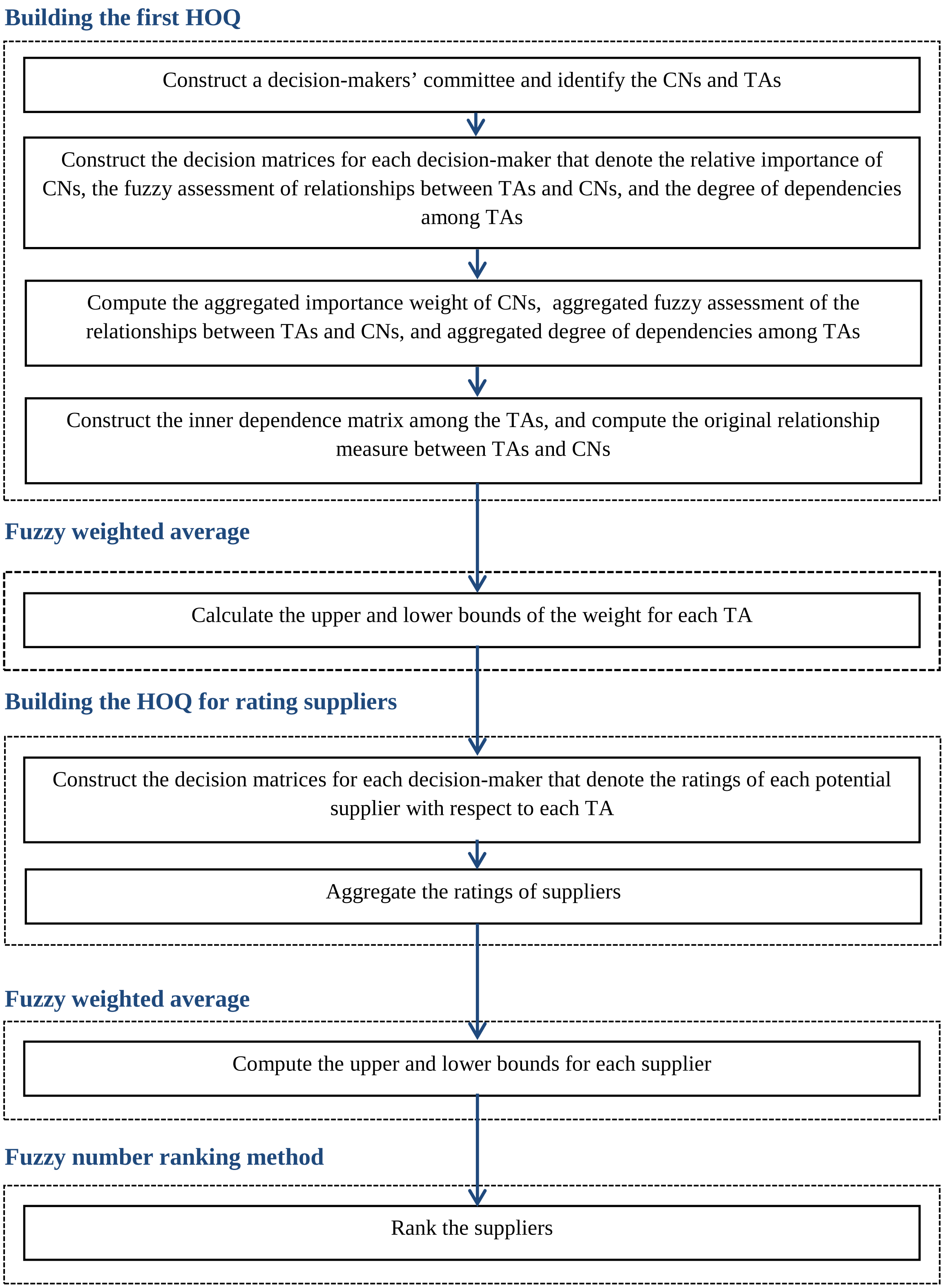


Figure 8.2 Representation of the first proposed fuzzy MCDM algorithm

Step 3. Let the fuzzy value assigned as the importance weight of the *i*th CN, relationship score between the *i*th CN (i=1,2,...,m) and the *j*th TA (j=1,2,...,n), degree of dependence of the *k*th TA on the *j*th TA, and rating of the *l*th supplier (l=1,2,...,L) with respect to the *j*th TA for the *z*th decision-maker be $\tilde{w}_{iz} = \left(w_{iz}^1, w_{iz}^2, w_{iz}^3\right)$, $\tilde{x}_{ijz} = \left(x_{ijz}^1, x_{ijz}^2, x_{ijz}^3\right)$, $\tilde{r}_{kjz} = \left(\tilde{r}_{kjz}^1, \tilde{r}_{kjz}^2, \tilde{r}_{kjz}^3\right)$, and $\tilde{y}_{ljz} = \left(\tilde{y}_{ljz}^1, \tilde{y}_{ljz}^2, \tilde{y}_{ljz}^3\right)$, respectively. Compute the aggregated importance weight of the *i*th CN $\left(\tilde{w}_i\right)$, aggregated fuzzy assessment of the relationship scores between *j*th TA and the *i*th CN $\left(\tilde{x}_{ij}\right)$, aggregated degree of dependence of the *k*th TA on the *j*th TA $\left(\tilde{r}_{kj}\right)$, and aggregated rating of the *l*th supplier with respect to the *j*th TA $\left(\tilde{y}_{lj}\right)$ as follows:

$$\tilde{w}_i = \sum_{z=1}^{Z} \Omega_z \tilde{w}_{iz} \tag{8.1}$$

$$\tilde{x}_{ij} = \sum_{z=1}^{Z} \Omega_z \tilde{x}_{ijz} \tag{8.2}$$

$$\tilde{r}_{kj} = \sum_{z=1}^{Z} \Omega_z \tilde{r}_{kjz} \tag{8.3}$$

$$\tilde{y}_{lj} = \sum_{z=1}^{Z} \Omega_z \tilde{y}_{ljz} \tag{8.4}$$

where $\Omega_z \in [0,1]$ denotes the weight of the *z*th decision-maker and $\sum_{z=1}^{Z} \Omega_z = 1$.

Step 4. Defuzzify the aggregated degree of dependence of the *k*th TA on the *j*th TA $\left(\tilde{r}_{kj}\right)$ (Chang, 2004) and construct the inner dependence matrix **D** among the TAs. Compute the original relationship measure between the *j*th TA and the *i*th CN, $\tilde{X}_{ij}^*$.

According to Fung et al. (2002) and Tang et al. (2002), the original relationship measure between the *j*th TA and the *i*th CN should be rewritten as

$$\tilde{X}_{ij}^{*} = \sum_{k=1}^{n} \tilde{x}_{ik} D_{kj} \tag{8.5}$$

where $\tilde{X}_{ij}^{*}$ is the actual relationship measure after consideration of the inner dependence among TAs and D_{kj} denote the degree of dependence of the *k*th TA on the *j*th TA. Note that the correlation matrix **D** is a symmetric matrix. A design requirement has the strongest dependence on itself, i.e. D_{jj} is assigned to be 1. If there is no dependence between the *k*th and the *j*th TAs, then $D_{kj} = 0$.

Step 5. Calculate the upper and lower bounds of the weight for each TA by employing formulations (5.7) and (5.8).

Step 6. Compute the upper and lower bounds for each supplier by utilizing formulations (5.7) and (5.8). This time, the relative importance expressed in formulations (5.7) and (5.8) are the upper and lower bounds of the weight for each TA calculated at *Step* 5.

Step 7. Rank the suppliers by employing Chen and Klein's (1997) ranking algorithm, which can be summarized as follows:

Let $\tilde{X}_1, \tilde{X}_2, ..., \tilde{X}_i, ..., \tilde{X}_m$ be *m* arbitrary bounded fuzzy numbers, and *h* denote the maximum height of $\mu_{\tilde{X}_i}$, *i*=1,2,…,*m*. Suppose *h* is equally divided into *s* intervals such that $\alpha_p = ph/s$, *i*=0,1,2,…,*s*. Chen and Klein (1997) devise the following index for ranking fuzzy numbers.

$$I_i = \sum_{p=o}^{s} \left((X_i)_{\alpha_p}^{U} - c \right) \Bigg/ \left(\sum_{p=0}^{s} \left((X_i)_{\alpha_p}^{U} - c \right) - \sum_{p=0}^{s} \left((X_i)_{\alpha_p}^{L} - d \right) \right), \quad n \to \infty \tag{8.6}$$

where $c = \min_{p,i}\left\{\left(X_{ip}\right)^{L}_{\alpha_p}\right\}$ and $c = \max_{p,i}\left\{\left(X_{ip}\right)^{U}_{\alpha_p}\right\}$. The larger the ranking index I_i, the more preferred the fuzzy number is.

8.2 The Second Proposed MCDM Algorithm for Supplier Selection

The proposed algorithm uses the fuzzy weighted average method proposed by Wang and Chin (2011) to calculate the upper and lower bounds of the weights of the TAs and the supplier assessments. Furthermore, the proposed algorithm enables to consider the impacts of inner dependence among design requirements. It utilizes the fuzzy number ranking method developed by Chen and Klein (1997).

The stepwise representation of the proposed fuzzy MCDM algorithm that is also illustrated in Figure 8.3 is given below.

Step 1-3. Same with the first MCDM method.
Step 4. Calculate the normalized fuzzy relationships using Eqs. (5.16) and (5.17).
Step 5. Compute the upper and lower bounds of the weight for each TA by employing formulations (5.21) and (5.22).
Step 6. Calculate the upper and lower bounds for each supplier by utilizing formulations (5.21) and (5.22). This time, the relative importance expressed in formulations (5.21) and (5.22) are the upper and lower bounds of the weight for each TA calculated at *Step* 5.
Step 7. Rank the suppliers using Eq. (8.6). The larger the ranking index I_i, the more preferred the fuzzy number is.

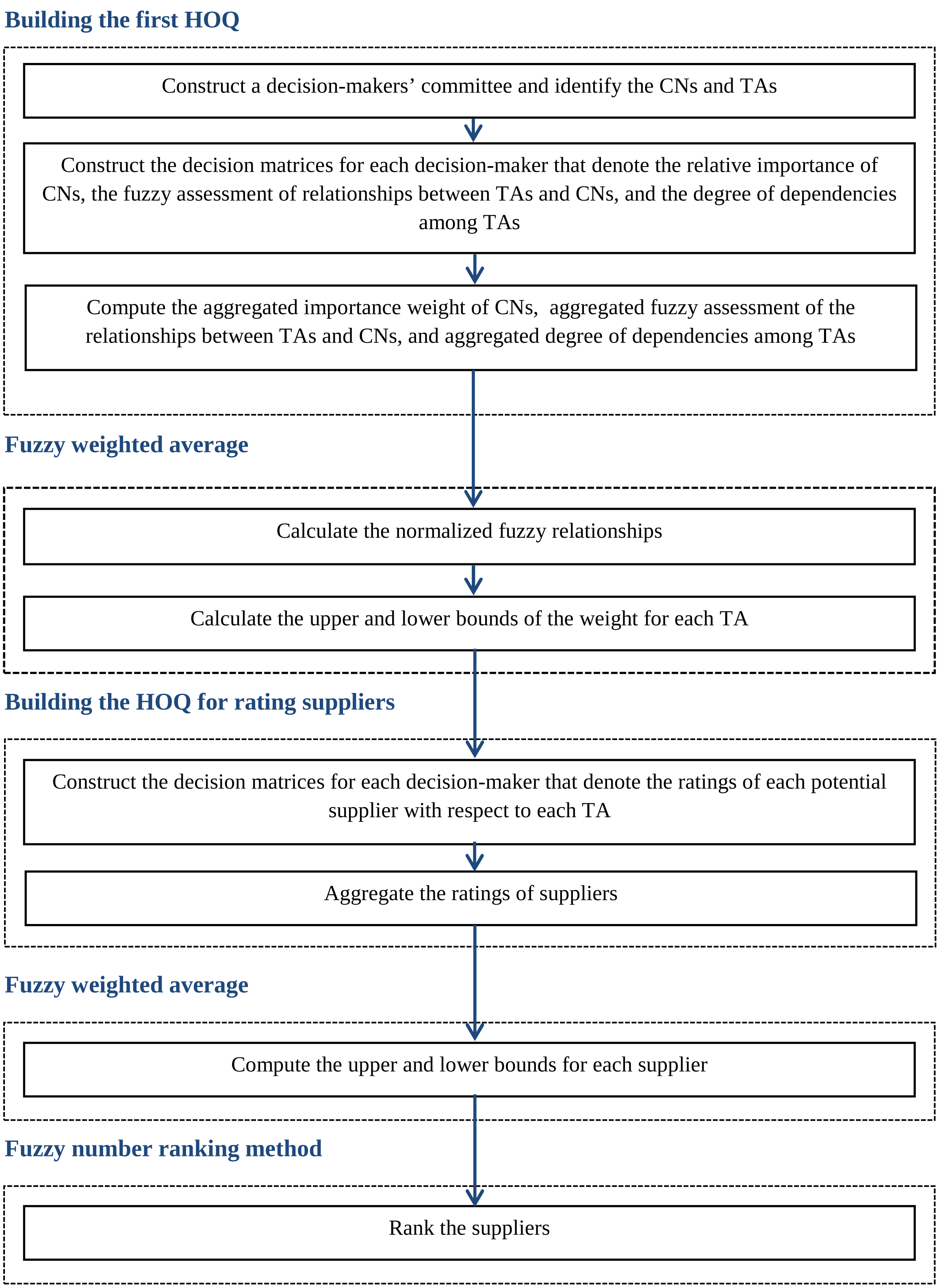


Figure 8.3 Representation of the second proposed fuzzy MCDM algorithm

8.3 The Third Proposed MCDM Algorithm for Supplier Selection

The proposed approach is based on fuzzy QFD, fusion of fuzzy information approach, and 2-tuple linguistic representation model. Utilization of the fusion of fuzzy information and the 2-tuple linguistic representation model enables decision-makers to deal with heterogeneous information, and rectify the problem of loss of information encountered using other fuzzy linguistic approaches. The proposed decision making approach uses the OWA operator to aggregate decision makers' preferences. The OWA operator is a common generalization of the three basic aggregation operators, i.e. max, min, and the arithmetic mean. Unlike the arithmetic mean, the OWA operator combines the information through assigning weights to the values with respect to their ordered position

The detailed stepwise representation of the proposed fuzzy MCDM algorithm that is also shown in Figure 8.4 is given below.

Step 1. Construct a decision-makers committee of Z $(z = 1,2,...,Z)$ experts. Identify the characteristics that the product being purchased must possess (CNs) in order to meet the company's needs and the criteria relevant to supplier assessment (TAs).

Step 2. Construct the decision matrices for each decision-maker that denote the relative importance of CNs, the fuzzy assessment to determine the CN-TA relationship scores, and the degree of dependencies among Tas.

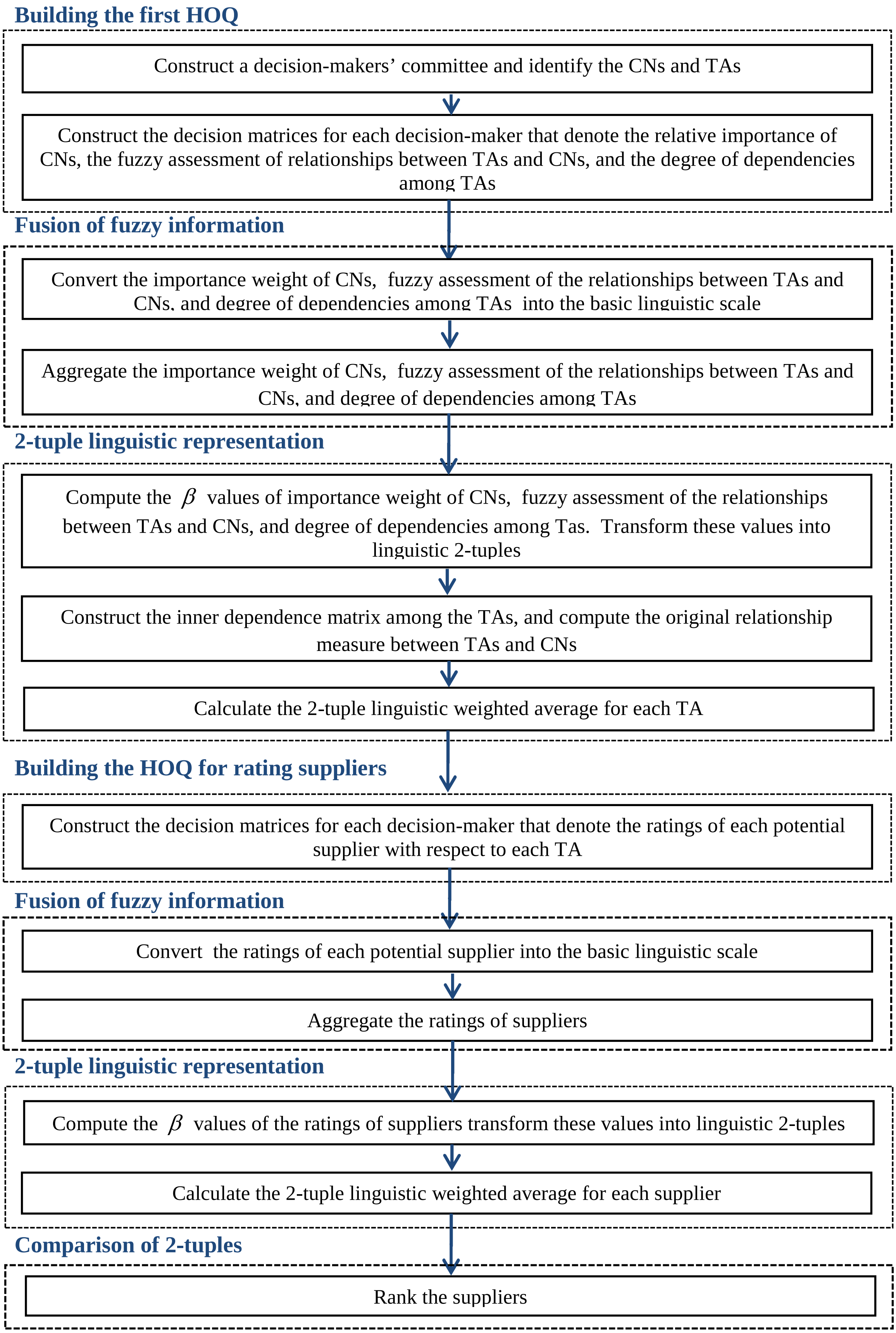


Figure 8.4 Representation of the third proposed fuzzy MCDM algorithm

Step 3. Let the fuzzy value assigned as the importance weight of the *i*th CN, relationship score between the *i*th CN (i=1,2,…,m) and *j*th TA (j=1,2,…,n), and degree of dependence of the *k*th TA on the *j*th TA for the *z*th decision-maker be $\tilde{w}_{iz} = \left(w_{iz}^1, w_{iz}^2, w_{iz}^3\right)$, $\tilde{x}_{ijz} = \left(x_{ijz}^1, x_{ijz}^2, x_{ijz}^3\right)$, and $\tilde{r}_{kjz} = \left(\tilde{r}_{kjz}^1, \tilde{r}_{kjz}^2, \tilde{r}_{kjz}^3\right)$, respectively. Convert $\tilde{w}_{iz}, \tilde{x}_{ijz}$, and $\tilde{r}_{kjz}$ into the basic linguistic scale S_T by using Eq. (6.1). The importance weight vector on S_T, the fuzzy assessment vector on S_T, and the degree of dependence vector on S_T, which are respectively denoted as $F(\tilde{w}_{iz})$, $F(\tilde{x}_{ijz})$, and $F(\tilde{r}_{kjz})$, can be represented as

$$F(\tilde{w}_{iz}) = \left(\gamma(\tilde{w}_{iz}, s_0), \gamma(\tilde{w}_{iz}, s_1), \ldots, \gamma(\tilde{w}_{iz}, s_8)\right), \quad \forall i, z \tag{8.7}$$

$$F(\tilde{x}_{ijz}) = \left(\gamma(\tilde{x}_{ijz}, s_0), \gamma(\tilde{x}_{ijz}, s_1), \ldots, \gamma(\tilde{x}_{ijz}, s_8)\right), \quad \forall i, j, z \tag{8.8}$$

$$F(\tilde{r}_{kjz}) = \left(\gamma(\tilde{r}_{kjz}, s_0), \gamma(\tilde{r}_{kjz}, s_1), \ldots, \gamma(\tilde{r}_{kjz}, s_8)\right), \quad \forall k, j, z \tag{8.9}$$

In this thesis, the label set given in Table 8.1 is used as the BLTS (Jiang et al., 2008).

Table 8.1 Label set (Jiang et al., 2008)

Label set	Fuzzy number
s_0:	(0,0,0.12)
s_1:	(0,0.12,0.25)
s_2:	(0.12,0.25,0.37)
s_3:	(0.25,0.37,0.50)
s_4:	(0.37,0.50,0.62)
s_5:	(0.50,0.62,0.75)
s_6:	(0.62,0.75,0.87)
s_7:	(0.75,0.87,1)
s_8:	(0.87,1,1)

Step 4. Aggregate $F(\tilde{w}_{iz})$, $F(\tilde{x}_{ijz})$, and $F(\tilde{r}_{kjz})$ to yield the importance weight vector $F(\tilde{w}_i)$, the fuzzy assessment vector $F(\tilde{x}_{ij})$, and the degree of dependence vector $F(\tilde{r}_{kj})$.

The aggregated parameters obtained from the assessment data of Z experts can be calculated using Eq. (6.2) as follows:

$$\tilde{w}_i(s_m) = \phi_Q(\gamma(\tilde{w}_{i1}, s_m), \gamma(\tilde{w}_{i2}, s_m), \ldots, \gamma(\tilde{w}_{iz}, s_m)), \ \forall i, m \tag{8.10}$$

$$\tilde{x}_{ij}(s_m) = \phi_Q(\gamma(\tilde{x}_{ij1}, s_m), \gamma(\tilde{x}_{ij2}, s_m), \ldots, \gamma(\tilde{x}_{ijz}, s_m)), \ \forall i, j, m \tag{8.11}$$

$$\tilde{r}_{kj}(s_m) = \phi_Q(\gamma(\tilde{r}_{kj1}, s_m), \gamma(\tilde{r}_{kj2}, s_m), \ldots, \gamma(\tilde{r}_{kjz}, s_m)), \ \forall k, j, m \tag{8.12}$$

where ϕ_Q denotes the OWA operator whose weights are computed using the linguistic quantifier, Q. Then, the importance weight vector on S_T, $F(\tilde{w}_i)$, the fuzzy assessment vector on S_T with respect to the ith CN, $F(\tilde{x}_{ij})$, and the degree of dependence vector on S_T, $F(\tilde{r}_{kj})$, are defined as follows:

$$F(\tilde{w}_i) = (\gamma(\tilde{w}_i, s_0), \gamma(\tilde{w}_i, s_1), \ldots, \gamma(\tilde{w}_i, s_8)), \quad \forall i \tag{8.13}$$

$$F(\tilde{x}_{ij}) = (\gamma(\tilde{x}_{ij}, s_0), \gamma(\tilde{x}_{ij}, s_1), \ldots, \gamma(\tilde{x}_{ij}, s_8)), \quad \forall i, j \tag{8.14}$$

$$F(\tilde{r}_{kj}) = (\gamma(\tilde{r}_{kj}, s_0), \gamma(\tilde{r}_{kj}, s_1), \ldots, \gamma(\tilde{r}_{kj}, s_8)), \quad \forall k, j \tag{8.15}$$

Step 5. Compute the β values of $F(\tilde{w}_i)$, $F(\tilde{x}_{ij})$ and $F(\tilde{r}_{kj})$, and transform these values into linguistic 2-tuples by using formulations (7.1) and (7.2), respectively.

Step 6. Compute the original relationship measure between the jth TA and the ith CN, $\tilde{X}^*_{ij}$. Let D_{kj} denote the degree of dependence of the kth TA on the jth TA. According to Fung et al. (2002) and Tang et al. (2002), the original relationship measure between the jth TA and the ith CN should be calculated by Eq. (8.5). Benefiting from Eq. (8.5), the original relationship measure is obtained employing 2-tuple linguistic weighted average.

Step 7. Calculate the 2-tuple linguistic weighted average for each TA.

Step 8. Construct the decision matrices for each decision-maker that denote the ratings of each potential supplier with respect to each TA.

Step 9. Apply *Steps* 3-5 to the ratings of each supplier obtained at *Step* 8.

Step 10. Calculate the 2-tuple linguistic weighted average for each supplier. The associated weights are considered as the 2-tuple linguistic weighted average score for each TA computed at *Step* 7.

Step 11. Rank the suppliers using the rules of comparison of 2-tuples given in Section 7.

9 CASE STUDY

In order to illustrate the application of the proposed decision making methods to medical supplier selection problem, a case study conducted in a private hospital on the Asian side of Istanbul is presented. The hospital operates with all major departments, and also includes facilities such as clinical laboratories, emergency service, intensive care units and operating room. As a result of discussions with experts from the purchasing department of the hospital, five fundamental characteristics required of products purchased from medical supplies (CNs) are determined. These can be listed as "cost (CN_1)" quality (CN_2)" product conformity (CN_3)" availability and customer support (CN_4)", and "efficacy of corrective action (CN_5)".

Seven criteria relevant to supplier assessment are identified as "product volume (TA_1)" delivery (TA_2)" payment method (TA_3)" supply variety (TA_4)" reliability (TA_5)" experience in the sector (TA_6)" earlier business relationship (TA_7)" management (TA_8)", and "geographical location (TA_9)". There are 12 suppliers who are in contact with the hospital.

The evaluation is conducted by a committee of five decision-makers (DM_1, DM_2, DM_3, DM_4, DM_5). DM_1, DM_2 and DM_3 used the linguistic term set shown in Figure 9.3, whereas the remaining two decision-makers, namely DM_4 and DM_5, preferred to use a different linguistic term set depicted in Figure 9.4 to denote the level of importance of each CN, the impact of each TA on each CN, the inner dependencies of TAs, and the ratings of suppliers with respect to each TA.

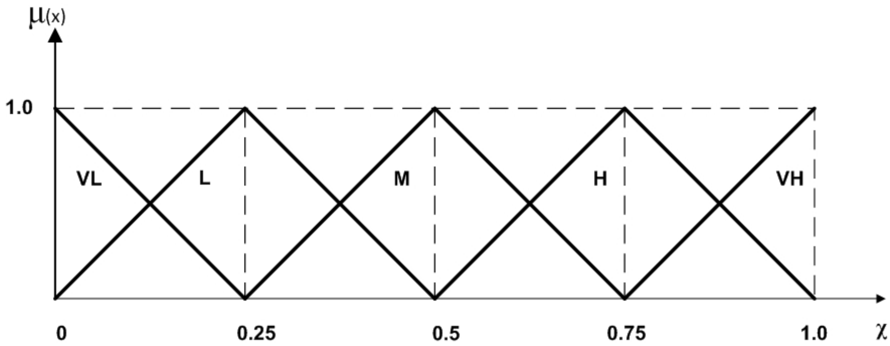


Figure 9.1 A linguistic term set where VL: (0, 0, 0.25), L: (0, 0.25, 0.5), M: (0.25, 0.5, 0.75), H: (0.5, 0.75, 1), VH: (0.75, 1, 1)

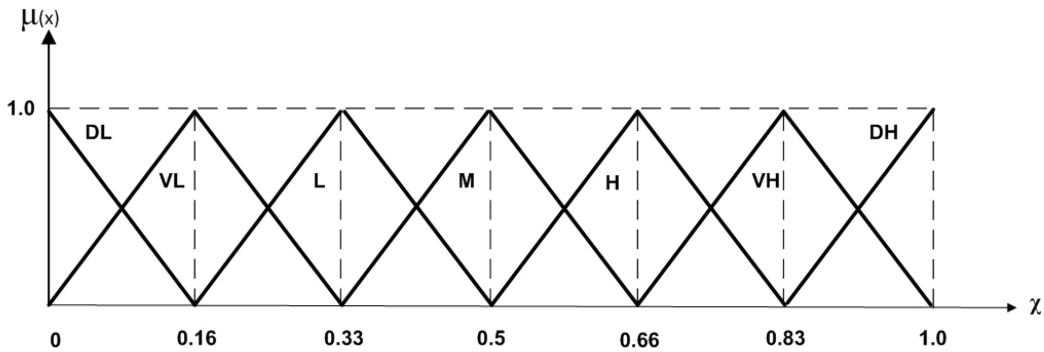
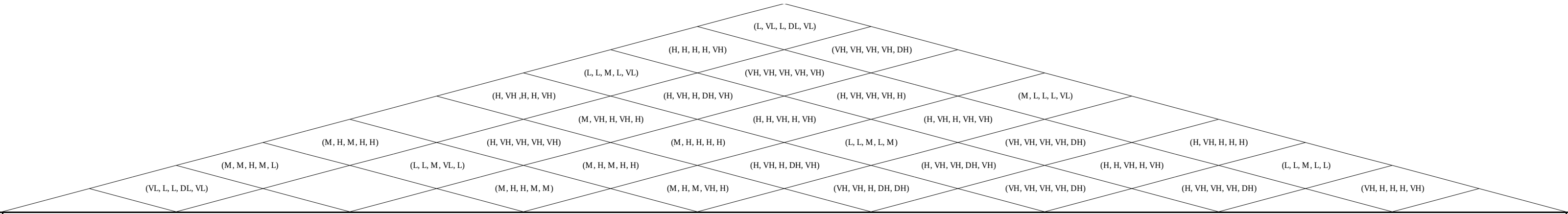


Figure 9.2 A linguistic term set where DL: (0, 0, 0.16), VL: (0, 0.16, 0.33), L: (0.16, 0.33, 0.50), M: (0.33, 0.50, 0.66), H: (0.50, 0.66, 0.83), VH: (0.66, 0.83, 1), DH: (0.83, 1, 1)

The data related to medical supplier selection that is provided in the HOQ depicted in Figure 9.3 and in Table 9.1 consist of assessments of five decision-makers employing linguistic variables defined in Figures 9.1 and 9.2.



TAs / CNs	TA_1	TA_2	TA_3	TA_4	TA_5	TA_6	TA_7	TA_8	TA_9	Importance of CNs
CN_1	(VH, VH, H, VH, VH)	(VL, VL, VL, DL, VL)	(VH, H, VH, DH, VH)	(VH, VH, H, VH, H)	(H, VH, H, M, H)	(H, H, VH, H, VH)	(H, M, L, M, H)	(H, H, VH, M, H)	(H, H, VH, H, VH)	(VH, H, H, VH, DH)
CN_2	(H, VH, H, VH, H)	(L, VL, VL, VL, L)	(VL, VL, VL, DL, VL)	(VH, H, H, VH, H)	(VH, VH, VH, DH, VH)	(VH, VH, VH, DH, VH)	(M, M, M, M, H)	(VH, VH, VH, H, H)	(L, L, VL, VL, DL)	(H, VH, H, DH, DH)
CN_3	(M, L, M, H, M)	(M, M, L, M, L)	(VL, L, L, VL, DL)	(VH, H, VH, VH, VH)	(VH, VH, VH, DH, VH)	(VH, H, VH, DH, VH)	(M, L, M, M, H)	(H, VH, H, VH, H)	(L, VL, VL, DL, VL)	(VH, VH, VH, DH, VH)
CN_4	(L, VL, VL, L, VL)	(VL, L, L, VL, DL)	(L, L, VL, VL, VL)	(H, H, M, VH, H)	(VH, H, H, VH, VH)	(H, VH, H, H, VH)	(VH, H, H, VH, DH)	(VH, H, H, H, H)	(M, L, L, M, M)	(VH, VH, H, VH, DH)
CN_5	(VL, L, VL, DL, VL)	(L, L, M, VL, VL)	(VL, L, L, DL, DL)	(M, M, H, L, M)	(VH, H, VH, DH, VH)	(H, VH, VH, VH, H)	(H, VH, H, VH, VH)	(H, VH, M, VH, VH)	(M, H, M, M, M)	(H, H, M, VH, H)

Figure 9.3 First HOQ for the medical supplier selection problem

Table 9.1 Ratings of suppliers with respect to TAs

	TA_1	TA_2	TA_3	TA_4	TA_5
Sup 1	(VH, VH, VH, VH, VH)	(H, H, M, H, L)	(VH, H, H, DH, H)	(VH, VH, VH, VH, VH)	(H, VH, H, VH, VH)
Sup 2	(H, H, M, VH, M)	(VH, H, H, VH, H)	(H, VH, M, M, M)	(H, M, H, H, H)	(H, H, VH, H, VH)
Sup 3	(M, L, M, M, M)	(VH, VH, H,DH, H)	(VH, H, H, H, M)	(M, L, M, H, M)	(H, M, M, H, H)
Sup 4	(M, M, L, M, L)	(H, VH, VH, VH, VH)	(H, VH, VH, H, VH)	(M, M, L, H, L)	(VH, M, H, DH, VH)
Sup 5	(M, L, M, M, M)	(H, M, H, VH, H)	(VH, VH, H, VH, H)	(M, H, M, M, M)	(M, H, L, L, L)
Sup 6	(H, H, H, H, H)	(M, M, H, H, H)	(VH, H, VH, DH, VH)	(H, VH, H, H, H)	(M, H, H, H, H)
Sup 7	(H, H, VH, DH, VH)	(H, M, M, H, VH)	(H, VH, VH, VH, DH)	(M, H, H, H, H)	(H, H, H, VH, VH)
Sup 8	(L, M, M, VL, L)	(M, L, M, M, M)	(VH, H, VH, DH, H)	(L, M, L, L, L)	(H, M, M, H, M)
Sup 9	(M, L, M, M, M)	(M, M, H, H, H)	(H, H, M, H, M)	(M, M, M, M, H)	(M, L, H, M, H)
Sup 10	(M, L, L, M, L)	(M, M, L, H, L)	(H, M, H, H, H)	(M, M, H, M, M)	(M, H, M, M, M)
Sup 11	(L,M,M,VL,M)	(M, L, L, M, VL)	(M, H, H, H, H)	(L, L, M, VL, M)	(L, M, L, L, L)
Sup 12	(VL,L,VL,DL,VL)	(L, VL, VL, L, DL)	(H, H, H, H, H)	(M, L, L, M, VL)	(H, M, H, H, H)

Table 9.1 Ratings of suppliers with respect to TAs (cont.)

	TA_6	TA_7	TA_8	TA_9
Sup 1	(VH, VH, VH, DH, VH)	(H, VH, H, H, M)	(M, M, H, H, H)	(L, M, M, VL, L)
Sup 2	(H, VH, VH, H, DH)	(H, H, H, VH, H)	(H, M, H, H, H)	(M, L, L, L, L)
Sup 3	(H, H, H, H, H)	(VH, H, VH, VH, VH)	(M, H, M, H, M)	(VH, H, H, VH, H)
Sup 4	(VH, VH, H, VH, H)	(VH, VH, H, DH, H)	(H, M, H, H, VH)	(M, L, M, H, H)
Sup 5	(M, L, M, M, M)	(H, VH, H, H, H)	(L, M, L, VL, L)	(M, L, M, M, M)
Sup 6	(M, H, L, M, L)	(VH, VH, H, VH, H)	(M, H, H, M, H)	(L, L, M, L, M)
Sup 7	(VH, VH, VH, DH, H)	(H, VH, H, VH, VH)	(H, H, VH, VH, VH)	(M, M, L, M, M)
Sup 8	(H, M, L, H, M)	(H, VH, VH, M, VH)	(H, M, M, H, M)	(VH, M, VH, DH, VH)
Sup 9	(M, H, M, L, M)	(M, M, H, H, H)	(M, L, M, M, H)	(H, L, M, VH, M)
Sup 10	(L, M, H, VL, H)	(M, M, M, M, H)	(M, M, M, M, M)	(H, L, L, H, L)
Sup 11	(M, H, H, M, H)	(H, VH, H, VH, M)	(M, H, H, H, H)	(VH, H, VH, DH, VH)
Sup 12	(M, M, M, M, M)	(L, VL, L, L, L)	(L, L, M, VL, M)	(VL, L, M, DL, M)

The first and second MCDM algorithms require the use of same linguistic scale. Then, the first three data given in Figure 9.3 and Table 9.1 were utilized for the computational processes of these algorithms.

By using Eqs. (8.1)-(8.4), the decision-makers' evaluations are aggregated to obtain the aggregated importance of each CN, aggregated impact of each TA on each CN, aggregated degree of dependence of TAs, and aggregated ratings of suppliers. In our case, one shall note that $\Omega_1 = \Omega_2 = \Omega_3 = 1/3$ since equal weights are assigned to each decision-maker. The results are presented in Figure 9.4 and in Table 9.2.

	TA_2	TA_3	TA_4	TA_5	TA_6	TA_7	TA_8	TA_9
TA_1	(0, 0.167, 0.417)	(0.333, 0.583, 0.833)	(0.333, 0.583, 0.833)		(0.583, 0.833, 1)	(0.083, 0.333, 0.583)	(0.500, 0.750, 1)	(0, 0.167, 0.417)
TA_2			(0.083, 0.333, 0.583)	(0.667, 0.917, 1)	(0.500, 0.750, 0.917)	(0.583, 0.833, 1)	(0.750, 1, 1)	(0.750, 1, 1)
TA_3			(0.417, 0.667, 0.917)	(0.333, 0.583, 0.833)	(0.417, 0.667, 0.917)	(0.583, 0.833, 1)	(0.667, 0.917, 1)	
TA_4				(0.333, 0.583, 0.833)	(0.583, 0.833, 1)	(0.083, 0.333, 0.583)	(0.583, 0.833, 1)	(0.083, 0.333, 0.583)
TA_5					(0.667, 0.917, 1)	(0.667, 0.917, 1)	(0.750, 1, 1)	
TA_6						(0.750, 1, 1)	(0.583, 0.833, 1)	(0.583, 0.833, 1)
TA_7							(0.667, 0.917, 1)	(0.083, 0.333, 0.583)
TA_8								(0.583, 0.833, 1)

CNs \ TAs	TA_1	TA_2	TA_3	TA_4	TA_5	TA_6	TA_7	TA_8	TA_9	Importance of CNs
CN_1	(0.667, 0.917, 1)	(0, 0, 0.250)	(0.667, 0.917, 1)	(0.667, 0.917, 1)	(0.583, 0.833, 1)	(0.583, 0.833, 1)	(0.250, 0.500, 0.750)	(0.583, 0.833, 1)	(0.583, 0.833, 1)	(0.583, 0.833, 1)
CN_2	(0.583, 0.833, 1)	(0, 0.083, 0.333)	(0, 0, 0.250)	(0.583, 0.833, 1)	(0.750, 1, 1)	(0.750, 1, 1)	(0.250, 0.500, 0.750)	(0.750, 1, 1)	(0, 0.167, 0.417)	(0.583, 0.833, 1)
CN_3	(0.167, 0.417, 0.667)	(0.167, 0.417, 0.667)	(0, 0.167, 0.417)	(0.667, 0.917, 1)	(0.750, 1, 1)	(0.667, 0.917, 1)	(0.167, 0.417, 0.667)	(0.583, 0.833, 1)	(0, 0.083, 0.333)	(0.750, 1, 1)
CN_4	(0, 0.083, 0.333)	(0, 0.167, 0.417)	(0, 0.167, 0.417)	(0.417, 0.667, 0.917)	(0.583, 0.833, 1)	(0.583, 0.833, 1)	(0.583, 0.833, 1)	(0.583, 0.833, 1)	(0.083, 0.333, 0.583)	(0.667, 0.917, 1)
CN_5	(0, 0.083, 0.333)	(0.083, 0.333, 0.583)	(0, 0.167, 0.417)	(0.333, 0.583, 0.833)	(0.667, 0.917, 1)	(0.667, 0.917, 1)	(0.583, 0.833, 1)	(0.500, 0.750, 0.917)	(0.333, 0.583, 0.833)	(0.417, 0.667, 0.917)

Figure 9.4 Aggregated importance of CNs, aggregated impact of TAs on CNs, aggregated degree of dependence of TAs

Table 9.2 Aggregated ratings of suppliers with respect to TAs

	TA_1	TA_2	TA_3	TA_4	TA_5
Sup 1	(0.750, 1, 1)	(0.417, 0.667, 0.917)	(0.583, 0.833, 1)	(0.750, 1, 1)	(0.583, 0.833, 1)
Sup 2	(0.417, 0.667, 0.917)	(0.583, 0.833, 1)	(0.500, 0.750, 0.971)	(0.417, 0.667, 0.917)	(0.583, 0.833, 1)
Sup 3	(0.167, 0.417, 0.667)	(0.667, 0.917, 1)	(0.583, 0.833, 1)	(0.167, 0.417, 0.667)	(0.333, 0.583, 0.833)
Sup 4	(0.167, 0.417, 0.667)	(0.667, 0.917, 1)	(0.667, 0.917, 1)	(0.167, 0.417, 0.667)	(0.500, 0.750, 0.971)
Sup 5	(0.167, 0.417, 0.667)	(0.417, 0.667, 0.917)	(0.667, 0.917, 1)	(0.333, 0.583, 0.833)	(0.250, 0.500, 0.750)
Sup 6	(0.500, 0.750, 1)	(0.333, 0.583, 0.833)	(0.667, 0.917, 1)	(0.583, 0.833, 1)	(0.417, 0.667, 0.917)
Sup 7	(0.583, 0.833, 1)	(0.333, 0.583, 0.833)	(0.667, 0.917, 1)	(0.417, 0.667, 0.917)	(0.500, 0.750, 1)
Sup 8	(0.167, 0.417, 0.667)	(0.167, 0.417, 0.667)	(0.667, 0.917, 1)	(0.083, 0.333, 0.583)	(0.333, 0.583, 0.833)
Sup 9	(0.167, 0.417, 0.667)	(0.333, 0.583, 0.833)	(0.417, 0.667, 0.917)	(0.250, 0.500, 0.750)	(0.250, 0.500, 0.750)
Sup 10	(0.083, 0.333, 0.583)	(0.167, 0.417, 0.667)	(0.417, 0.667, 0.917)	(0.333, 0.583, 0.833)	(0.333, 0.583, 0.833)
Sup 11	(0.167, 0.417, 0.667)	(0.083, 0.333, 0.583)	(0.417, 0.667, 0.917)	(0.083, 0.333, 0.583)	(0.083, 0.333, 0.583)
Sup 12	(0, 0.083, 0.333)	(0, 0.083, 0.333)	(0.500, 0.750, 1)	(0.083, 0.333, 0.583)	(0.417, 0.667, 0.917)

Table 9.2 Aggregated ratings of suppliers with respect to TAs (cont.)

	TA_6	TA_7	TA_8	TA_9
Sup 1	(0.750, 1, 1)	(0.583, 0.833, 1)	(0.333, 0.583, 0.833)	(0.167, 0.417, 0.667)
Sup 2	(0.667, 0.917, 1)	(0.500, 0.750, 1)	(0.417, 0.667, 0.917)	(0.083, 0.333, 0.583)
Sup 3	(0.500, 0.750, 1)	(0.667, 0.917, 1)	(0.333, 0.583, 0.833)	(0.583, 0.833, 1)
Sup 4	(0.667, 0.917, 1)	(0.667, 0.917, 1)	(0.417, 0.667, 0.917)	(0.167, 0.417, 0.667)
Sup 5	(0.167, 0.417, 0.667)	(0.583, 0.833, 1)	(0.083, 0.333, 0.583)	(0.167, 0.417, 0.667)
Sup 6	(0.250, 0.500, 0.750)	(0.667, 0.917, 1)	(0.417, 0.667, 0.917)	(0.083, 0.333, 0.583)
Sup 7	(0.750, 1, 1)	(0.583, 0.833, 1)	(0.583, 0.833, 1)	(0.167, 0.417, 0.667)
Sup 8	(0.250, 0.500, 0.750)	(0.667, 0.917, 1)	(0.333, 0.583, 0.833)	(0.583, 0.833, 1)
Sup 9	(0.333, 0.583, 0.833)	(0.333, 0.583, 0.833)	(0.167, 0.417, 0.667)	(0.250, 0.500, 0.750)
Sup 10	(0.250, 0.500, 0.750)	(0.250, 0.500, 0.750)	(0.250, 0.500, 0.750)	(0.167, 0.417, 0.667)
Sup 11	(0.417, 0.667, 0.917)	(0.583, 0.833, 1)	(0.417, 0.667, 0.917)	(0.667, 0.917, 1)
Sup 12	(0.250, 0.500, 0.750)	(0, 0.167, 0.417)	(0.083, 0.333, 0.583)	(0.083, 0.250, 0.500)

The computational procedure for the first and second decision making approach is identical up to and including the aggregation step. First, the remaining steps of the first fuzzy decision making framework, which employs the FWA method proposed by Kao and Liu (2001) are summarized below.

The inner dependence matrix among the TAs is constructed, and the original relationship measure between TAs and CNs is computed as in Table 9.3 by employing Eq. (8.5).

Table 9.3 Original relationship measure between TAs and CNs

CNs	TAs TA_1	TA_2	TA_3	TA_4	TA_5
CN_1	(2.549, 3.611, 4.214)	(2.580, 3.783, 4.859)	(2.943, 4.240, 4.984)	(3.066, 4.347, 5.125)	(2.637, 3.851, 4.854)
CN_2	(2.179, 3.095, 3.683)	(2.413, 3.622, 4.396)	(2.526, 3.573, 4.234)	(2.663, 3.778, 4.458)	(2.668, 3.809, 4.490)
CN_3	(1.622, 2.651, 3.465)	(2.245, 3.542, 4.521)	(2.069, 3.283, 4.139)	(2.328, 3.582, 4.431)	(2.561, 3.944, 4.806)
CN_4	(1.365, 2.243, 3.194)	(2.174, 3.512, 4.686)	(1.991, 3.108, 4.160)	(1.927, 3.111, 4.264)	(2.394, 3.705, 4.830)
CN_5	(1.384, 2.278, 3.161)	(2.519, 3.941, 4.981)	(1.967, 3.083, 4.031)	(2.003, 3.215, 4.252)	(2.497, 3.880, 4.849)

Table 9.3 Original relationship measure between TAs and CNs (cont.)

CNs	TA_6	TA_7	TA_8	TA_9
CN_1	(3.804, 5.486, 6.677)	(2.998, 4.373, 5.443)	(3.922, 5.641, 6.891)	(1.962, 2.832, 3.630)
CN_2	(3.198, 4.707, 5.764)	(2.655, 3.866, 4.717)	(3.193, 4.703, 5.839)	(1.606, 2.470, 3.125)
CN_3	(2.752, 4.425, 5.701)	(2.372, 3.826, 4.901)	(2.797, 4.542, 5.906)	(1.481, 2.418, 3.264)
CN_4	(2.521, 4.134, 5.696)	(2.318, 3.705, 4.976)	(2.521, 4.198, 5.849)	(1.365, 2.359, 3.300)
CN_5	(2.806, 4.479, 5.885)	(2.519, 3.974, 5.094)	(2.797, 4.552, 6.057)	(1.665, 2.738, 3.611)

The upper and lower bounds of the weight of TAs are calculated through formulations (5.7) and (5.8) as represented in Table 9.4.

Table 9.4 Upper and lower bounds of the weight of TAs

TAs		α										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
TA_1	$(Y_{TA_1})_\alpha^L$	1.717	1.823	1.929	2.035	2.141	2.247	2.354	2.460	2.567	2.673	2.780
	$(Y_{TA_1})_\alpha^U$	3.637	3.554	3.470	3.386	3.301	3.215	3.129	3.042	2.955	2.868	2.780
TA_2	$(Y_{TA_2})_\alpha^L$	2.339	2.472	2.605	2.737	2.870	3.002	3.134	3.266	3.398	3.529	3.661
	$(Y_{TA_2})_\alpha^U$	4.724	4.617	4.509	4.402	4.295	4.189	4.083	3.977	3.871	3.766	3.661
TA_3	$(Y_{TA_3})_\alpha^L$	2.217	2.341	2.465	2.589	2.713	2.837	2.961	3.086	3.210	3.334	3.458
	$(Y_{TA_3})_\alpha^U$	4.394	4.299	4.205	4.112	4.018	3.924	3.831	3.739	3.646	3.552	3.458
TA_4	$(Y_{TA_4})_\alpha^L$	2.309	2.440	2.571	2.702	2.832	2.962	3.092	3.222	3.352	3.482	3.611
	$(Y_{TA_4})_\alpha^U$	4.584	4.487	4.389	4.292	4.194	4.098	4.002	3.905	3.808	3.710	3.611
TA_5	$(Y_{TA_5})_\alpha^L$	2.530	2.662	2.794	2.926	3.057	3.188	3.318	3.448	3.578	3.708	3.838
	$(Y_{TA_5})_\alpha^U$	4.790	4.693	4.596	4.500	4.405	4.310	4.215	4.121	4.026	3.932	3.838
TA_6	$(Y_{TA_6})_\alpha^L$	2.921	3.093	3.265	3.437	3.609	3.780	3.951	4.122	4.293	4.464	4.634
	$(Y_{TA_6})_\alpha^U$	6.019	5.880	5.741	5.602	5.463	5.325	5.186	5.048	4.910	4.772	4.634
TA_7	$(Y_{TA_7})_\alpha^L$	2.521	2.665	2.807	2.950	3.092	3.233	3.375	3.516	3.656	3.797	3.938
	$(Y_{TA_7})_\alpha^U$	5.072	4.958	4.844	4.730	4.617	4.503	4.390	4.277	4.164	4.051	3.938
TA_8	$(Y_{TA_8})_\alpha^L$	2.947	3.125	3.303	3.481	3.658	3.835	4.012	4.189	4.365	4.541	4.716
	$(Y_{TA_8})_\alpha^U$	6.190	6.042	5.894	5.747	5.599	5.452	5.304	5.157	5.010	4.863	4.716
TA_9	$(Y_{TA_9})_\alpha^L$	1.569	1.667	1.766	1.864	1.961	2.059	2.156	2.254	2.352	2.449	2.547
	$(Y_{TA_9})_\alpha^U$	3.424	3.336	3.247	3.159	3.071	2.984	2.896	2.809	2.721	2.634	2.547

By utilizing formulations (5.7) and (5.8), the upper and lower bounds for supplier ratings are calculated as given in Table 9.5.

Table 9.5 Upper and lower bounds of the supplier ratings

Suppliers		α										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Sup 1	$(Y_{\text{sup}_1})_\alpha^L$	0.492	0.524	0.556	0.587	0.619	0.650	0.681	0.712	0.742	0.773	0.803
	$(Y_{\text{sup}_1})_\alpha^U$	0.966	0.952	0.937	0.922	0.907	0.891	0.874	0.857	0.840	0.821	0.803
Sup 2	$(Y_{\text{sup}_2})_\alpha^L$	0.443	0.472	0.501	0.531	0.560	0.589	0.617	0.646	0.675	0.704	0.732
	$(Y_{\text{sup}_2})_\alpha^U$	0.955	0.934	0.912	0.890	0.868	0.846	0.824	0.801	0.779	0.756	0.732
Sup 3	$(Y_{\text{sup}_3})_\alpha^L$	0.388	0.419	0.450	0.481	0.512	0.543	0.574	0.605	0.635	0.666	0.696
	$(Y_{\text{sup}_3})_\alpha^U$	0.932	0.910	0.887	0.864	0.841	0.818	0.794	0.770	0.746	0.721	0.696
Sup 4	$(Y_{\text{sup}_4})_\alpha^L$	0.409	0.442	0.475	0.507	0.538	0.570	0.602	0.633	0.665	0.696	0.727
	$(Y_{\text{sup}_4})_\alpha^U$	0.926	0.908	0.890	0.871	0.852	0.832	0.812	0.792	0.771	0.749	0.727
Sup 5	$(Y_{\text{sup}_5})_\alpha^L$	0.257	0.287	0.318	0.348	0.379	0.409	0.440	0.470	0.501	0.531	0.562
	$(Y_{\text{sup}_5})_\alpha^U$	0.833	0.806	0.780	0.753	0.726	0.699	0.672	0.644	0.617	0.589	0.562
Sup 6	$(Y_{\text{sup}_6})_\alpha^L$	0.388	0.419	0.449	0.480	0.510	0.541	0.570	0.600	0.630	0.660	0.690
	$(Y_{\text{sup}_6})_\alpha^U$	0.926	0.903	0.881	0.858	0.835	0.811	0.787	0.763	0.739	0.714	0.690
Sup 7	$(Y_{\text{sup}_7})_\alpha^L$	0.478	0.509	0.540	0.570	0.600	0.630	0.660	0.690	0.719	0.749	0.778
	$(Y_{\text{sup}_7})_\alpha^U$	0.970	0.952	0.934	0.916	0.897	0.878	0.859	0.839	0.819	0.799	0.778
Sup 8	$(Y_{\text{sup}_8})_\alpha^L$	0.299	0.330	0.361	0.392	0.423	0.453	0.484	0.514	0.545	0.575	0.606
	$(Y_{\text{sup}_8})_\alpha^U$	0.847	0.824	0.801	0.778	0.755	0.731	0.706	0.682	0.657	0.631	0.606
Sup 9	$(Y_{\text{sup}_9})_\alpha^L$	0.256	0.284	0.311	0.338	0.366	0.393	0.420	0.447	0.475	0.502	0.529
	$(Y_{\text{sup}_9})_\alpha^U$	0.803	0.776	0.748	0.721	0.693	0.666	0.638	0.611	0.584	0.557	0.529
Sup 10	$(Y_{\text{sup}_{10}})_\alpha^L$	0.231	0.259	0.287	0.315	0.343	0.370	0.398	0.425	0.452	0.479	0.507
	$(Y_{\text{sup}_{10}})_\alpha^U$	0.783	0.754	0.727	0.699	0.671	0.643	0.616	0.588	0.561	0.534	0.507
Sup 11	$(Y_{\text{sup}_{11}})_\alpha^L$	0.256	0.289	0.321	0.353	0.385	0.417	0.448	0.480	0.511	0.542	0.573
	$(Y_{\text{sup}_{11}})_\alpha^U$	0.855	0.827	0.799	0.772	0.744	0.716	0.688	0.659	0.631	0.602	0.573
Sup 12	$(Y_{\text{sup}_{12}})_\alpha^L$	0.116	0.139	0.163	0.187	0.212	0.236	0.261	0.286	0.312	0.338	0.364
	$(Y_{\text{sup}_{12}})_\alpha^U$	0.684	0.651	0.618	0.585	0.553	0.521	0.489	0.458	0.426	0.395	0.364

Finally, the ranking index (I) for each supplier is computed employing Eq. (8.6). The ranking order of the suppliers is Sup 1 $\succ$ Sup 7 $\succ$ Sup 2 $\succ$ Sup 4 $\succ$ Sup 3 $\succ$ Sup 6 $\succ$ Sup 8 $\succ$ Sup 11 $\succ$ Sup 5 $\succ$ Sup 9 $\succ$ Sup10 $\succ$ Sup 12.

According to the results of the analysis, supplier 1 is determined as the most suitable supplier, which is followed by supplier 7, and then by supplier 2 and supplier 4. Suppliers 10 and 12 are ranked at the bottom due to late delivery time, inadequate experience in the sector, unsatisfactory earlier business relationships, and improper geographical location.

The computational procedure of the second fuzzy decision making framework, which employs the FWA method proposed by Wang and Chin (2011) is presented below.

The normalized fuzzy relationships are calculated using Eqs. (5.16) and (5.17). The upper and lower bounds of the weight of TAs are computed via formulations (5.21) and (5.22). The results are shown in Table 9.6.

Table 9.6 Upper and lower bounds of the weight of TAs

TAs		α										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
TA_1	$(Y_{TA_1})_\alpha^L$	0.033	0.037	0.042	0.046	0.051	0.056	0.061	0.066	0.071	0.076	0.081
	$(Y_{TA_1})_\alpha^U$	0.163	0.153	0.143	0.134	0.125	0.117	0.109	0.102	0.095	0.088	0.081
TA_2	$(Y_{TA_2})_\alpha^L$	0.052	0.057	0.063	0.069	0.074	0.080	0.087	0.093	0.099	0.106	0.112
	$(Y_{TA_2})_\alpha^U$	0.190	0.180	0.171	0.162	0.154	0.146	0.139	0.132	0.125	0.118	0.112
TA_3	$(Y_{TA_3})_\alpha^L$	0.050	0.055	0.059	0.064	0.069	0.075	0.080	0.085	0.091	0.097	0.103
	$(Y_{TA_3})_\alpha^U$	0.189	0.178	0.167	0.157	0.148	0.139	0.131	0.124	0.116	0.109	0.103
TA_4	$(Y_{TA_4})_\alpha^L$	0.053	0.058	0.063	0.068	0.074	0.079	0.084	0.090	0.096	0.101	0.107
	$(Y_{TA_4})_\alpha^U$	0.193	0.181	0.171	0.161	0.152	0.143	0.135	0.128	0.120	0.114	0.107
TA_5	$(Y_{TA_5})_\alpha^L$	0.065	0.069	0.074	0.079	0.084	0.090	0.095	0.100	0.106	0.111	0.117
	$(Y_{TA_5})_\alpha^U$	0.188	0.178	0.170	0.162	0.154	0.147	0.140	0.134	0.128	0.123	0.117
TA_6	$(Y_{TA_6})_\alpha^L$	0.088	0.093	0.098	0.103	0.108	0.113	0.118	0.123	0.129	0.134	0.140
	$(Y_{TA_6})_\alpha^U$	0.220	0.209	0.199	0.190	0.182	0.173	0.166	0.159	0.152	0.146	0.140
TA_7	$(Y_{TA_7})_\alpha^L$	0.061	0.067	0.072	0.078	0.084	0.090	0.096	0.102	0.108	0.114	0.120
	$(Y_{TA_7})_\alpha^U$	0.192	0.183	0.174	0.166	0.159	0.152	0.145	0.138	0.132	0.126	0.120
TA_8	$(Y_{TA_8})_\alpha^L$	0.091	0.096	0.101	0.106	0.111	0.116	0.121	0.126	0.131	0.137	0.143
	$(Y_{TA_8})_\alpha^U$	0.223	0.212	0.202	0.193	0.185	0.177	0.169	0.162	0.155	0.149	0.143
TA_9	$(Y_{TA_9})_\alpha^L$	0.028	0.032	0.037	0.041	0.046	0.051	0.056	0.061	0.066	0.071	0.076
	$(Y_{TA_9})_\alpha^U$	0.151	0.142	0.133	0.125	0.117	0.109	0.102	0.095	0.089	0.082	0.076

By utilizing formulations (5.21) and (5.22), the upper and lower bounds for supplier ratings are calculated as given in Table 9.7.

Table 9.7 Upper and lower bounds of the supplier ratings

Suppliers		α										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Sup 1	$\left(Y_{\sup_1}\right)_\alpha^L$	0.451	0.487	0.523	0.559	0.595	0.630	0.665	0.700	0.734	0.768	0.802
	$\left(Y_{\sup_1}\right)_\alpha^U$	0.978	0.964	0.950	0.935	0.919	0.901	0.884	0.865	0.845	0.824	0.802
Sup 2	$\left(Y_{\sup_2}\right)_\alpha^L$	0.417	0.449	0.481	0.512	0.544	0.576	0.607	0.639	0.671	0.702	0.733
	$\left(Y_{\sup_2}\right)_\alpha^U$	0.971	0.949	0.926	0.903	0.880	0.857	0.832	0.808	0.783	0.759	0.733
Sup 3	$\left(Y_{\sup_3}\right)_\alpha^L$	0.345	0.381	0.416	0.452	0.487	0.522	0.558	0.593	0.628	0.663	0.698
	$\left(Y_{\sup_3}\right)_\alpha^U$	0.954	0.931	0.908	0.884	0.859	0.834	0.808	0.781	0.754	0.726	0.698
Sup 4	$\left(Y_{\sup_4}\right)_\alpha^L$	0.352	0.392	0.431	0.470	0.509	0.546	0.583	0.620	0.657	0.693	0.729
	$\left(Y_{\sup_4}\right)_\alpha^U$	0.952	0.934	0.914	0.894	0.873	0.851	0.828	0.804	0.780	0.755	0.729
Sup 5	$\left(Y_{\sup_5}\right)_\alpha^L$	0.223	0.257	0.291	0.326	0.359	0.393	0.426	0.460	0.494	0.528	0.562
	$\left(Y_{\sup_5}\right)_\alpha^U$	0.862	0.833	0.804	0.774	0.744	0.714	0.684	0.654	0.624	0.593	0.562
Sup 6	$\left(Y_{\sup_6}\right)_\alpha^L$	0.347	0.382	0.418	0.453	0.487	0.522	0.556	0.590	0.623	0.656	0.689
	$\left(Y_{\sup_6}\right)_\alpha^U$	0.948	0.925	0.901	0.876	0.851	0.825	0.799	0.772	0.745	0.717	0.689
Sup 7	$\left(Y_{\sup_7}\right)_\alpha^L$	0.443	0.478	0.512	0.546	0.580	0.614	0.647	0.680	0.713	0.745	0.778
	$\left(Y_{\sup_7}\right)_\alpha^U$	0.983	0.965	0.947	0.928	0.909	0.889	0.868	0.847	0.825	0.802	0.778
Sup 8	$\left(Y_{\sup_8}\right)_\alpha^L$	0.257	0.291	0.326	0.362	0.397	0.432	0.467	0.502	0.537	0.571	0.606
	$\left(Y_{\sup_8}\right)_\alpha^U$	0.879	0.855	0.830	0.804	0.778	0.750	0.722	0.694	0.665	0.636	0.606
Sup 9	$\left(Y_{\sup_9}\right)_\alpha^L$	0.241	0.271	0.301	0.329	0.358	0.386	0.415	0.443	0.472	0.501	0.530
	$\left(Y_{\sup_9}\right)_\alpha^U$	0.817	0.789	0.760	0.731	0.702	0.673	0.644	0.616	0.587	0.558	0.530
Sup 10	$\left(Y_{\sup_{10}}\right)_\alpha^L$	0.209	0.239	0.270	0.300	0.330	0.360	0.389	0.419	0.448	0.477	0.507
	$\left(Y_{\sup_{10}}\right)_\alpha^U$	0.805	0.775	0.745	0.714	0.684	0.654	0.624	0.595	0.565	0.536	0.507
Sup 11	$\left(Y_{\sup_{11}}\right)_\alpha^L$	0.213	0.249	0.286	0.322	0.358	0.394	0.430	0.466	0.502	0.538	0.573
	$\left(Y_{\sup_{11}}\right)_\alpha^U$	0.886	0.857	0.827	0.797	0.766	0.735	0.703	0.672	0.639	0.606	0.573
Sup 12	$\left(Y_{\sup_{12}}\right)_\alpha^L$	0.092	0.116	0.141	0.167	0.193	0.219	0.247	0.275	0.304	0.333	0.364
	$\left(Y_{\sup_{12}}\right)_\alpha^U$	0.742	0.702	0.663	0.624	0.585	0.547	0.510	0.472	0.436	0.400	0.364

Finally, the ranking index (I) for each supplier is computed employing Eq. (8.6). The ranking order of the suppliers is Sup $1 \succ$ Sup $7 \succ$ Sup $2 \succ$ Sup $4 \succ$ Sup $3 \succ$ Sup $6 \succ$ Sup $8 \succ$ Sup $11 \succ$ Sup $5 \succ$ Sup $9 \succ$ Sup $10 \succ$ Sup 12, which is the same ranking as the first MCDM method. The results of these two methods are compared in Table 9.8.

Table 9.8 Ranking of suppliers using the first and second proposed decision making frameworks

Suppliers	Ranking indices obtained from the first algorithm	Rank	Ranking indices obtained from the first algorithm	Rank
Sup 1	0.7066	1	0.6943	1
Sup 2	0.6567	3	0.6517	3
Sup 3	0.6215	5	0.6156	5
Sup 4	0.6410	4	0.6322	4
Sup 5	0.5098	9	0.5128	9
Sup 6	0.6176	6	0.6122	6
Sup 7	0.6909	2	0.6817	2
Sup 8	0.5426	7	0.5429	7
Sup 9	0.4883	10	0.4932	10
Sup 10	0.4682	11	0.4742	11
Sup 11	0.5198	8	0.5210	8
Sup 12	0.3571	12	0.3756	12

The computational procedure of the third MCDM method is summarized as follows:

First, the fuzzy assessment corresponding to the impact of each TA on each CN, the importance of CNs, and the degree of dependencies among TAs are converted into the BLTS employing formulations (8.7)-(8.9). Next, by using the linguistic quantifier ‘most’ and the formulations (6.3) and (6.4), the OWA weights for five decision-makers are computed as $\mathbf{w} = (0,0.2,0.4,0.4,0)$. Then, the importance of CNs, the fuzzy assessment with respect to the impact of each TA on each CN, and the dependencies among TAs converted into the BLTS are aggregated employing formulations (8.10)-(8.15). The β values of these importance, ratings, and dependencies are computed and transformed into linguistic 2-tuples via formulations (7.1) and (7.2) as delineated in Figure 9.5.

	TA_1	TA_2	TA_3	TA_4	TA_5	TA_6	TA_7	TA_8	TA_9
TA_1		$(s_1,0.39)$	$(s_4,0.01)$	$(s_5,-0.05)$		$(s_6,0.19)$	$(s_2,0.19)$	$(s_6,0.02)$	$(s_1,0.39)$
TA_2				$(s_2,0.19)$	$(s_7,-0.19)$	$(s_6,0)$	$(s_7,-0.38)$	$(s_7,0.13)$	$(s_7,0.34)$
TA_3				$(s_5,-0.33)$	$(s_5,-0.05)$	$(s_6,-0.43)$	$(s_6,0.19)$	$(s_7,-0.36)$	
TA_4					$(s_5,0.13)$	$(s_7,-0.38)$	$(s_3,-0.22)$	$(s_6,0.43)$	$(s_2,0.19)$
TA_5						$(s_7,0.40)$	$(s_7,0.13)$	$(s_7,0.34)$	
TA_6							$(s_7,0.34)$	$(s_6,0.19)$	$(s_6,-0.19)$
TA_7								$(s_7,0.13)$	$(s_2,0.43)$
TA_8									$(s_6,0.19)$

CNs \ TAs	TA_1	TA_2	TA_3	TA_4	TA_5	TA_6	TA_7	TA_8	TA_9	Importance of CNs
CN_1	$(s_7,-0.19)$	$(s_1,-0.33)$	$(s_7,0.13)$	$(s_7,-0.36)$	$(s_6,-0.17)$	$(s_6,0.19)$	$(s_4,0.43)$	$(s_6,-0.17)$	$(s_6,0.19)$	$(s_7,-0.38)$
CN_2	$(s_6,0.30)$	$(s_1,0.37)$	$(s_1,-0.33)$	$(s_6,0.19)$	$(s_7,0.34)$	$(s_7,0.34)$	$(s_4,0.08)$	$(s_7,-0.23)$	$(s_1,0.39)$	$(s_7,-0.05)$
CN_3	$(s_4,0.01)$	$(s_4,-0.44)$	$(s_1,0.39)$	$(s_7,-0.19)$	$(s_7,0.34)$	$(s_7,0.13)$	$(s_4,0.01)$	$(s_6,0.19)$	$(s_1,-0.13)$	$(s_7,0.34)$
CN_4	$(s_1,0.37)$	$(s_1,0.39)$	$(s_2,-0.43)$	$(s_6,-0.17)$	$(s_6,0.43)$	$(s_6,0.19)$	$(s_7,-0.38)$	$(s_6,-0.19)$	$(s_3,0.35)$	$(s_7,0.13)$
CN_5	$(s_1,-0.13)$	$(s_2,-0.19)$	$(s_1,0.07)$	$(s_4,0.01)$	$(s_7,0.13)$	$(s_7,-0.36)$	$(s_6,0.43)$	$(s_6,0.47)$	$(s_4,0.08)$	$(s_6,-0.17)$

Figure 9.5 2-tuple linguistic ratings related to the first HOQ for the medical supplier selection problem

The original relationship measure between TAs and CNs is computed employing Equation (8.5) and 2-tuple linguistic weighted average. Then, the 2-tuple linguistic weighted averages for each TA are calculated. The results are represented in Table 9.9.

Table 9.9 Prioritization of the TAs using the proposed decision making framework

CNs	Weights of CNs	TAs								
		TA_1	TA_2	TA_3	TA_4	TA_5	TA_6	TA_7	TA_8	TA_9
CN_1	$(s_7, -0.38)$	$(s_6, 0.11)$	$(s_5, -0.11)$	$(s_6, 0.12)$	$(s_6, -0.05)$	$(s_5, 0.15)$	$(s_6, -0.47)$	$(s_5, 0.24)$	$(s_5, 0.46)$	$(s_5, -0.16)$
CN_2	$(s_7, -0.05)$	$(s_5, 0.35)$	$(s_5, -0.32)$	$(s_5, 0.17)$	$(s_5, 0.38)$	$(s_5, 0.05)$	$(s_5, -0.18)$	$(s_5, -0.29)$	$(s_5, -0.36)$	$(s_4, 0.14)$
CN_3	$(s_7, 0.34)$	$(s_5, -0.09)$	$(s_5, -0.19)$	$(s_5, 0.02)$	$(s_5, 0.27)$	$(s_5, 0.38)$	$(s_5, -0.21)$	$(s_5, -0.12)$	$(s_5, -0.35)$	$(s_4, 0.29)$
CN_4	$(s_7, 0.13)$	$(s_4, 0.12)$	$(s_5, -0.24)$	$(s_5, -0.22)$	$(s_5, -0.32)$	$(s_5, 0.01)$	$(s_4, 0.49)$	$(s_5, -0.34)$	$(s_4, 0.36)$	$(s_4, 0.19)$
CN_5	$(s_6, -0.17)$	$(s_4, -0.09)$	$(s_5, 0.09)$	$(s_5, -0.36)$	$(s_5, -0.48)$	$(s_5, 0.08)$	$(s_4, 0.49)$	$(s_5, -0.21)$	$(s_4, 0.38)$	$(s_5, -0.50)$
2-tuple linguistic weighted average		$(s_5, -0.10)$	$(s_5, -0.16)$	$(s_5, 0.15)$	$(s_5, 0.17)$	$(s_5, 0.14)$	$(s_5, -0.17)$	$(s_5, -0.15)$	$(s_5, -0.30)$	$(s_4, 0.38)$

The ratings of each supplier converted into the BLTS are aggregated and transformed into linguistic 2-tuples as in Table 9.10.

Table 9.10 2-tuple linguistic ratings of suppliers

	TA_1	TA_2	TA_3	TA_4	TA_5	TA_6	TA_7	TA_8	TA_9
Sup 1	$(s_7, 0.13)$	$(s_5, 0.21)$	$(s_6, 0.34)$	$(s_7, 0.13)$	$(s_7, -0.19)$	$(s_7, 0.34)$	$(s_6, -0.17)$	$(s_5, -0.05)$	$(s_3, -0.12)$
Sup 2	$(s_6, -0.48)$	$(s_6, 0.19)$	$(s_5, -0.43)$	$(s_6, -0.43)$	$(s_6, 0.25)$	$(s_7, -0.06)$	$(s_6, 0.02)$	$(s_6, -0.43)$	$(s_2, 0.43)$
Sup 3	$(s_4, -0.06)$	$(s_7, -0.06)$	$(s_6, -0.17)$	$(s_4, 0.01)$	$(s_5, -0.05)$	$(s_6, -0.17)$	$(s_7, -0.19)$	$(s_4, 0.45)$	$(s_6, 0.19)$
Sup 4	$(s_4, -0.44)$	$(s_7, -0.19)$	$(s_7, -0.36)$	$(s_4, -0.37)$	$(s_7, -0.32)$	$(s_7, -0.36)$	$(s_7, -0.06)$	$(s_6, -0.17)$	$(s_4, 0.40)$
Sup 5	$(s_4, -0.06)$	$(s_6, -0.17)$	$(s_7, -0.36)$	$(s_4, 0.08)$	$(s_3, -0.03)$	$(s_4, -0.06)$	$(s_6, -0.19)$	$(s_2, 0.19)$	$(s_4, -0.06)$
Sup 6	$(s_6, -0.17)$	$(s_5, -0.05)$	$(s_7, 0.13)$	$(s_6, -0.19)$	$(s_6, -0.43)$	$(s_4, -0.43)$	$(s_7, -0.36)$	$(s_5, 0.22)$	$(s_3, -0.22)$
Sup 7	$(s_7, -0.38)$	$(s_5, 0.13)$	$(s_7, 0.13)$	$(s_6, -0.43)$	$(s_6, 0.20)$	$(s_7, 0.35)$	$(s_6, 0.43)$	$(s_6, 0.43)$	$(s_4, -0.06)$
Sup 8	$(s_3, -0.12)$	$(s_4, -0.06)$	$(s_7, -0.06)$	$(s_2, 0.43)$	$(s_4, 0.45)$	$(s_4, 0.43)$	$(s_7, -0.30)$	$(s_4, 0.45)$	$(s_7, 0.18)$
Sup 9	$(s_4, -0.06)$	$(s_5, -0.05)$	$(s_5, 0.22)$	$(s_4, 0.08)$	$(s_4, 0.43)$	$(s_4, 0.01)$	$(s_5, -0.05)$	$(s_4, 0.01)$	$(s_5, -0.37)$
Sup 10	$(s_3, -0.22)$	$(s_4, -0.37)$	$(s_6, -0.43)$	$(s_4, 0.08)$	$(s_4, 0)$	$(s_4, -0.18)$	$(s_4, 0.08)$	$(s_4, 0.01)$	$(s_3, 0.04)$
Sup 11	$(s_3, 0.40)$	$(s_3, -0.49)$	$(s_6, -0.43)$	$(s_3, -0.49)$	$(s_3, 0.04)$	$(s_5, 0.22)$	$(s_6, 0.22)$	$(s_6, -0.43)$	$(s_7, 0.13)$
Sup 12	$(s_1, -0.13)$	$(s_1, 0.08)$	$(s_6, -0.17)$	$(s_3, -0.49)$	$(s_5, -0.05)$	$(s_4, 0.01)$	$(s_2, 0.21)$	$(s_3, -0.49)$	$(s_2, 0.26)$

Finally, the 2-tuple linguistic weighted average for each supplier is computed and the suppliers are ranked as shown in Table 9.11. The rank order of the suppliers is Sup 7 $\succ$ Sup 1 $\succ$ Sup 4 $\succ$ Sup 2 $\succ$ Sup 3 $\succ$ Sup 6 $\succ$ Sup 8 $\succ$ Sup 11 $\succ$ Sup 9 $\succ$ Sup 5 $\succ$ Sup 10 $\succ$ Sup 12. According to the results of the analysis, supplier 7 is determined as the most suitable supplier, which is followed by supplier 1, and then by supplier 4 and supplier 2. Suppliers 10 and 12 are ranked at the bottom due to late delivery time, inadequate experience in the sector, unsatisfactory earlier business relationships, and improper geographical location.

Table 9.11 Ranking of suppliers using the proposed decision making framework

Suppliers	2-tuple linguistic weighted average score	Rank
Sup 1	(s_6, 0.01)	2
Sup 2	(s_5, 0.48)	4
Sup 3	(s_5, 0.42)	5
Sup 4	(s_6, -0.31)	3
Sup 5	(s_4, 0.39)	10
Sup 6	(s_5, 0.32)	6
Sup 7	(s_6, 0.11)	1
Sup 8	(s_5, -0.21)	7
Sup 9	(s_4, 0.47)	9
Sup 10	(s_4, -0.09)	11
Sup 11	(s_5, -0.47)	8
Sup 12	(s_3, -0.05)	12

10 CONCLUSIONS

Considering the global challenges in manufacturing environment, organizations are forced to optimize their business processes to remain competitive. To reach this aim, firms must work with its supply chain partners to improve the chain's total performance. As the key process in the upstream chain and affecting all areas of an organization, the purchasing function is increasingly seen as a strategic issue in supply chain hierarchy. Selecting the right suppliers significantly reduces the purchasing cost and improves corporate competitiveness. Supplier selection problem, which requires considering multiple conflicting criteria incorporating vagueness and imprecision with the involvement of a group of experts, is an important multi-criteria group decision making problem. The classical MCDM methods that consider deterministic or random processes cannot effectively address supplier selection problems since fuzziness, imprecision and interaction coexist in real-world. In this thesis, fuzzy multi-criteria group decision making algorithms are presented to rectify the problems encountered when using classical decision making methods in supplier selection.

The methodologies developed in this thesis consider QFD planning as a fuzzy multi-criteria group decision tool and construct two interrelated HOQ matrices to compute the weights of supplier selection criteria and the ratings of suppliers. The first and second methods employ FWA method to calculate the upper and lower bounds of the weights of supplier selection criteria and the ratings of suppliers. The upper and lower bounds of the weights of supplier selection criteria are computed by applying FWA to the data given in the first HOQ, whereas the upper and lower bounds of the ratings of suppliers are subsequently determined by employing FWA considering the weights of supplier selection criteria as inputs in the second HOQ. As most fuzzy number ranking methods can hardly be applied in this case, a ranking method that is reported to be more efficient and accurate than its predecessors is employed to rank the suppliers (Chen & Klein, 1997). The third MCDM approach utilizes the fusion of fuzzy information and the 2-

tuple linguistic representation model, which enable decision-makers to tackle the problems of multi-granularity and loss of information.

The proposed methodologies possess a number of merits compared to some other MCDM techniques presented in the literature for supplier selection. First, the developed methods are group decision making processes which enable the group to identify and better appreciate the differences and similarities of their judgments. Second, the proposed approaches are apt to incorporate imprecise data into the analysis using fuzzy set theory. Third, these methodologies enable to consider not only the impacts of relationships among the purchased product features and supplier selection criteria, but also the correlations among supplier selection criteria for achieving higher satisfaction to meet company's requirements.

Apart from these merits, in order to calculate the upper and lower bounds of the weights of the supplier selection criteria and the supplier assessments, the first and second methods use fuzzy weighted average method that rectifies the problem of loss of information that occurs when integrating imprecise and subjective information. Thus, they are likely to produce more realistic overall desirability levels. Furthermore, these approaches employ a fuzzy number ranking method based on area measurement, which has a high ability to discriminate among the fuzzy numbers to be ranked.

Besides, the third methodology uses the 2-tuple linguistic representation model that inherits the existing characters of fuzzy linguistic assessment and also that enables decision-makers to manage non-homogeneous information in a decision making problem with multiple information sources. Moreover, this linguistic representation model rectifies the problem of loss of information faced with other fuzzy linguistic approaches. The proposed methodology employs the OWA operator as the aggregation operator. OWA operator differs from the classical weighted average in that coefficients are not associated directly with a particular attribute but rather with an ordered position. It encompasses several operators since it can implement different aggregation rules by changing the order weights.

It is worth noting that the decision models presented here are not restricted to medical supplier selection and could be applied to a supplier selection problem in another discipline without any difficulty. One shall also note that the MCDM approaches proposed in here for evaluating medical suppliers can be easily programmed. Future research might focus on applying the decision frameworks presented in here to real-world group decision making problems in diverse disciplines that can be represented in HOQ structures. Moreover, a user interface can be developed for users who are novice in mathematical programming. Incorporating supply chain flexibility into the analysis also remains as an issue to be addressed in the future.

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BIOGRAPHICAL SKETCH

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