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A QFD-based fuzzy MCDM approach for supplier selection

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ABSTRACT

Supplier selection is a highly important multi-criteria group decision making problem, which requires a trade-off between multiple criteria exhibiting vagueness and imprecision with the involvement of a group of experts. In this paper, a fuzzy multi-criteria group decision making approach that makes use of the quality function deployment (QFD) concept is developed for supplier selection process. The proposed methodology initially identifies the features that the purchased product should possess in order to satisfy the company's needs, and then it seeks to establish the relevant supplier assessment criteria. Moreover, the proposed algorithm enables to consider the impacts of inner dependence among supplier assessment criteria. The upper and the lower bounds of the weights of supplier assessment criteria and ratings of suppliers are computed by using the fuzzy weighted average (FWA) method. The FWA method allows for the fusion of imprecise and subjective information expressed as linguistic variables or fuzzy numbers. The method produces less imprecise and more realistic overall desirability levels, and thus it rectifies the problem of loss of information. A fuzzy number ranking method that is based on area measurement is used to obtain the final ranking of suppliers. The computational procedure of the proposed framework is illustrated through a supplier selection problem reported in an earlier study.

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 [1]. 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 [2].

Supplier's performance has a key role on cost, quality, delivery and service in achieving the objectives of a supply chain. Gencer and Gürpinar [3] pointed out that the cost of purchased goods and services accounts for more than 60% of the cost of goods sold, and over 50% of all quality defects can be traced back to purchase material. 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 [4]. 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 has become a crucial element in a company's quality success or failure, and clearly influences the responsiveness of the company [5]. 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 [6].

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At the beginning of the 1980s, Evans [7] found price to be the most important attribute in the purchase of routine products. However, recent studies have discovered a shift away from price as a primary determinant of supplier selection [8]. 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 problem. The classical multi-criteria decision making (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 study is to propose a fuzzy multi-criteria group decision making approach based on the quality function deployment (QFD) concept for supplier selection. In supplier selection process, the company's ultimate aim is to have access to suppliers that ensure a certain quality standard in terms of the characteristics of the purchased products or services [9]. 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 decision framework developed in this paper considers QFD planning as a fuzzy multi-criteria group decision making tool and utilizes two interrelated HOQ matrices to evaluate alternative suppliers. When relative weight of purchased product feature, relationship measure between purchased product feature and supplier assessment criteria and ratings of suppliers with respect to each supplier assessment criteria are represented as fuzzy numbers, computation of the weights of supplier assessment criteria and the ratings of suppliers fall into the category of fuzzy weighted average [10]. The proposed approach calculates both the weights of supplier selection criteria and the ratings of suppliers by using a fuzzy weighted average method, which develops a pair of fractional programs to calculate the upper and lower bounds of the criteria weights and the supplier ratings. The FWA method enables the fusion of imprecise and subjective information expressed as linguistic variables or fuzzy numbers, and alleviates the concern for loss of information. The proposed algorithm allows for considering the impacts of inner dependence among supplier assessment criteria, thus it disregards the unrealistic mutual independence assumption of attributes. A ranking method based on area measurement that attempts to alleviate the drawbacks of the existing fuzzy number ranking methods is employed to rank the potential suppliers. Most ranking methods observe the order of fuzzy numbers and do not measure the degree of difference between them. Furthermore, some of the ranking methods can only be applied when membership functions are known. This issue can be problematic when one considers that fuzzy numbers to be ranked are generally the output of fuzzy number aggregation operations and their exact membership functions are unknown. Moreover, the inclusion or omission of fuzzy numbers to or from the comparison may alter the original ranking [11].

The rest of the paper is organized as follows: The following section presents the literature review on supplier selection. Section 3 outlines the developed methodology and provides a stepwise representation of the proposed fuzzy decision making approach. In Section 4, the application of the proposed framework to a previously reported case study concerning an enterprise that manufactures complete clutch coupling is illustrated. Finally, conclusions are provided in Section 5.

2. Literature review

Recently, buyer and supplier relationships in manufacturing enterprises have received considerable attention in the business–management literature. The purchasing function is increasingly seen as a strategic issue in supply chain hierarchy. Weber and Current [12] stated that in high-technology industries, material purchased externally can represent up to 80% of total product cost. It is vital for the competitiveness of most firms to reduce such purchasing costs to a minimum. In order to accomplish this, the firm must determine its business partners. This decision was referred as supplier selection problem by Weber and Current [12]. The complexity of the supplier evaluation and selection problem has motivated the researchers to develop models for helping decision-makers.

Earlier studies on supplier selection focused on identifying the criteria used to select suppliers. Dickson [13] 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.

Ellram [14] noted that supplier selection models may be based on the way in which model proponents believe a decision should be made (prescriptive) or the way they believe decisions are actually made (descriptive). Descriptive research provides information on what buyers actually do in selecting suppliers, while prescriptive research emphasizes what should be done in a normative sense. Descriptive studies have addressed a wide array of issues, and have been extended to identify supplier selection under specific buying conditions [15–18]. Prescriptive research in supplier selection has used a variety of methodologies including mathematical programming, weighted average methods, payoff matrices, and the analytic hierarchy process (AHP) [19–21].

Most of the research on supplier selection focuses on the quantifiable aspects of the supplier selection decision such as cost, quality, and delivery reliability. However, 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. These criteria are subjective factors that are difficult to quantify. Fuzzy set theory appears as an effective tool to deal with uncertainty inherent in supplier selection process. In the literature, there are a number of studies that use alternative fuzzy decision making techniques to evaluate suppliers.

Several authors have used fuzzy mathematical programming approaches. Amid et al. [22] presented a fuzzy multi-objective linear model that considered the vagueness of information in supplier selection problem. Araz et al. [23] proposed a supplier evaluation and management system for a textile company using fuzzy goal programming. Amid et al. [24] formulated a fuzzy multi-objective model for the supplier selection problem under price breaks that depend on the sizes of order quantities. Chen [25] employed a fuzzy-based mathematical programming approach to account for multiple criteria and vagueness within the supplier selection procedure. Recently, Amid et al. [26] developed a weighted max–min fuzzy multi-objective model to deal with the vagueness of input data and criteria weights effectively in supplier selection.

A number of studies have focused on the use of fuzzy multi-attribute decision making (MADM) techniques for supplier selection process. Chen et al. [6] extended the technique for order preference by similarity to ideal solution (TOPSIS) to address the supplier selection problem under fuzzy environment. Haq and Kannan [27] presented an approach using fuzzy AHP and genetic algorithm for supplier selection of an original equipment manufacturing company. Chan and Kumar [28] introduced a fuzzy extended AHP based methodology to select the most appropriate global supplier for a manufacturing firm. Bottani and Rizzi [29] presented a structured approach that integrates cluster analysis and MCDM techniques to identify the most suitable supplier and purchased items. Chen and Wang [30] employed the fuzzy VIKOR method to construct a systematic process for evaluating and assessing possible suppliers. Lang et al. [2] combined analytic network process (ANP) and Choquet integral to assess the supply chain management strategy. Wang [31] proposed a group decision making approach based on 2-tuple fuzzy linguistic computation model to evaluate the supplier performance.

Lately, a few researchers have employed the QFD in supplier selection. Bevilacqua et al. [9] 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. Amin and Razmi [32] proposed 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 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. [33] integrated AHP with QFD to rank and subsequently select candidate-suppliers under multiple, conflicting nature criteria environment.

Although previously reported studies developed approaches for supplier selection process, further studies are necessary to integrate imprecise information concerning the importance of purchased product features, relationship between purchased product features and supplier assessment criteria, and dependencies between supplier assessment criteria into the analysis. A sound decision aid for supplier selection should also aim to rectify the problem of loss of information when computing with linguistic variables. In this paper, a fuzzy multi-criteria group decision making approach based on QFD is developed. The proposed approach calculates both the weights of supplier selection criteria and the ratings of the suppliers by using fuzzy weighted average, which produces less imprecise and more realistic overall desirability levels. Then, the final ranking of the suppliers is obtained through a fuzzy number ranking method enabling to avoid inconsistencies that may be realized with other ranking methods.

3. Methodology

The proposed decision making framework uses the concepts of QFD, fuzzy weighted average, and a fuzzy number ranking method based on area measurement. The essentials of QFD and fuzzy weighted average are briefly reviewed in the following subsections. Then, the proposed decision making methodology is presented.

3.1. Quality function deployment

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.

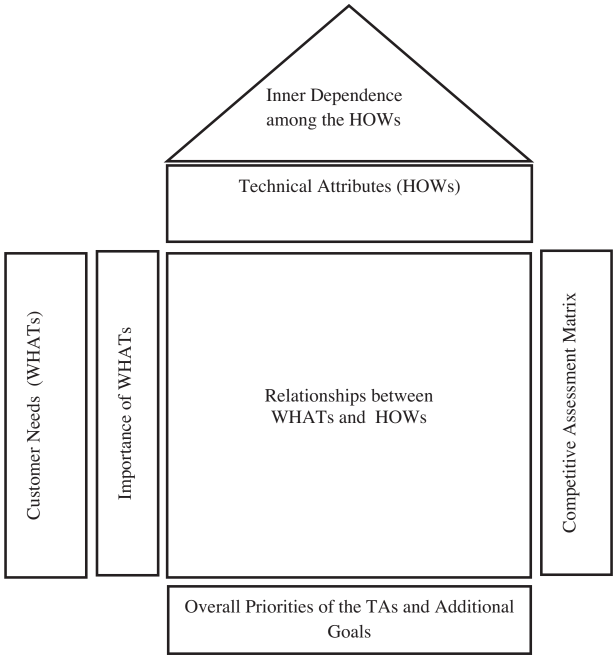

Fig. 1. The house of quality.

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 [34].

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 [35]. 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 CNs into 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 [36]. In this paper, we focus on the first and the most widely used of the four matrices, also called the house of quality (HOQ). According to Hauser and Clausing [37], the HOQ is a kind of conceptual map that provides the means for interfunctional planning and communications. It contains seven elements as shown in Fig. 1. The seven elements of the HOQ shown in Fig. 1 can be briefly described as follows:

(1) *CNs (WHATs).* 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) *TAs (HOWs).* TAs are also known as design requirements, product features, engineering attributes, engineering characteristics or substitute quality characteristics. They describe the product in the language of the engineer; thus, are sometimes referred as the voice of the company. They are used to determine how well the company satisfies the CNs [34].

(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 [34].

(4) *Relationships between WHATs and HOWs.* The relationship matrix indicates how much each TA affects each CN. In this paper, linguistic variables are used to denote the relationships between WHATs and HOWs as adopted by several researchers in earlier studies to address imprecision and vagueness [35,38].

(5) *Competitive assessment matrix.* This matrix contains a competitive analysis of the company's product with main competitors' products for needs. Thus, relative position of the company's product can be assessed in terms of CNs. 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 various TAs that have to be improved collaterally, providing a basis to calculate to what extent a change in one feature will affect other features.

(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 HOWs, also called TA ratings.

3.2. Fuzzy weighted average

Consider the general fuzzy weighted average with n criteria. Define

$$\widetilde{W}_j = \{(w_j, \mu_{\widetilde{W}_j}(w_j))|w_j \in W_j\}, \quad j = 1, 2, \ldots, n \tag{1}$$

and

$$\widetilde{X}_{ij} = \{(x_{ij}, \mu_{\widetilde{X}_{ij}}(x_{ij}))|x_{ij} \in X_{ij}\}, \quad i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n \tag{2}$$

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

$$\widetilde{Y}_i = \sum_{j=1}^{n} \widetilde{W}_j \widetilde{X}_{ij} \Big/ \sum_{j=1}^{n} \widetilde{W}_j, \quad i = 1, 2, \ldots, m \tag{3}$$

Since $\widetilde{W}_j$ and $\widetilde{X}_{ij}$ are fuzzy numbers, the weighted average $\widetilde{Y}_i$ is also a fuzzy number. There are several methods devised for calculating fuzzy weighted average [39–42]. In this paper, the method proposed by Kao and Liu [42] is employed since the computational complexity of their method is lower compared to other methods. Kao and Liu [42] approached the problem via mathematical programming technique and developed a pair of fractional programs to find the α-cut of $\widetilde{Y}_i$ based on the extension principle. A brief summary of the method is given below.

Denote the α-cuts of $\widetilde{W}_j$ and $\widetilde{X}_{ij}$ as

$$(W_j)_\alpha = \{w_j \in W_j | \mu_{\widetilde{W}_j}(w_j) \geq \alpha\}, \quad \forall j \tag{4}$$

$$(X_{ij})_\alpha = \{x_{ij} \in X_{ij} | \mu_{\widetilde{X}_{ij}}(x_{ij}) \geq \alpha\}, \quad \forall i, j \tag{5}$$

where $(W_j)_\alpha$ is the interval with the lower bound $(W_j)_\alpha^L$ and the upper bound $(W_j)_\alpha^U$ at the α-level. Similarly, $(X_{ij})_\alpha$ is the interval bounded by $(X_{ij})_\alpha^L$ and $(X_{ij})_\alpha^U$ for a given α. These intervals can also be expressed as

$$(W_j)_\alpha = \left[(W_j)_\alpha^L, (W_j)_\alpha^U\right] = \left[\min_{w_j}\left\{w_j \in W_j | \mu_{\widetilde{W}_j}(w_j) \geq \alpha\right\}, \max_{w_j}\left\{w_j \in W_j | \mu_{\widetilde{W}_j}(w_j) \geq \alpha\right\}\right] \tag{6}$$

$$(X_{ij})_\alpha = \left[(X_{ij})_\alpha^L, (X_{ij})_\alpha^U\right] = \left[\min_{x_{ij}}\left\{x_{ij} \in X_{ij} | \mu_{\widetilde{X}_{ij}}(x_{ij}) \geq \alpha\right\}, \max_{x_{ij}}\left\{x_{ij} \in X_{ij} | \mu_{\widetilde{X}_{ij}}(x_{ij}) \geq \alpha\right\}\right] \tag{7}$$

According to Zadeh's extension principle [43], the membership function $\mu_{\widetilde{Y}_i}$ can be derived from the following equation:

$$\mu_{\widetilde{Y}_i}(y_i) = \sup_{x,w} \min\left\{\mu_{\widetilde{W}_j}(w_j), \mu_{\widetilde{X}_{ij}}(x_{ij}), \forall i, j \,\middle|\, y_i = \sum_{j=1}^{n} w_j x_{ij} \Big/ \sum_{j=1}^{n} w_j\right\}. \tag{8}$$

At a specific α-level of $\widetilde{Y}_i$, Eq. (8) states that one needs $\mu_{\widetilde{W}_j}(w_j) \geq \alpha$ and $\mu_{\widetilde{X}_{ij}}(x_{ij}) \geq \alpha$ for $\forall i, j$, and at least one $\mu_{\widetilde{W}_j}(w_j)$ or $\mu_{\widetilde{X}_{ij}}(x_{ij})$ equal to α such that $y_i = \sum_{j=1}^{n} w_j x_{ij} / \sum_{j=1}^{n} w_j$ to satisfy $\mu_{\widetilde{Y}_i}(y_i) = \alpha$. To find the membership function $\mu_{\widetilde{Y}_i}$, it suffices to find the right shape function and the left shape function of $\mu_{\widetilde{Y}_i}$, which is equivalent to finding the upper bound $(Y_i)_\alpha^U$ and the lower bound $(Y_i)_\alpha^L$ of $\widetilde{Y}_i$ at the α-level. Since $(Y_i)_\alpha^U$ and $(Y_i)_\alpha^L$ are respectively the maximum and the minimum of $\sum_{j=1}^{n} w_j x_{ij} / \sum_{j=1}^{n} w_j$, the upper and the lower bounds of the α-cut of $\widetilde{Y}_i$ can be solved as

$$(Y_i)_\alpha^U = \max \sum_{j=1}^{n} w_j x_{ij} \Big/ \sum_{j=1}^{n} w_j$$

subject to

$$(W_j)_\alpha^L \leq w_j \leq (W_j)_\alpha^U, \quad j = 1, 2, \ldots, n \tag{9}$$

$$(X_{ij})_\alpha^L \leq x_{ij} \leq (X_{ij})_\alpha^U, \quad i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n$$

$$(Y_i)_\alpha^L = \min \sum_{j=1}^{n} w_j x_{ij} \Big/ \sum_{j=1}^{n} w_j$$

subject to

$$(W_j)_\alpha^L \leq w_j \leq (W_j)_\alpha^U, \quad j = 1,2,\ldots,n \tag{10}$$

$$(X_{ij})_\alpha^L \leq x_{ij} \leq (X_{ij})_\alpha^U, \quad i = 1,2,\ldots,m, \quad j = 1,2,\ldots,n$$

It is obvious that the maximum of y_i 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 (9) and (10) can be replaced by $(X_{ij})_\alpha^U$ and $(X_{ij})_\alpha^L$, respectively. Following the variable substitution of Charnes and Cooper [44], by letting $t^{-1} = \sum_{j=1}^n w_j$ and $v_j = tw_j$, formulations (9) and (10) can be transformed to the following linear programs:

$$(Y_i)_\alpha^U = \max \sum_{j=1}^n v_j (X_{ij})_\alpha^U$$

subject to

$$t(W_j)_\alpha^L \leq v_j \leq t(W_j)_\alpha^U, \quad j = 1,2,\ldots,n \tag{11}$$

$$\sum_{j=1}^n v_j = 1$$

$$t, v_j \geq 0, \quad j = 1,2,\ldots,n$$

$$(Y_i)_\alpha^L = \min \sum_{j=1}^n v_j (X_{ij})_\alpha^L$$

subject to

$$t(W_j)_\alpha^L \leq v_j \leq t(W_j)_\alpha^U, \quad j = 1,2,\ldots,n \tag{12}$$

$$\sum_{j=1}^n v_j = 1$$

$$t, v_j \geq 0, \quad j = 1,2,\ldots,n$$

The α-cuts of $\widetilde{Y}_i$ is the crisp interval $\left[(Y_i)_\alpha^L, (Y_i)_\alpha^U\right]$ solved from formulations (11) and (12). By enumerating different α values, the membership function $\mu_{\widetilde{Y}_i}$ can be constructed.

3.3. Proposed decision making algorithm

This subsection outlines the fuzzy multi-criteria group decision making algorithm based on the principles of 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 [9].

Bevilacqua et al. [9] used the QFD in supplier selection process. The algorithm proposed here differs from Bevilacqua et al.'s approach in several aspects. First, the proposed algorithm uses the fuzzy weighted average 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 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 [11].

The detailed stepwise representation of the proposed fuzzy MCDM algorithm that is also depicted in Fig. 2 is given below.

Step 1. Construct a decision-makers' committee of Z experts ($z = 1,2,\ldots,Z$). 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, and the fuzzy assessment to determine the CN–TA relationship scores.

Step 3. Let the fuzzy value assigned as the relationship score between the lth CN ($l = 1,2,\ldots,L$) and the kth TA ($k = 1,2,\ldots,K$), and importance weight of the lth CN for the zth decision-maker be $\widetilde{x}_{klz} = (x_{klz}^1, x_{klz}^2, x_{klz}^3)$ and

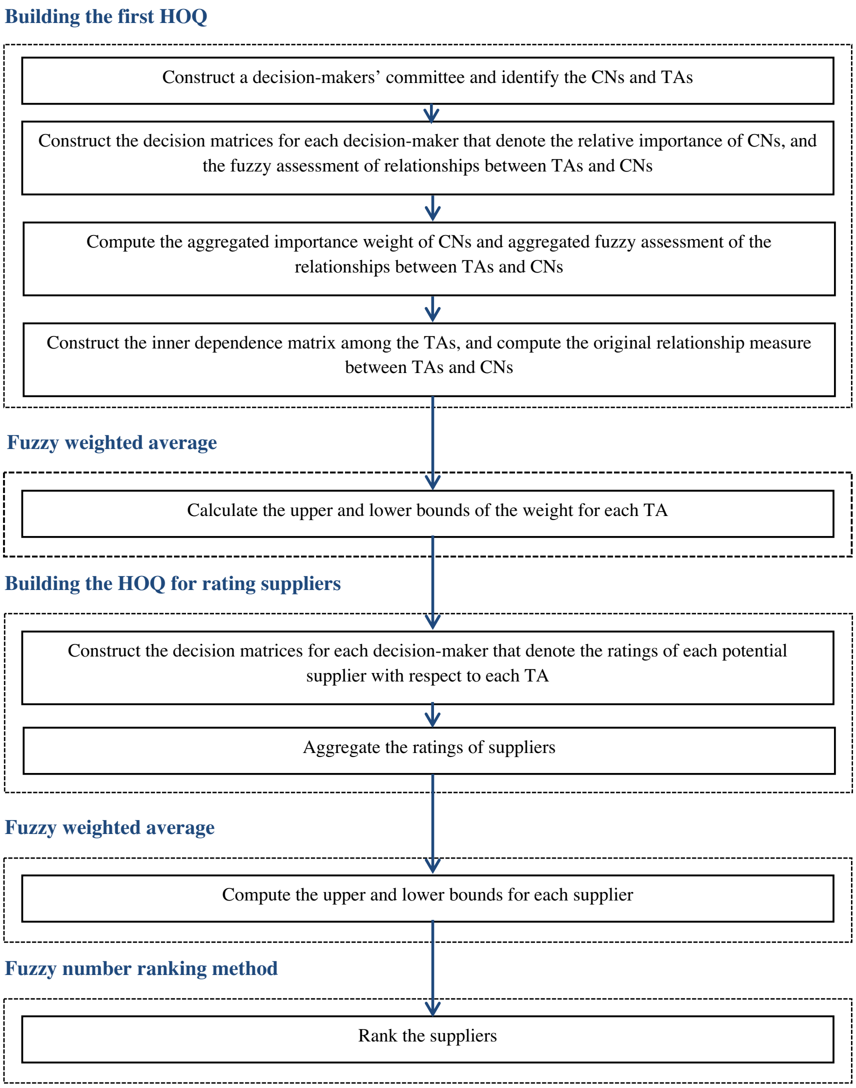

Fig. 2. Representation of the fuzzy MCDM algorithm.

$\widetilde{w}_{lz} = (w^1_{lz}, w^2_{lz}, w^3_{lz})$, respectively. Compute the aggregated fuzzy assessment of the relationship scores between the kth TA and the lth CN ($\widetilde{x}_{kl}$), and aggregated importance weight of the lth CN ($\widetilde{w}_l$) as follows:

$$\widetilde{x}_{kl} = \sum_{z=1}^{Z} \Omega_z \widetilde{x}_{klz} \tag{13}$$

$$\widetilde{w}_{l} = \sum_{z=1}^{Z} \Omega_z \widetilde{w}_{lz} \tag{14}$$

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

Step 4. Construct the inner dependence matrix among the TAs, and compute the original relationship measure between the kth TA and the lth CN, $\widetilde{X}^*_{kl}$. Let $D_{kk'}$ denote the degree of dependence of the kth TA on the k'th TA. Then, according to Fung et al. [45] and Tang et al. [46], the original relationship measure between the kth TA and the lth CN should be rewritten as

$$\widetilde{X}^*_{kl} = \sum_{k'=1}^{K} D_{kk'} \widetilde{x}_{k'l} \tag{15}$$

where $\widetilde{X}^*_{kl}$ is the actual relationship measure after consideration of the inner dependence among TAs. Note that the correlation matrix $\boldsymbol{D}$ is a symmetric matrix. A design requirement has the strongest dependence on itself, i.e. D_{kk} is assigned to be 1. If there is no dependence between the kth and the k'th TAs, then $D_{kk'} = 0$.

Step 5. Calculate the upper and lower bounds of the weight for each TA by employing formulations (11) and (12).

Step 6. Construct the decision matrices for each decision-maker that denote the ratings of each potential supplier with respect to each TA.

Step 7. Aggregate the ratings of suppliers using Eq. (13).

Step 8. Compute the upper and lower bounds for each supplier by utilizing formulations (11) and (12). This time, the relative importance expressed in formulations (11) and (12) are the upper and lower bounds of the weight for each TA calculated at Step 5.

Step 9. Rank the suppliers by employing Chen and Klein's [11] ranking algorithm, which can be summarized as follows:

Let $\widetilde{X}_1, \widetilde{X}_2, \ldots, \widetilde{X}_i, \ldots, \widetilde{X}_m$ be m arbitrary bounded fuzzy numbers, and h denote the maximum height of $\mu_{\widetilde{X}_i}$, $i = 1, 2, \ldots, m$. Suppose h is equally divided into s intervals such that $\alpha_p = ph/s$, $p = 0, 1, 2, \ldots, s$. Chen and Klein [11] devise the following index for ranking fuzzy numbers

$$I_i = \sum_{p=0}^{s}\left((X_i)_{\alpha_p}^{U} - c\right) \Big/ \left(\sum_{p=0}^{s}\left((X_i)_{\alpha_p}^{U} - c\right) - \sum_{p=0}^{s}\left((X_i)_{\alpha_p}^{L} - d\right)\right), \quad n \to \infty \tag{16}$$

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

4. Illustrative example

A supplier selection problem addressed in an earlier work by Bevilacqua et al. [9] is used to test the effectiveness of the proposed fuzzy MCDM framework. The problem can be summarized as follows.

The analysis is performed for the selection of clutch plate suppliers for a medium-to-large enterprise that manufactures complete clutch coupling. The main features sought in this component are an excellent design and a very accurate construction to ensure a trouble-free, smooth operation even at high production rates. There are 10 suppliers who are in contact with the company.

There are six fundamental characteristics (CNs) required of products or services purchased from outside suppliers by the company considered in this study. These can be listed as "product conformity", "cost", "punctuality of deliveries", "efficacy of corrective action", "programming of deliveries", and "availability and customer support".

Seven criteria relevant to supplier assessment are identified as "experience of the sector (EF)", "capacity for innovation to follow up the customer's evolution in terms of changes in its strategy and market (IN)", "quality system certification (SQ)", "flexibility of response to the customer's requests (FL)", "financial stability (FS)", "ability to manage orders on-line (RR)", and "geographical position (PG)".

The evaluation is conducted by a committee of three decision-makers. The decision-makers use the linguistic variables given in Table 1 to denote the level of importance of each CN and the impact of each TA on each CN as shown in Fig. 3, and the ratings of the suppliers with respect to each TA as provided in Table 2. The data related to supplier selection that

Table 1
Linguistic term set [9].

Very low (VL)	(0, 1, 2)
Low (L)	(2, 3, 4)
Medium (M)	(4, 5, 6)
High (H)	(6, 7, 8)
Very high (VH)	(8, 9, 10)

Technical Attributes / Customer Needs	EF	IN	SQ	FL	FS	RR	PG	Importance of Customer Needs
Conformity	(VH,H,H)	(VH,VH,VH)	(L,VL,VL)	(M,L,L)	(L,VL,VL)	(H,H,H)	(L,L,L)	(VH,VH,H)
Cost	(M,M,L)	(H,H,M)	(VH,VH,VH)	(L,L,L)	(M,M,M)	(L,L,VL)	(M,M,H)	(M,L,M)
Punctuality	(H,M,H)	(M,M,M)	(L,L,L)	(H,VH,VH)	(L,L,L)	(VH,VH,VH)	(H,H,H)	(H,M,M)
Efficacy	(H,H,VH)	(VH,VH,VH)	(M,L,L)	(H,VH,VH)	(L,L,L)	(M,VL,H)	(L,VL,VL)	(M,M,L)
Programming	(H,H,H)	(H,H,M)	(L,L,L)	(M,M,M)	(L,VL,VL)	(H,H,H)	(VL,VL,VL)	(L,VL,L)
Availability	(H,M,H)	(VH,VH,H)	(VL,L,L)	(H,VH,VH)	(M,M,M)	(H,H,VH)	(H,H,VH)	(M,L,L)

Fig. 3. First house of quality for the supplier selection problem.

Table 2
Ratings of suppliers with respect to TAs.

TAs	Suppliers									
	Sup 1	Sup 2	Sup 3	Sup 4	Sup 5	Sup 6	Sup 7	Sup 8	Sup 9	Sup 10
EF	(M,L,M)	(H,H,H)	(L,M,VL)	(M,M,L)	(VH,VH,VH)	(H,VH,VH)	(VL,L,VL)	(L,L,H)	(M,M,M)	(H,H,H)
IN	(L,M,L)	(H,M,M)	(VH,H,VH)	(H,H,H)	(VH,VH,VH)	(L,VL,L)	(M,M,M)	(M,H,M)	(H,H,H)	(VL,L,VL)
SQ	(M,L,M)	(M,M,H)	(VH,VH,H)	(VL,VL,L)	(VL,VL,VL)	(M,M,L)	(VH,VH,VH)	(H,H,H)	(M,M,L)	(M,M,H)
FL	(M,M,H)	(VH,VH,H)	(L,L,L)	(VL,VL,L)	(H,H,H)	(M,M,M)	(H,VH,VH)	(VL,VL,L)	(L,H,L)	(L,L,VL)
FS	(M,M,M)	(VH,VH,VH)	(L,L,L)	(H,H,H)	(M,M,L)	(H,H,VH)	(L,L,L)	(H,H,H)	(VL,VL,VL)	(VH,VH,H)
RR	(VL,L,L)	(VL,L,VL)	(VL,L,L)	(VL,VL,VL)	(L,L,M)	(VL,VL,VL)	(M,M,H)	(VH,VH,VH)	(VL,VL,L)	(VL,VL,M)
PG	(VL,M,L)	(L,L,M)	(VL,L,VL)	(VH,H,H)	(VL,VL,M)	(VL,VL,L)	(L,M,L)	(VL,VL,L)	(VL,VL,L)	(VL,VL,M)

Table 3
Aggregated importance of each CN.

Customer needs	Importance
Conformity	(7.333,8.333,9.333)
Cost	(3.333,4.333,5.333)
Punctuality	(4.667,5.667,6.667)
Efficacy	(3.333,4.333,5.333)
Programming	(1.333,2.333,3.333)
Availability	(2.667,3.667,4.667)

Table 4
Aggregated impact of each TA on each CN.

CNs	TAs						
	EF	IN	SQ	FL	FS	RR	PG
Conformity	(6.667,7.667,8.667)	(8,9,10)	(0.667,1.667,2.667)	(2.667,3.667,4.667)	(0.667,1.667,2.667)	(6,7,8)	(2,3,4)
Cost	(3.333,4.333,5.333)	(5.333,6.333,7.333)	(8,9,10)	(2,3,4)	(4,5,6)	(1.333,2.333,3.333)	(4.667,5.667,6.667)
Punctuality	(5.333,6.333,7.333)	(4,5,6)	(2,3,4)	(7.333,8.333,9.333)	(2,3,4)	(8,9,10)	(6,7,8)
Efficacy	(6.667,7.667,8.667)	(8,9,10)	(2.667,3.667,4.667)	(7.333,8.333,9.333)	(2,3,4)	(3.333,4.333,5.333)	(0.667,1.667,2.667)
Programming	(6,7,8)	(5.333,6.333,7.333)	(2,3,4)	(4,5,6)	(0.667,1.667,2.667)	(6,7,8)	(0,1,2)
Availability	(5.333,6.333,7.333)	(7.333,8.333,9.333)	(1.333,2.333,3.333)	(7.333,8.333,9.333)	(4,5,6)	(6.667,7.667,8.667)	(6.667,7.667,8.667)

Table 5
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
EF	$(Y_{EF})_\alpha^L$	5.488	5.607	5.726	5.844	5.963	6.081	6.2	6.319	6.437	6.556	6.674
	$(Y_{EF})_\alpha^U$	7.861	7.742	7.623	7.505	7.386	7.267	7.149	7.03	6.912	6.793	6.674
IN	$(Y_{IN})_\alpha^L$	6.201	6.332	6.462	6.592	6.722	6.853	6.983	7.113	7.243	7.373	7.504
	$(Y_{IN})_\alpha^U$	8.806	8.676	8.546	8.415	8.285	8.155	8.025	7.894	7.764	7.634	7.504
SQ	$(Y_{SQ})_\alpha^L$	2.217	2.347	2.478	2.608	2.739	2.871	3.003	3.135	3.268	3.401	3.535
	$(Y_{SQ})_\alpha^U$	4.919	4.775	4.633	4.491	4.351	4.213	4.075	3.939	3.804	3.669	3.535
FL	$(Y_{FL})_\alpha^L$	4.434	4.581	4.727	4.874	5.02	5.167	5.313	5.46	5.606	5.753	5.899
	$(Y_{FL})_\alpha^U$	7.364	7.218	7.071	6.925	6.778	6.632	6.485	6.339	6.192	6.046	5.899
FS	$(Y_{FS})_\alpha^L$	1.817	1.943	2.069	2.194	2.319	2.444	2.568	2.692	2.815	2.939	3.062
	$(Y_{FS})_\alpha^U$	4.317	4.19	4.063	3.937	3.811	3.685	3.56	3.435	3.31	3.186	3.062
RR	$(Y_{RR})_\alpha^L$	4.95	5.095	5.239	5.383	5.526	5.669	5.811	5.952	6.092	6.233	6.372
	$(Y_{RR})_\alpha^U$	7.739	7.605	7.47	7.334	7.198	7.062	6.925	6.788	6.65	6.511	6.372
PG	$(Y_{PG})_\alpha^L$	2.915	3.066	3.217	3.368	3.52	3.671	3.822	3.973	4.124	4.275	4.427
	$(Y_{PG})_\alpha^U$	5.938	5.787	5.636	5.485	5.334	5.182	5.031	4.88	4.729	4.578	4.427

are provided in the HOQ depicted in Fig. 3 and in Table 2 consist of assessments of three decision-makers employing linguistic variables represented in Table 1.

By using Eqs. (13) and (14), the decision-makers' evaluations are aggregated to obtain the aggregated importance of each CN and the aggregated impact of each TA on each CN. 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 Tables 3 and 4.

Table 6
Aggregated ratings of suppliers.

Suppliers	TAs						
	EF	IN	SQ	FL	FS	RR	PG
Sup 1	(3.333, 4.333,5.333)	(2.667, 3.667, 4.667)	(3.333, 4.333, 5.333)	(4.667, 5.667, 6.667)	(4.000, 5.000, 6.000)	(1.333, 2.333, 3.333)	(2.000, 3.000, 4.000)
Sup 2	(6.000, 7.000, 8.000)	(4.667, 5.667, 6.667)	(4.667, 5.667, 6.667)	(7.333, 8.333, 9.333)	(8.000, 9.000, 10.000)	(0.667, 1.667, 2.667)	(2.667, 3.667, 4.667)
Sup 3	(2.000, 3.000, 4.000)	(7.333, 8.333, 9.333)	(7.333, 8.333, 9.333)	(2.000, 3.000, 4.000)	(2.000, 3.000, 4.000)	(1.333, 2.333, 3.333)	(0.667, 1.667, 2.667)
Sup 4	(3.333, 4.333, 5.333)	(6.000, 7.000, 8.000)	(0.667, 1.667, 2.667)	(0.667, 1.667, 2.667)	(6.000, 7.000, 8.000)	(0.000, 1.000, 2.000)	(6.667, 7.667, 8.667)
Sup 5	(8.000, 9.000, 10.000)	(8.000, 9.000, 10.000)	(0.000, 1.000, 2.000)	(6.000, 7.000, 8.000)	(3.333, 4.333, 5.333)	(2.667, 3.667, 4.667)	(1.333, 2.333, 3.333)
Sup 6	(7.333, 8.333, 9.333)	(1.333, 2.333, 3.333)	(3.333, 4.333, 5.333)	(4.000, 5.000, 6.000)	(6.667, 7.667, 8.667)	(0.000, 1.000, 2.000)	(0.667, 1.667, 2.667)
Sup 7	(0.667, 1.667, 2.667)	(4.000, 5.000, 6.000)	(8.000, 9.000, 10.000)	(7.333, 8.333, 9.333)	(2.000, 3.000, 4.000)	(4.667, 5.667, 6.667)	(2.667, 3.667, 4.667)
Sup 8	(3.333, 4.333, 5.333)	(4.667, 5.667, 6.667)	(6.000, 7.000, 8.000)	(0.667, 1.667, 2.667)	(6.000, 7.000, 8.000)	(8.000, 9.000, 10.000)	(0.667, 1.667, 2.667)
Sup 9	(4.000, 5.000, 6.000)	(6.000, 7.000, 8.000)	(3.333, 4.333, 5.333)	(3.333, 4.333, 5.333)	(0.000, 1.000, 2.000)	(0.667, 1.667, 2.667)	(0.667, 1.667, 2.667)
Sup 10	(6.000, 7.000, 8.000)	(0.667, 1.667, 2.667)	(4.667, 5.667, 6.667)	(1.333, 2.333, 3.333)	(7.333, 8.333, 9.333)	(1.333, 2.333, 3.333)	(1.333, 2.333, 3.333)

In the supplier selection problem presented in Bevilacqua et al. [9], inner dependencies among the TAs do not exist. Thus, the aggregated impact of each TA on each CN is equivalent to the original relationship measure between TAs and CNs.

The upper and lower bounds of the weight of TAs are calculated through formulations (11) and (12) as represented in Table 5.

The ratings of suppliers are aggregated by employing Eq. (13). The results are shown in Table 6.

By utilizing formulations (11) and (12), the upper and lower bounds for supplier ratings are calculated as given in Table 7.

Finally, the ranking index (I) for each supplier is computed employing Eq. (16). The ranking indices are $I(\text{sup}1) = 0.350$, $I(\text{sup}2) = 0.608$, $I(\text{sup}3) = 0.410$, $I(\text{sup}4) = 0.399$, $I(\text{sup}5) = 0.632$, $I(\text{sup}6) = 0.383$, $I(\text{sup}7) = 0.523$, $I(\text{sup}8) = 0.526$, $I(\text{sup}9) = 0.351$, and $I(\text{sup}10) = 0.340$. Hence, the ranking order of the suppliers is Sup5 $\succ$ Sup2 $\succ$ Sup8 $\succ$ Sup7 $\succ$ Sup3 $\succ$ Sup4 $\succ$ Sup6 $\succ$ Sup9 $\succ$ Sup1 $\succ$ Sup10.

In here, the results of the proposed decision algorithm are compared with the results obtained by Bevilacqua et al. [9]. Table 8 summarizes the results obtained from these two alternative procedures. We observe that supplier 5 is determined

Table 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	$(Y_{\text{sup1}})^L_\alpha$	2.726	2.850	2.975	3.099	3.223	3.348	3.472	3.596	3.719	3.843	3.967
	$(Y_{\text{sup1}})^U_\alpha$	5.198	5.075	4.952	4.829	4.706	4.583	4.460	4.337	4.214	4.090	3.967
Sup 2	$(Y_{\text{sup2}})^L_\alpha$	4.146	4.304	4.461	4.617	4.772	4.926	5.079	5.231	5.381	5.531	5.680
	$(Y_{\text{sup2}})^U_\alpha$	7.194	7.040	6.886	6.734	6.582	6.430	6.279	6.128	5.978	5.829	5.680
Sup 3	$(Y_{\text{sup3}})^L_\alpha$	2.764	2.913	3.062	3.213	3.364	3.517	3.671	3.827	3.983	4.141	4.300
	$(Y_{\text{sup3}})^U_\alpha$	5.978	5.804	5.630	5.457	5.287	5.118	4.951	4.786	4.623	4.461	4.300
Sup 4	$(Y_{\text{sup4}})^L_\alpha$	2.580	2.748	2.916	3.083	3.250	3.416	3.582	3.747	3.912	4.077	4.241
	$(Y_{\text{sup4}})^U_\alpha$	5.902	5.733	5.565	5.398	5.231	5.065	4.899	4.734	4.569	4.405	4.241
Sup 5	$(Y_{\text{sup5}})^L_\alpha$	4.177	4.343	4.509	4.676	4.843	5.011	5.179	5.347	5.516	5.685	5.855
	$(Y_{\text{sup5}})^U_\alpha$	7.585	7.409	7.234	7.059	6.885	6.712	6.539	6.367	6.196	6.025	5.855
Sup 6	$(Y_{\text{sup6}})^L_\alpha$	2.557	2.717	2.877	3.036	3.194	3.353	3.511	3.669	3.826	3.984	4.141
	$(Y_{\text{sup6}})^U_\alpha$	5.726	5.565	5.404	5.244	5.084	4.925	4.767	4.610	4.454	4.298	4.141
Sup 7	$(Y_{\text{sup7}})^L_\alpha$	3.560	3.716	3.872	4.027	4.182	4.336	4.490	4.643	4.796	4.948	5.101
	$(Y_{\text{sup7}})^U_\alpha$	6.647	6.490	6.334	6.178	6.023	5.868	5.714	5.560	5.407	5.254	5.101
Sup 8	$(Y_{\text{sup8}})^L_\alpha$	3.516	3.680	3.842	4.005	4.167	4.328	4.489	4.650	4.810	4.969	5.129
	$(Y_{\text{sup8}})^U_\alpha$	6.706	6.547	6.391	6.234	6.077	5.920	5.762	5.604	5.446	5.288	5.129
Sup 9	$(Y_{\text{sup9}})^L_\alpha$	2.489	2.636	2.783	2.929	3.075	3.221	3.366	3.511	3.656	3.801	3.945
	$(Y_{\text{sup9}})^U_\alpha$	5.385	5.235	5.092	4.950	4.807	4.663	4.520	4.377	4.233	4.089	3.945
Sup 10	$(Y_{\text{sup10}})^L_\alpha$	2.299	2.451	2.603	2.755	2.908	3.061	3.215	3.369	3.524	3.680	3.836
	$(Y_{\text{sup10}})^U_\alpha$	5.436	5.272	5.110	4.948	4.787	4.626	4.467	4.308	4.150	3.992	3.836

Table 8
Comparative rankings of the suppliers using the proposed algorithm and Bevilacqua et al.'s algorithm.

Suppliers	Ranking index values of the proposed algorithm	Rank	Bevilacqua et al.'s algorithm	
			Rank obtained using fuzzy suitability index	Rank obtained using defuzzification
Sup 1	0.350	9	Incomparable	8
Sup 2	0.608	2	2	2
Sup 3	0.410	5	5	5
Sup 4	0.399	6	6	6
Sup 5	0.632	1	1	1
Sup 6	0.383	7	7	7
Sup 7	0.523	4	4	4
Sup 8	0.526	3	3	3
Sup 9	0.351	8	Incomparable	9
Sup 10	0.340	10	Incomparable	10

as the most suitable supplier by the two methods, which is followed by supplier 2 and then by supplier 8 and supplier 7. The fuzzy ranking principle of Bevilacqua et al. [9] cannot compare suppliers 1, 9, and 10, while the algorithm proposed in this study provides a complete ranking of all suppliers. This is due to the minimization of the loss of information by using the fuzzy weighted average method and the higher discriminating power of the fuzzy number ranking method employed in this paper. Further, Bevilacqua et al. [9] implemented a fuzzy number defuzzification scheme to obtain a complete ranking of the suppliers, which also identifies supplier 5 as the most appropriate supplier. However, defuzzification approaches suffer from the limitation of associating each fuzzy quantity with only one real number. Freeling [47] pointed out that by reducing the whole analysis to a single number, much of the information which has been intentionally kept throughout calculations is lost. Thus, defuzzification basically contradicts with the key objective of minimizing the loss of information throughout the analysis.

5. Conclusions

Supplier selection is an important multi-criteria group decision making problem, which possesses the need to evaluate multiple criteria incorporating vagueness and imprecision with the involvement of a group of experts. 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 paper, a fuzzy multi-criteria group decision making algorithm is presented to rectify the problems encountered when using classical decision making methods in supplier selection.

The procedure used in this paper considers the QFD planning, which incorporates two interrelated HOQ matrices, as a fuzzy multi-criteria group decision tool and employs FWA method to calculate the upper and lower bounds of the weights of supplier selection criteria and the ratings of the 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 [11].

The proposed methodology possesses a number of merits compared to other MCDM techniques presented in the literature for supplier selection. First, the developed method is a group decision making process which enables the group to identify and better appreciate the differences and similarities of their judgments. Second, the proposed approach is apt to incorporate imprecise data into the analysis using fuzzy set theory. Third, this methodology enables to consider the impacts of relationships among the purchased product features and supplier selection criteria, and also the inner dependence among supplier selection criteria for achieving higher satisfaction to meet company's requirements. Fourth, in order to calculate the upper and lower bounds of the weights of the supplier selection criteria and the supplier assessments, the proposed method uses the fuzzy weighted average method that rectifies the problem of loss of information that occurs when integrating imprecise and subjective information. Thus, it is likely to produce more realistic overall desirability levels. Finally, the proposed approach employs a fuzzy number ranking method based on area measurement, which has a high ability to discriminate among the fuzzy numbers to be ranked. Future research will focus on applying the decision framework presented in here to real-world group decision making problems in diverse disciplines that can be represented in a HOQ structure.

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