An integrated fuzzy MCDM approach for supplier evaluation and selection

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A fuzzy multi-criteria group decision making approach that makes use of quality function deployment (QFD), fusion of fuzzy information and 2-tuple linguistic representation model is developed for supplier selection. The proposed methodology seeks to establish the relevant supplier assessment criteria while also considering the impacts of inner dependence among them. Two interrelated house of quality matrices are constructed, and fusion of fuzzy information and 2-tuple linguistic representation model are employed to compute the weights of supplier selection criteria and subsequently the ratings of suppliers. The proposed method is apt to manage non-homogeneous information in a decision setting with multiple information sources. The decision framework presented in this paper employs ordered weighted averaging (OWA) operator, and the aggregation process is based on combining information by means of fuzzy sets on a basic linguistic term set. The proposed framework is illustrated through a case study conducted in a private hospital in Istanbul.

Keywords: supplier selection; quality function deployment; multi-criteria decision making; decision support; fuzzy methods; 2-tuple linguistic representation

1. Introduction

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). 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).

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.

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.

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. In a study which has become a reference for the majority of papers on supplier selection, Dickson (1966) identified 23 supplier attributes that managers consider when choosing a supplier.

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).

Most of the research studies in the area of supplier selection have focused on determining the best supplier to supply all needed items. At the final choice stage, the ultimate supplier is identified while considering the system's constraints and taking into account various quantitative and/or qualitative criteria.

According to the vast literature on supplier selection, the following properties need to be considered while resolving the supplier selection problem (Chen et al., 2006). First, the supplier selection process requires considering multiple conflicting criteria. Second, several decision-makers are oftentimes involved in the decision process. Third, decision-making is often influenced by uncertainty in practice. With its need to trade-off multiple criteria exhibiting vagueness and imprecision, supplier selection is a highly important multi-criteria decision making (MCDM) problem. The classical MCDM methods that consider deterministic or random processes cannot effectively address decision problems incorporating imprecise and linguistic information. Fuzzy set theory is one of the effective tools to deal with uncertainty and vagueness.

The objective of this study is to propose a fuzzy multi-criteria group decision making approach based on the quality function deployment (QFD) methodology, fusion of fuzzy information, and 2-tuple linguistic representation model 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 (Bevilacqua et al., 2006). Achieving these objectives depends largely on considering not only the relationships between purchased product features and supplier assessment criteria, but 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 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. Fusion of fuzzy information approach is used to manage information assessed using different linguistic scales. In this context, first the non-homogeneous fuzzy information is made uniform using a linguistic term set as the uniform representation base, called basic linguistic term set (BLTS). This approach enables the sources that participate in the decision process express their judgments by means of information of a different nature according to their preferences (Herrera et al., 2000). The collective performance values of the alternatives that are also fuzzy sets on BLTS are obtained by means of an aggregation operator.

In this paper, ordered weighted averaging (OWA) operator is employed as the aggregation operator. This operator provides an aggregation which lies in between the "and" requiring all the criteria to be satisfied, and the "or" requiring at least one criterion to be satisfied. OWA operator differs from the classical weighted average in that coefficients are ibute but rather to an ordered position. The aggregation process is based on combining information by means of fuzzy sets on BLTS. Then, the collective preference values are transformed into linguistic 2-tuples which enable to calculate both the weights of supplier selection criteria and the ratings of suppliers using the QFD methodology that incorporates interrelated HOQ matrices. The 2-tuple fuzzy linguistic approach inherits the existing characters of fuzzy linguistic assessment, and it also rectifies the problem of loss of information of other fuzzy linguistic approaches (Herrera-Viedma et al., 2004).

The rest of the paper is organized as follows: The following section presents a brief literature review on supplier selection. In Section 3, a concise treatment of the basic concepts of QFD is presented. Section 4 and Section 5 delineate the fusion of fuzzy information approach and 2-tuple fuzzy linguistic representation model, respectively. Section 6 presents the developed decision making approach and provides its stepwise representation. The implementation of the proposed framework for evaluating medical suppliers of a private hospital in Istanbul is provided in Section 7. Finally, concluding observations and directions for future research are given in the last section.

2. Literature review

Supplier evaluation is a management decision-making process that addresses how organizations select strategic suppliers to enhance their competitive advantage. 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. Among these criteria, quality, on-time delivery, and performance history were noted as the most significant ones. 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 between 1966 and 1990 according to the considered criteria. Based on 74 papers, they concluded that supplier selection is a multi-criteria problem, and price, delivery, quality, and production facility and location are the most frequently employed criteria.

In light of the multi-criteria nature of supplier selection problem, it would appear that the application of MCDM techniques to the problem is a fruitful area of research. Such techniques would allow purchasers to systematically examine the trade-offs among various criteria when selecting specific suppliers. 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 in supplier selection decisions. 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. This section will briefly review the research works on supplier selection that employ fuzzy MCDM techniques and QFD-based methods.

Several authors have used fuzzy MCDM techniques such as fuzzy analytic hierarchy process (AHP), fuzzy analytic network process (ANP), fuzzy technique for order preference by similarity to ideal solution (TOPSIS), fuzzy multi-criteria optimization and compromise solution (VIKOR), fuzzy preference-ranking-organization-method-for-enrichment-of-evaluation (PROMETHEE), fuzzy suitability index, 2-tuple fuzzy linguistic representation model, and grey approach. Bevilacqua and Petroni (2002) proposed a methodology for supplier selection based on the use of fuzzy suitability index. 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. Benefiting from TOPSIS, Chen et al. (2006) developed a methodology for solving supplier selection problems in fuzzy environment. 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) employed a fuzzy modified AHP approach to select the best global supplier. Wang (2008) used 2-tuple fuzzy linguistic representation model to determine the overall supplier performance with dynamic supply behaviors. 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. Kavita et al. (2009) extended TOPSIS for interval-valued intuitionistic fuzzy data. Wang (2010) developed a model based on 2-tuple fuzzy linguistic representation model to evaluate the supplier performance. Vinodh et al. (2011) utilized fuzzy ANP for supplier selection process and presented a case study in an electronics switches manufacturing company. Recently, Baskaran et al. (2012) evaluated the Indian textile and clothing industry suppliers employing grey approach. The sustainability criteria are considered in the evaluation process. Chu and Varma (2012) suggested a hierarchical MCDM model under fuzzy environment to evaluate and select suppliers. Govindan et al. (2013) employed fuzzy TOPSIS for supplier selection considering environmental, social, and economic aspects of supplier

fuzzy hierarchical TOPSIS for evaluating suppliers in detergent production industry. Lately, Junior et al. (2014) applied fuzzy TOPSIS and fuzzy AHP to supplier selection problem and compared the obtained results.

Integrated MCDM techniques based approaches have also been developed to select the most appropriate supplier. Haq and Kannan (2006) proposed an integrated supplier selection and multi-echelon distribution inventory model utilizing fuzzy AHP and genetic algorithm (GA). Sevkli et al. (2008) developed a supplier selection approach that integrates AHP and fuzzy linear programming. 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) presented a hierarchical supplier evaluation framework combining ANP and Choquet integral. Razmi et al. (2009) proposed a hybrid model based on ANP to evaluate and select supplier under fuzzy environment. The proposed approach was enhanced with a non-linear programming model to elicit weights of comparisons from comparison matrices in the ANP structure. Ordoobadi (2010) combined Taguchi loss function and AHP to develop a decision making model for the selection of the appropriate supplier. 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. Chen and Yang (2011) combined constrained fuzzy AHP and fuzzy TOPSIS for supplier selection. Liao and Kao (2011) proposed an integrated fuzzy TOPSIS and multi-choice goal programming model to solve multi-sourcing *et al.* (2013) proposed a structured decision model for evaluating suppliers by integrating fuzzy AHP and grey relational analysis. Rodriguez *et al.* (2013) proposed a combination of AHP and TOPSIS in fuzzy environment for the selection of customized equipment suppliers. Shidpour et al. (2013) integrated fuzzy AHP, TOPSIS and multi-objective linear programming to determine the most appropriate configuration product design, assembly process, and supplier of components in the new product development process. In a recent work, Singh (2014) combined TOPSIS and mixed linear integer programming for supplier selection and order allocation problem. Hashemian et al. (2014) integrated fuzzy AHP and fuzzy PROMETHEE for supplier evaluation. Fuzzy AHP was used to determine the weight of the criteria and fuzzy PROMETHEE was employed for obtaining the final ranking of suppliers.

Lately, a few researchers have employed QFD in supplier selection. 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) developed a supplier selection methodology based on QFD and data mining techniques. 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 account for 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. Ho et al. (2011) developed a combined QFD and AHP approach to measure the performance of alternative suppliers. Soroor et al. (2012) proposed a hybrid model, which implements fuzzy AHP and QFD to provide an intelligent solution to evaluate suppliers. In a recent work, Alinezad *et al.* (2013) proposed a methodology for selecting the vendors in pharmaceutical company. QFD was employed for selecting the vendors, where fuzzy AHP was used to determine the importance weights in QFD.

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, fusion of fuzzy information, and 2-tuple linguistic representation model is developed. The weights of supplier selection criteria and the final ranking of suppliers are obtained benefiting from QFD methodology using interrelated HOQ matrices. The proposed approach uses the fusion method to manage information assessed using multi-granular linguistic information. The non-homogeneous information provided by decision-makers is unified into a specific linguistic domain, named BLTS. The collective performance values that are also fuzzy sets on BLTS are obtained via OWA operator. Then, the collective preference values are transformed into linguistic 2-tuples.

3. Quality function deployment

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.

In order to remain competitive in the global market, the improvement of mature-period product in a short time and at a minimum cost is one of the key factors. As far as the decisions for mature-period product improvement are concerned, the use of QFD has gained extensive international support for helping decision-making in product planning and improvement (Li et al., 2011).

QFD is a crucial product development method dedicated to translating customer requirements into activities to develop products and services (Carnevelli & 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 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 customer needs, and thus, helps to decrease production costs and reduce 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 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). In this paper, we focus on the first and the most widely used of the four matrices, also called the house of quality (HOQ). Relationships between CNs and TAs and among the TAs are defined by answering a specific question corresponding to each cell in HOQ. The HOQ contains seven elements as shown in Figure 1.

[Insert Figure 1 about here]

The elements of the HOQ shown in Figure 1 can be briefly described as follows:

(1) CNs: They are also known as customer attributes, customer requirements or demanded quality. The initial step in constructing the HOQ includes determining, clarifying, and specifying the customer needs. As the initial input for the HOQ, the CNs highlight the product

characteristics that should be paid attention to. The purpose of this step is to capture the "voice of the customer".

(2) 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). In this paper, linguistic variables are used to denote the relationships between CNs and TAs.

(5) Competitive assessment matrix: Understanding how customers rate the competition can be a tremendous competitive advantage. The required information can be acquired through 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.

4. 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). In any linguistic approach, a crucial task for dealing with linguistic information is to determine the "granularity of uncertainty", i.e., the level of discrimination among different counts of uncertainty (Herrera and Martinez, 2000a). In group decision making problems, depending on their cultural and educational backgrounds, experts can have different uncertainty degrees in qualifying a phenomenon. Thus, the linguistic term set chosen to provide their knowledge will have more or less terms. When different experts have different uncertainty degrees over the alternatives, then the linguistic information that manages the problem is assessed in different linguistic domains with different granularity (Herrera and Martínez, 2001). The linguistic term set with small cardinality is useful for experts to express their clear assessment information whereas the linguistic term set with large cardinality presents experts more choices to express their assessment information. Hence, the research on group decision making problems with multi-granularity linguistic information is essential in modeling real world problems (Jiang et al., 2008).

Fusion approach of fuzzy information 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.

4.1. 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

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

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).

4.2. 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 altern
information source (Herrera et al., 2000). This collective performance value is a new fuzzy set defined on a BLTS.

This paper employs ordered weighted averaging (OWA) operator, initially proposed by Yager (1988), as the aggregation operator. 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

$$F(a_1, a_2, ..., a_n) = \mathbf{w}\mathbf{b}^T = \sum_{i=1}^{n} w_i b_i \tag{2}$$

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 $\mathbf{b}$ is the associated ordered value vector where $b_i \in \mathbf{b}$ is the ith 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

$$w_i = Q(i/n) - Q((i-1)/n), \quad i = 1,\ldots,n \tag{3}$$

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

$$Q(y) = \begin{cases} 0 & , y < a, \\ \dfrac{y-a}{b-a} & , a \le y \le b, \\ 1 & , y > b, \end{cases} \tag{4}$$

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.

5. 2-tuple fuzzy linguistic representation model

The 2-tuple linguistic model that was presented by Herrera and Martínez (2000b) 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 1 (Herrera & Martínez, 2000a)**:** 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

$$\chi : F(S_T) - [0, g],$$
$$\chi(F(S_T)) = \chi(\{(s_j, \gamma_j), j = 0,1,..., g\}) = \frac{\sum_{j=0}^{g} j\gamma_j}{\sum_{j=0}^{g} \gamma_j} = \beta \tag{5}$$

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

Definition 2 (Herrera & Martínez, 2000b)**:** 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:

$$\Delta : [0, g] \to S \times [-0.5, 0.5),$$
$$\Delta(\beta) = \begin{cases} s_i, & i = \text{round}(\beta) \\ \alpha = \beta - i, & \alpha \in [-0.5, 0.5) \end{cases} \tag{6}$$

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 1 (Herrera & Martínez, 2000b)**:** 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

$$\Delta^{-1} : S \times [-0.5, 0.5) \to [0, g],$$
$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta \tag{7}$$

Definition 3 (Herrera-Viedma et al., 2004)**:** Let $x = \{(s_1, \alpha_1),...,(s_n, \alpha_n)\}$ be a set of linguistic 2-tuples and $W = \{w_1,..., w_n\}$ be their associated weights. The 2-tuple weighted average $\bar{x}^w$ is computed as

$$\bar{x}^w[(s_1,\alpha_1),...,(s_n,\alpha_n)] = \Delta\left(\frac{\sum_{i=1}^{n}\Delta^{-1}(s_i,\alpha_i).w_i}{\sum_{i=1}^{n}w_i}\right) = \Delta\left(\frac{\sum_{i=1}^{n}\beta_i.w_i}{\sum_{i=1}^{n}w_i}\right) \tag{8}$$

Definition 4 (Herrera-Viedma et al., 2004, Wang, 2010)**:** Let $x = \{(s_1, \alpha_1),...,(s_n, \alpha_n)\}$ be a set of linguistic 2-tuples and $W = \{(w_1, \alpha_1^w),...,(w_n, \alpha_n^w)\}$ be their linguistic 2-tuple associated weights. The 2-tuple linguistic weighted average $\bar{x}_l^w$ is calculated with the following function:

$$\bar{x}_l^w\left(\left[(s_1,\alpha_1),\left(w_1,\alpha_1^w\right)\right]..\left[(s_n,\alpha_n),\left(w_n,\alpha_n^w\right)\right]\right) = \Delta\left(\frac{\sum_{i=1}^{n}\beta_i.\beta_{w_i}}{\sum_{i=1}^{n}\beta_{w_i}}\right) \tag{9}$$

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

6. Proposed decision making algorithm

This section outlines the fuzzy multi-criteria group decision making algorithm that builds on fuzzy QFD, fusion of fuzzy information approach, and 2-tuple linguistic representation model. 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 proposed algorithm computes the weights of supplier selection criteria and the ratings of suppliers using two interrelated HOQ matrices as depicted in Figure 2. Furthermore, 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.

[Insert Figure 2 about here]

The detailed stepwise representation of the proposed fuzzy MCDM algorithm 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 fuzzy assessment to determine the CN-TA relationship scores, the relative importance of CNs, and the degree of dependencies among the TAs.

Step 3. Let the fuzzy value assigned as the relationship score between the lth CN $(l = 1,2,...,L)$ and kth TA $(k = 1,2,...,K)$, importance weight of the lth CN, and degree of dependence of the kth TA on the k'th TA for the zth decision-maker be $\tilde{x}_{klz} = (x_{klz}^1, x_{klz}^2, x_{klz}^3)$, $\tilde{w}_{lz} = (w_{lz}^1, w_{lz}^2, w_{lz}^3)$, and $\tilde{r}_{kk'z} = \left(r_{kk'z}^1, r_{kk'z}^2, r_{kk'z}^3\right)$, respectively. Convert $\tilde{x}_{klz}$, $\tilde{w}_{lz}$, and $\tilde{r}_{kk'z}$ into the basic linguistic scale S_T by using Equation (1). The fuzzy assessment vector on S_T, the importance weight vector on S_T, and the degree of dependence vector on S_T, which are respectively denoted as $F(\tilde{x}_{klz})$, $F(\tilde{w}_{lz})$, and $F(\tilde{r}_{kk'z})$, can be represented as

$$F(\tilde{x}_{klz}) = (\gamma(\tilde{x}_{klz}, s_0), \gamma(\tilde{x}_{klz}, s_1), ..., \gamma(\tilde{x}_{klz}, s_8)), \quad \forall k, l, z \tag{10}$$

$$F(\tilde{w}_{lz}) = (\gamma(\tilde{w}_{lz}, s_0), \gamma(\tilde{w}_{lz}, s_1), ..., \gamma(\tilde{w}_{lz}, s_8)), \quad \forall l, z \tag{11}$$

$$F(\tilde{r}_{kk'z}) = (\gamma(\tilde{r}_{kk'z}, s_0), \gamma(\tilde{r}_{kk'z}, s_1), ..., \gamma(\tilde{r}_{kk'z}, s_8)), \quad \forall k, k', z \tag{12}$$

In this study, the label set given in Table 1 is used as the BLTS (Jiang et al., 2008).

[Insert Table 1 about here]

Step 4. Aggregate $F(\tilde{x}_{klz})$, $F(\tilde{w}_{lz})$, and $F(\tilde{r}_{kk'z})$ to yield the fuzzy assessment vector $F(\tilde{x}_{kl})$, the importance weight vector $F(\tilde{w}_l)$, and the degree of dependence vector $F(\tilde{r}_{kk'})$. The aggregated parameters obtained from the assessment data of Z experts can be calculated using Equation (2) as follows:

$$\tilde{x}_{kl}(s_m) = \phi_Q(\gamma(\tilde{x}_{kl1}, s_m), \gamma(\tilde{x}_{kl2}, s_m), \ldots, \gamma(\tilde{x}_{klz}, s_m)),\ \forall k, l, m \tag{13}$$

$$\tilde{w}_l(s_m) = \phi_Q(\gamma(\tilde{w}_{l1}, s_m), \gamma(\tilde{w}_{l2}, s_m), \ldots, \gamma(\tilde{w}_{lz}, s_m)),\ \forall l, m \tag{14}$$

$$\tilde{r}_{kk'}(s_m) = \phi_Q(\gamma(\tilde{r}_{kk'1}, s_m), \gamma(\tilde{r}_{kk'2}, s_m), \ldots, \gamma(\tilde{r}_{kk'z}, s_m)),\ \forall k, k', m \tag{15}$$

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

$$F(\tilde{x}_{kl}) = (\gamma(\tilde{x}_{kl}, s_0), \gamma(\tilde{x}_{kl}, s_1), \ldots, \gamma(\tilde{x}_{kl}, s_8)),\ \forall k, l \tag{16}$$

$$F(\tilde{w}_l) = (\gamma(\tilde{w}_l, s_0), \gamma(\tilde{w}_l, s_1), \ldots, \gamma(\tilde{w}_l, s_8)),\ \forall l \tag{17}$$

$$F(\tilde{r}_{kk'}) = (\gamma(\tilde{r}_{kk'}, s_0), \gamma(\tilde{r}_{kk'}, s_1), \ldots, \gamma(\tilde{r}_{kk'}, s_8)),\ \forall k, k' \tag{18}$$

Step 5. Compute the β values of $F(\tilde{x}_{kl})$, $F(\tilde{w}_l)$ and $F(\tilde{r}_{kk'})$, and transform these values into linguistic 2-tuples by using formulations (5) and (6), respectively.

Step 6. Compute the original relationship measure between the kth TA and the lth CN, $\tilde{X}^*_{kl}$. Let $D_{kk'}$ denote the degree of dependence of the kth TA on the k'th TA. According to Fung et al. (2002) and Tang et al. (2002), the original relationship measure between the kth TA and the lth CN should be rewritten as

$$\tilde{X}^{*}_{kl} = \sum_{k'=1}^{K} D_{kk'} \tilde{x}_{k'l} \tag{19}$$

where $\tilde{X}^{*}_{kl}$ is the original relationship measure after consideration of the inner dependence among TAs. Note that the correlation matrix **D** is symmetric. 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 *k*th and the k'th TAs, then $D_{kk'} = 0$.

Benefiting from Equation (19), 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 5.

7. Case study

Growing health expenditures, increased quality and competition in the health sector require hospitals to use their resources efficiently. In order to illustrate the application of the proposed decision making method to medical supplier selection problem, a case study conducted in a private hospital on the Asian side of Istanbul is presented (Dursun Usta, 2013). The hospital operates with all major departments, and also includes facilities such as clinical laboratories, emergency service, intensive care units and operating room. First, through interviewing the experts from the purchasing department of the hospital, the existing purchasing process of the hospital was reviewed and analyzed, and the problems encountered in supplier selection were discussed. It was reported that the purchasing department considered only three major supplier selection criteria, which were cost, quality, and delivery, and the suppliers were evaluated on the basis of mean scores of these criteria values. The hospital manager has been seeking to improve the purchasing process in order to sharpen the hospital's competitive edge in the sector. As a result of discussions with experts, five fundamental characteristics required of products purchased from medical suppliers (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)”.

Determining the most preferred supplier depends on a number of distinct features. Benefiting from the literature on the evaluation of suppliers, nine 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) that includes purchasing manager of the hospital, two field experts from administrative personnel, and a doctor and a nurse from the emergency service of the hospital, who have all been working for more than three years in the case hospital. A questionnaire is prepared concerning the evaluation of characteristics required of products purchased from medical suppliers, supplier assessment criteria and supplier alternatives. The experts are asked to provide their opinions on the importance weights 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. DM_1, DM_2 and DM_3 used the linguistic term set very low (VL), low (L), moderate (M), high (H) and very high (VH) as shown in Figure 3, whereas DM_4 and DM_5, who have medical expertise and thus different backgrounds compared with other decision-makers, preferred to use a different linguistic term set with more choices to express their assessment information including definitely low (DL), very low (VL), low (L), moderate (M), high (H), very high (VH) and definitely high (DH) as depicted in Figure 4.

[Insert Figure 3 about here]

[Insert Figure 4 about here]

The data related to medical supplier selection that is provided in the HOQ depicted in Figure 5 and in Table 2 consist of assessments of five decision-makers employing linguistic variables defined in Figures 3 and 4.

[Insert Figure 5 about here]

[Insert Table 2 about here]

The computational procedure 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 (10)-(12). Next, by using the linguistic quantifier 'most' and the formulations (3) and (4), the OWA weights for five decision-makers are computed as $\mathbf{w} = (0, 0.2, 0.4, 0.4, 0)$. Then, the fuzzy assessment with respect to the impact of each TA on each CN, the importance of CNs, and the dependencies among TAs converted into the BLTS are aggregated employing formulations (13)-(18). The β values of these ratings, importance, and dependencies are computed and transformed into linguistic 2-tuples via formulations (5) and (6) as delineated in Figure 6.

[Insert Figure 6 about here]

The original relationship measure between TAs and CNs is computed employing Equation (19) and 2-tuple linguistic weighted average. Then, the 2-tuple linguistic weighted averages for each TA are calculated. The results are represented in Table 3.

[Insert Table 3 about here]

The ratings of each supplier converted into the BLTS are aggregated and transformed into linguistic 2-tuples as in Table 4.

[Insert Table 4 about here]

Finally, the 2-tuple linguistic weighted average for each supplier is computed and the suppliers are ranked as shown in Table 5. 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.

[Insert Table 5 about here]

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. Prior to our analysis, the hospital has been working with suppliers 7, 1 and 2 using their own evaluation system. The results obtained from the proposed decision making approach are similar to the findings from real life selection of suppliers by the hospital, which has demonstrated the robustness of the methodology and promoted its use as a decision aid for further supplier evaluation and selection situations faced by hospital's management.

Over the past decade, several researchers have used various fuzzy MCDM techniques for supplier selection process. While fuzzy MCDM techniques enable to consider imprecision and vagueness inherent in supplier evaluation, they also incorporate several shortcomings. Defuzzification has been commonly employed in a number of fuzzy MCDM methods. Freeling (1980) revealed 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 might essentially contradict with the key objective of minimizing the loss of information throughout the analysis. Moreover, obtaining pairwise comparisons in widely used techniques such as AHP and ANP may become quite complex especially when the number of attributes and/or alternatives increases. Apart from this, Saaty and Tran (2007) claimed that uncertainty in the AHP was successfully remedied by using intermediate values in the 1–9 scale combined with the verbal scale and that seemed to work better to obtain accurate results than using fuzzy AHP. Fuzzy TOPSIS and fuzzy VIKOR assume mutual independence of attributes, which can be highly restrictive for supplier selection decisions that usually incorporate inner dependencies among supplier attributes. The lack of a precise justification for the values chosen for concordance and discordance thresholds in fuzzy ELECTRE as well as the absence of a clear methodology for the weight assignment in fuzzy PROMETHEE may pose limitations for their use in supplier selection.

To the best of our knowledge, an earlier study, which is apt to account for the impacts of relationships among the purchased product features and supplier selection criteria as well as the correlations among supplier selection criteria while also enabling to manage non-homogeneous information in a decision setting with multiple information sources, does not exist in the supplier selection literature. In here, the supplier selection methodology proposed in Bevilacqua et al. (2006), which also made use of fuzzy QFD approach for supplier selection, is employed for comparison purposes. However, differing from the methodology developed in this paper, their approach has neither considered the inner dependencies among supplier attributes that are denoted in the roof matrix of the HOQ nor enabled the use of different semantic types by decision-makers. Thus, the data obtained from the first three decision-makers (DM_1, DM_2 and DM_3), who use the same linguistic scale for preference judgments, are considered to implement Bevilacqua et al.'s method and then compare the obtained results with those of the proposed method.

Bevilacqua et al. (2006) initially identified the features that the purchased product should possess in order to satisfy the company's needs, and then they attempted to determine the importance of relevant supplier assessment criteria without considering the correlations between them. Afterwards, the importance of supplier attributes and the ratings of suppliers with respect to the related supplier attributes were employed to obtain the final rankings of suppliers on the basis of fuzzy suitability index.

Bevilacqua et al.'s methodology provides the rank-order of suppliers as represented in Table 6. It is perceived that the rank-order derived from the proposed approach differs from that of Bevilacqua et al.'s method. In particular, it is observed that higher rankings are obtained for suppliers 3, 4, 7 and 9, mainly due to taking into account the roof matrix in the proposed method. For example, supplier 7 is ranked first according to the results of the proposed methodology, whereas it is ranked in the second place and supplier 1 is ranked first when Bevilacqua et al.'s method is employed. As the roof matrix that accounts for the dependencies among TAs is considered in the proposed approach, the importance weights of TAs 3 and 7 increase, and thus, supplier 7, which has more favorable results compared with supplier 1 for the respective TAs, supersedes supplier 1. Likewise, the proposed approach ranks supplier 4 as third and supplier 2 as fourth while supplier 4 and supplier 2 are ranked fifth and third, respectively, according to Bevilacqua et al.'s method. The proposed model yields a higher ranking for supplier 4, which has a superior performance with respect to TAs 3 and 7 compared with supplier 2, due to the increase in importance weights of the respective TAs that results from considering the correlations among the TAs. Albeit differences in the supplier rankings obtained from Bevilacqua et al. and the proposed approach due to the abovementioned reasons, in particular resulting in identifying different suppliers as the best one as well as changes in rankings in the top half of suppliers, the results of Spearman's rank correlation test for $\alpha = 0.01$ ($r_s = 0.951 > r_{s,\alpha} = 0.703$) indicate a positive association between the sets of rankings of the two approaches.

[Insert Table 6 about here]

8. 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 the consideration of 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 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 as a fuzzy multi-criteria group decision tool and constructs two interrelated HOQ matrices to compute the weights of supplier selection criteria and the ratings of suppliers. It utilizes the fusion of fuzzy information and the 2-tuple linguistic representation model, which enables decision-makers to tackle the problems of multi-granularity and loss of information.

The proposed methodology possesses a number of merits compared to some 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 correlations among supplier selection criteria for achieving higher satisfaction to meet company's requirements. Fourth, the 2-tuple linguistic representation model that inherits the existing characters of fuzzy linguistic assessment and rectifies the problem of loss of information faced with other fuzzy linguistic approaches was used in the developed approach. Fifth, the proposed framework enables managers to deal with heterogeneous information, and thus, allows for the use of different semantic types by decision-makers. Sixth, it 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. Finally, the decision making approach set forth in this paper disregards the troublesome fuzzy number ranking process, which may yield inconsistent results for different ranking methods, and as a result improves the quality of decision.

Future research will focus on implementation of the decision framework presented in here for real-world group decision making problems in diverse disciplines that can be represented using HOQ structure. Incorporating supply chain flexibility into the analysis also remains as an issue to be addressed in the future. Moreover, as pointed out in several recent works (Rezaei & Ortt, 2012; Rezaei & Ortt, 2013), supplier segmentation has an important role in supply chain management. Supplier segmentation that succeeds supplier selection is the process of classifying the suppliers on the basis of their similarities. This classification or segmentation enables to choose the most suitable strategies for handling different segments of selected suppliers. Therefore, further development of the proposed method for supplier segmentation may also be considered as a direction for future research.

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