Fuzzy Decision Approach Based on QFD and FWA for Selection of Medical Suppliers

Mehtap Dursun and E. Ertugrul Karsak

Abstract— **The objective of this paper is to develop a fuzzy multi-criteria group decision making technique that utilizes the quality function deployment (QFD) methodology for supplier evaluation and selection. The proposed decision approach enables the decision-makers to use linguistic terms, and thus, reduces their cognitive burden in the evaluation process. Furthermore, the proposed algorithm allows for considering the impacts of inner dependence among supplier assessment criteria. The lower and upper bounds of the weights of supplier assessment criteria and ratings of suppliers are computed by using fuzzy weighted average (FWA), which enables the fusion of imprecise and subjective information expressed as linguistic variables or fuzzy numbers and rectifies the problem of loss of information. The final ranking of suppliers is obtained by employing a fuzzy number ranking method that is based on area measurement. The computational procedure of the proposed framework is illustrated through a case study, and a comparative analysis with a well-known fuzzy decision making approach used lately for supplier selection is performed.**

Index Terms— **Supplier selection, MCDM, decision support systems, group decision making, QFD, fuzzy weighted average.**

I. INTRODUCTION

IN order to sharpen the competitive edge in a supply chain, a higher level of integration with suppliers and customers is essential. Supplier management is considered as one of the key issues of supply chain management since cost of raw materials and component parts constitutes the main cost item of a product [1]. Today, a significant number of manufacturers spend roughly half its revenue to purchase goods and services, which makes a company's success dependent on its interactions with suppliers. In a globally competitive environment, organizations give particular importance to the identification and selection of alternative supply sources. A well-selected set of suppliers makes a strategic difference to an organization's ability to reduce costs and improve quality of its end products.

In an exhaustive review of 74 articles, Weber et al. [2] noted that 47 of the 74 articles discussed more than one criterion. This demonstrates the inherent multi-criteria nature of many supplier selection decisions.

The uncertainty of subjective judgment is present when carrying out a supplier selection process. Moreover, decision making becomes more complicated when the available information is incomplete or imprecise. The classical multi-criteria decision making (MCDM) methods cannot effectively tackle decision problems including subjective information. In practice, decision making in supplier selection encompasses a high degree of vagueness and imprecision. Fuzzy set theory sets forth a sound decision support methodology to overcome the inherent uncertainty.

This study focuses on proposing a fuzzy multi-criteria group decision making approach based on the quality function deployment (QFD) concept for supplier selection. QFD focuses on delivering value by taking into account the customer needs (CNs), and then deploying this information throughout the development process [3]. The essence of QFD is to translate the desires of customers into technical attributes (TAs), and subsequently into parts characteristics, process plans and production requirements. 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 [4]. Fulfilling these aims 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. Hence, constructing a house of quality (HOQ), which allows for the relationships among purchased product features and supplier assessment criteria as well as inner dependence of supplier assessment criteria to be considered, is crucial in identifying how well each supplier characteristic succeeds in fulfilling the requirements established for the product being purchased.

The contributions of this research to supplier selection can be summarized as follows. First, the proposed methodology is a group decision making tool that enables to account for imprecise data using fuzzy set theory. Further, the developed approach is apt to consider the impacts of relationships among the purchased product features and supplier selection criteria as well as the inner dependence among supplier selection criteria for achieving higher satisfaction to meet company's requirements. Besides, the proposed framework employs the fuzzy weighted average (FWA) method that rectifies the problem of loss of information that occurs when integrating imprecise and subjective information. Furthermore, differing from previously proposed FWA approach that does not normalize fuzzy relationships, the FWA method used in this paper produces normalized fuzzy importance ratings for supplier

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assessment criteria while considering inner dependence among supplier criteria. At last, the proposed approach utilizes a fuzzy number ranking method based on area measurement, which enables higher discrimination among the fuzzy numbers to be ranked. In short, considering its effectiveness in quantifying vagueness and imprecision in human judgment as well as all pertinent relationships in the supplier selection process, the proposed decision making approach appears as a sound alternative to existing methods.

In the literature, there are a vast number of papers that employed different MCDM techniques for supplier selection. Tam and Tummala [5] investigated the feasibility of applying analytic hierachy process (AHP) in supplier selection for a telecommunications system. Bottani and Rizzi [6] addressed the problem of supplier selection in an e-procurement environment. Fuzzy AHP was employed to determine the most viable supplier. Chen et al. [7] improved the concept of TOPSIS to develop a methodology for solving supplier selection problems in fuzzy environment. Chan et al. [8] used a fuzzy modified AHP approach to select the best global supplier. Zhu et al. [9] developed a methodology to evaluate suppliers using portfolio analysis based on ANP and environmental factors. Awasthi et al. [10] used fuzzy TOPSIS for evaluating environmental performance of suppliers. Sanayei et al. [11] proposed fuzzy VIKOR method to select the suitable supplier in a supply chain system. Shemshadi et al. [12] handled supplier selection as a multiple criteria group decision making problem and developed a fuzzy VIKOR method to solve this problem. More recently, Wu et al. [13] employed fuzzy TOPSIS to select the most appropriate supplier.

Although fuzzy MCDM techniques enable to consider imprecision and vagueness inherent in supplier evaluation, they incorporate several shortcomings. Defuzzification, which may cause loss of information, is commonly employed in fuzzy MCDM methods such as fuzzy AHP and fuzzy ANP. Apart from this, uncertainty in the AHP is successfully remedied by using intermediate values in the 1–9 scale combined with the verbal scale and that seems to work better to obtain accurate results than using fuzzy AHP [14]. Fuzzy TOPSIS and fuzzy VIKOR assume mutual independence of attributes, which is highly restrictive for supplier selection decisions. Moreover, fuzzy TOPSIS does not consider the relative importance of the distances to ideal and anti-ideal solutions.

Recently, QFD has been utilized in supplier selection. Bevilacqua et al. [4] constructed an HOQ 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. Ho et al. [15] developed a combined QFD and AHP approach to measure the performance of alternative suppliers. Soroor et al. [16] combined fuzzy logic, AHP, and QFD for the evaluation of suppliers. In a recent work, Dursun and Karsak [17] integrated QFD and fuzzy weighted average for supplier selection process.

Even though prior researches developed approaches for supplier selection process, further studies are required to incorporate 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. The proposed methodology makes use of two interrelated HOQ matrices for supplier evaluation. In the first HOQ, the characteristics required of products purchased from medical suppliers are taken into consideration to compute the lower and upper bounds of the weights of supplier selection criteria through the FWA method, which enables to rate the importance of supplier assessment criteria in fuzzy environment accurately through α-level sets. In the second HOQ, the FWA method is utilized to compute the lower and upper bounds of the supplier ratings using the weights of supplier selection criteria obtained from the first HOQ. The FWA method, which calculates both the weights of supplier selection criteria and the ratings of the suppliers, enables to produce less imprecise and more realistic overall desirability levels.

II. Fuzzy weighted average

Consider the general fuzzy weighted average with q criteria. Define $\tilde{W}_p$ as the relative importance of criterion p (p = 1,…, q) and $\tilde{X}_{pr}$ as the rating of alternative r with respect to criterion p (p = 1,…, q; r = 1, …,s). Then, the fuzzy weighted average can be defined as

$$\tilde{\Theta}_r = \sum_{p=1}^{q} \tilde{W}_p \tilde{X}_{pr} \bigg/ \sum_{p=1}^{q} \tilde{W}_p \,,\ r = 1,\ldots,s \tag{1}$$

Since $\tilde{W}_p$ and $\tilde{X}_{pr}$ are fuzzy numbers, the weighted average $\tilde{\Theta}_r$ is also a fuzzy number. When the relative weights of customer needs, the relationship measures between customer needs and technical attributes, and the inner dependencies of technical attributes are denoted as fuzzy numbers, the computation of the overall priorities of technical attributes falls into the category of fuzzy weighted average [18]. There are several methods developed for computing fuzzy weighted average [19-21]. In this paper, the technique proposed by Wang and Chin [21], which produces normalized fuzzy importance ratings for TAs, is employed. Existing approaches that do not normalize fuzzy relationships between CNs and TAs may produce erroneous results. According to Wasserman [22], the relationships between CNs and TAs need to be normalized; otherwise, the importance of TAs cannot be correctly rated. This is also valid for fuzzy relationships. The use of fuzzy arithmetic to perform fuzzy normalization or calculate FWA is also inappropriate since fuzzy arithmetic operations increase the fuzziness of normalized fuzzy relationships and FWA, and make their support intervals much wider than actual ones [21].

Wang and Chin's method enables rating the importance of TAs and supplier assessments in fuzzy environments accurately through α-level sets. They developed a pair of nonlinear programming models and two equivalent pairs of linear programming models to find the α-cut of $\tilde{\Theta}_r$. The method can be summarized as follows:

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Let $\tilde{W}_p$ denote the fuzzy relative weight of CN_p, $\tilde{X}_{pr}$ denote the fuzzy relationship measure between TA_r and customer need p, and $\tilde{\rho}_{kr}$ denote the degree of dependence of the kth TA on the rth TA. Denote $\left[\left(W_p\right)_\alpha^L, \left(W_p\right)_\alpha^U\right]$, $\left[\left(X_{pr}\right)_\alpha^L, \left(X_{pr}\right)_\alpha^U\right]$ and $\left[\left(\rho_{kr}\right)_\alpha^L, \left(\rho_{kr}\right)_\alpha^U\right]$ as the α-level sets of the fuzzy relative weight, fuzzy relationships, and fuzzy correlations, respectively. The normalized fuzzy relationships can be calculated as follows:

$$\tilde{X}'_{pr} = \frac{\sum_{k=1}^{s} \tilde{X}_{pk}\tilde{\rho}_{kr}}{\sum_{\substack{l=1 \\ l\neq r}}^{s}\sum_{k=1}^{s} \tilde{X}_{pk}\tilde{\rho}_{kl} + \sum_{k=1}^{s} \tilde{X}_{pk}\tilde{\rho}_{kr}}, \; p=1,...,q; r=1,...,s \quad (2)$$

Once the normalized fuzzy relationships are generated, the fuzzy weighted average of the normalized fuzzy relationship can be formulated as

$$\tilde{\Theta}_r = \sum_{p=1}^{q} \tilde{W}_p \tilde{X}'_{pr} \Big/ \sum_{p=1}^{q} \tilde{W}_p, \quad r=1,2,...,s \quad (3)$$

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

$$\left(\Theta_r\right)_\alpha^L = \min \sum_{p=1}^{q} \eta_p \left(X'_{pr}\right)_\alpha^L$$

subject to

$$\lambda\left(W_p\right)_\alpha^L \le \eta_p \le \lambda\left(W_p\right)_\alpha^U, \quad p=1,2,...,q \quad (4)$$

$$\sum_{p=1}^{q} \eta_p = 1$$

$$\lambda, \eta_p \ge 0$$

$$\left(\Theta_r\right)_\alpha^U = \max \sum_{p=1}^{q} \eta_p \left(X'_{pr}\right)_\alpha^U$$

subject to

$$\lambda\left(W_p\right)_\alpha^L \le \eta_p \le \lambda\left(W_p\right)_\alpha^U, \quad p=1,2,...,q \quad (5)$$

$$\sum_{p=1}^{q} \eta_p = 1$$

$$\lambda, \eta_p \ge 0$$

where, $\lambda^{-1} = \sum_{p=1}^{q} w_p$ and $\eta_p = \lambda w_p$, according to the variable substitution of Charnes and Cooper [23].

The α-cuts of $\tilde{\Theta}_r$ is the crisp interval $\left[\left(\Theta_r\right)_\alpha^L, \left(\Theta_r\right)_\alpha^U\right]$ obtained from formulations (4) and (5). By enumerating different α values, the membership function $\mu_{\tilde{\Theta}_r}$ can be constructed.

III. Proposed Fuzzy Decision Approach

This section delineates the fuzzy multi-criteria group decision making algorithm that builds on fuzzy QFD methodology. In conventional 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. Alternatively, when the HOQ is used in supplier selection, the company commences 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 [4].

The proposed algorithm uses FWA method to compute the lower and upper bounds of the weights of TAs and the supplier assessments using two interrelated HOQ matrices. In addition, the proposed algorithm enables to consider the impacts of inner dependence among TAs. Furthermore, 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. This in turn increases the ability of this method to discriminate among the numbers to be ranked, and thus yields better sensitivity compared with other existing ranking methods [24].

The detailed stepwise representation of the proposed fuzzy MCDM algorithm is given below.

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

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

Step 3. Let the fuzzy value assigned as the importance weight of the pth CN, relationship score between the pth CN $(p=1,2,...,q)$ and the rth TA $(r=1,2,...,s)$, degree of dependence of the kth TA on the rth TA, and rating of the jth supplier $(j=1,2,...,n)$ with respect to the rth TA for the ζth decision-maker be $\tilde{W}_{p\zeta} = \left(W_{p\zeta}^1, W_{p\zeta}^2, W_{p\zeta}^3\right)$, $\tilde{X}_{pr\zeta} = \left(X_{pr\zeta}^1, X_{pr\zeta}^2, X_{pr\zeta}^3\right)$, $\tilde{\rho}_{kr\zeta} = \left(\rho_{kr\zeta}^1, \rho_{kr\zeta}^2, \rho_{kr\zeta}^3\right)$, and $\tilde{y}_{rj\zeta} = \left(y_{rj\zeta}^1, y_{rj\zeta}^2, y_{rj\zeta}^3\right)$, respectively. Compute the aggregated importance weight of the pth CN $\left(\tilde{W}_p\right)$, aggregated fuzzy assessment of the relationship scores between the rth TA and the pth CN $\left(\tilde{X}_{pr}\right)$,aggregated degree of dependence of the kth TA on the rth TA $\left(\tilde{\rho}_{kr}\right)$,

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and aggregated rating of the jth supplier with respect to the rth TA $\left(\tilde{y}_{rj}\right)$ as follows:

$$\tilde{W}_p = \sum_{\zeta=1}^{Z} \Omega_\zeta \tilde{W}_{p\zeta} \tag{6}$$

$$\tilde{X}_{pr} = \sum_{\zeta=1}^{Z} \Omega_\zeta \tilde{X}_{pr\zeta} \tag{7}$$

$$\tilde{\rho}_{kr} = \sum_{\zeta=1}^{Z} \Omega_\zeta \tilde{\rho}_{kr\zeta} \tag{8}$$

$$\tilde{y}_{rj} = \sum_{\zeta=1}^{Z} \Omega_\zeta \tilde{y}_{rj\zeta} \tag{9}$$

where $\Omega_\zeta \in [0,1]$ represents the weight of the ζth decision-maker and $\sum_{\zeta=1}^{Z} \Omega_\zeta = 1$.

Step 4. Calculate the normalized fuzzy relationships, and then compute the lower and upper bounds of the weight for each TA by employing formulations (4) and (5).

Step 5. Calculate the lower and upper bounds for each supplier by utilizing formulations (4) and (5). This time, the relative importance expressed in formulations (4) and (5) are the lower and upper bounds, respectively, of the weight for each TA calculated at *Step* 4.

Step 6. Rank the suppliers by employing Chen and Klein's [24] ranking algorithm, which can be summarized as follows:

Let $\tilde{\beta}_1, \tilde{\beta}_2, ..., \tilde{\beta}_\gamma, ..., \tilde{\beta}_\Gamma$ be Γ arbitrary bounded fuzzy numbers, and h specify the maximum height of $\mu_{\tilde{\beta}_\gamma}$, $\gamma = 1,2,...,\Gamma$. Suppose h is equally divided into v intervals such that $\alpha_e = eh/v, e = 0,1,2,...,v$. Chen and Klein [24] devised the following index for ranking fuzzy numbers.

$$I_\gamma = \sum_{e=0}^{v}\left(\left(\beta_\gamma\right)_{\alpha_e}^{U} - c\right) \Big/ \left(\sum_{e=0}^{v}\left(\left(\beta_\gamma\right)_{\alpha_e}^{U} - c\right) - \sum_{e=0}^{v}\left(\left(\beta_\gamma\right)_{\alpha_e}^{L} - d\right)\right)$$
$$v \to \infty \tag{10}$$

where $c = \min_{e,\gamma}\left\{\left(\beta_{\gamma e}\right)_{\alpha_e}^{L}\right\}$ and $d = \max_{e,\gamma}\left\{\left(\beta_{\gamma e}\right)_{\alpha_e}^{U}\right\}$.

The larger the ranking index I_γ, the more preferred the fuzzy number is.

IV. Evaluating Medical Suppliers Using Fuzzy MCDM Approach

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 [25]. The hospital operates with all major departments, and possesses facilities such as clinical laboratories, emergency service, intensive care units and operating room as well. Following the discussions with experts from the purchasing department of the hospital, five fundamental characteristics required of products purchased from medical supplies (CNs) are determined. These can be listed as "cost (CN_1)", "quality (CN_2)", "product conformity (CN_3)", "availability and customer support (CN_4)", and "efficacy of corrective action (CN_5)".

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.

TABLE I
Linguistic scale for the evaluation of medical suppliers.

Very low/poor (VL/VP)	(0, 0, 0.25)
Low/poor (L/P)	(0, 0.25, 0.50)
Moderate/fair (M/F)	(0.25, 0.50, 0.75)
High/good (H/G)	(0.50, 0.75, 1)
Very high/good (VH/VG)	(0.75, 1, 1)

The evaluation is performed by a committee of three decision-makers. The decision-makers use the linguistic scale defined in Table I to denote the level of importance of each CN, the impact of each TA on each CN, the inner dependencies of TAs, and the ratings of the suppliers with respect to each TA.

By using Eqs. (6)-(9), the decision-makers' evaluations are aggregated to obtain aggregated importance of each CN, aggregated impact of each TA on each CN, aggregated degree of dependence of TAs, and aggregated ratings of suppliers. In here, one shall note that $\Omega_1 = \Omega_2 = \Omega_3 = 1/3$ since equal weights are allocated to each decision-maker. The lower and upper bounds of the weight of TAs are computed via formulations (4) and (5).

By employing formulations (4) and (5), the lower and upper bounds for supplier ratings are computed as given in Table II. Finally, the ranking index (I) for each supplier is calculated using Eq. (10). The ranking indices are as $I(\text{Sup1}) = 0.6943$, $I(\text{Sup2}) = 0.6517$, $I(\text{Sup3}) = 0.6156$, $I(\text{Sup4}) = 0.6322$, $I(\text{Sup5}) = 0.5128$, $I(\text{Sup6}) = 0.6122$, $I(\text{Sup7}) = 0.6817$, $I(\text{Sup8}) = 0.5429$, $I(\text{Sup9}) = 0.4932$, $I(\text{Sup10}) = 0.4742$, I(Sup11)=0.5210, and I(Sup12)=0.3756. Thus, the rank-order of the suppliers is $\text{Sup1} \succ \text{Sup7} \succ \text{Sup2} \succ \text{Sup4} \succ \text{Sup3} \succ \text{Sup6} \succ \text{Sup8} \succ \text{Sup11} \succ \text{Sup5} \succ \text{Sup9} \succ \text{Sup10} \succ \text{Sup12}$.

According to the results of the analysis, supplier 1 is determined as the most suitable supplier, which is followed by supplier 7, and then by supplier 2 and supplier 4. Suppliers 10 and 12 are ranked at the bottom due to late delivery time, inadequate experience in the sector, unsatisfactory earlier business relationships, and improper geographical location. The results obtained from the proposed methodology are comparable to those already in use by the hospital management, which reveal the robustness of the proposed methodology and promote its use as a decision aid for imminent supplier selection situations.

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TABLE II
LOWER AND UPPER BOUNDS OF THE SUPPLIER RATINGS.

Suppliers		α 0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Sup 1	$(Y_{\text{sup}_1})^L_\alpha$	0.451	0.487	0.523	0.559	0.595	0.630	0.665	0.700	0.734	0.768	0.802
	$(Y_{\text{sup}_1})^U_\alpha$	0.978	0.964	0.950	0.935	0.919	0.901	0.884	0.865	0.845	0.824	0.802
Sup 2	$(Y_{\text{sup}_2})^L_\alpha$	0.417	0.449	0.481	0.512	0.544	0.576	0.607	0.639	0.671	0.702	0.733
	$(Y_{\text{sup}_2})^U_\alpha$	0.971	0.949	0.926	0.903	0.880	0.857	0.832	0.808	0.783	0.759	0.733
Sup 3	$(Y_{\text{sup}_3})^L_\alpha$	0.345	0.381	0.416	0.452	0.487	0.522	0.558	0.593	0.628	0.663	0.698
	$(Y_{\text{sup}_3})^U_\alpha$	0.954	0.931	0.908	0.884	0.859	0.834	0.808	0.781	0.754	0.726	0.698
Sup 4	$(Y_{\text{sup}_4})^L_\alpha$	0.352	0.392	0.431	0.470	0.509	0.546	0.583	0.620	0.657	0.693	0.729
	$(Y_{\text{sup}_4})^U_\alpha$	0.952	0.934	0.914	0.894	0.873	0.851	0.828	0.804	0.780	0.755	0.729
Sup 5	$(Y_{\text{sup}_5})^L_\alpha$	0.223	0.257	0.291	0.326	0.359	0.393	0.426	0.460	0.494	0.528	0.562
	$(Y_{\text{sup}_5})^U_\alpha$	0.862	0.833	0.804	0.774	0.744	0.714	0.684	0.654	0.624	0.593	0.562
Sup 6	$(Y_{\text{sup}_6})^L_\alpha$	0.347	0.382	0.418	0.453	0.487	0.522	0.556	0.590	0.623	0.656	0.689
	$(Y_{\text{sup}_6})^U_\alpha$	0.948	0.925	0.901	0.876	0.851	0.825	0.799	0.772	0.745	0.717	0.689
Sup 7	$(Y_{\text{sup}_7})^L_\alpha$	0.443	0.478	0.512	0.546	0.580	0.614	0.647	0.680	0.713	0.745	0.778
	$(Y_{\text{sup}_7})^U_\alpha$	0.983	0.965	0.947	0.928	0.909	0.889	0.868	0.847	0.825	0.802	0.778
Sup 8	$(Y_{\text{sup}_8})^L_\alpha$	0.257	0.291	0.326	0.362	0.397	0.432	0.467	0.502	0.537	0.571	0.606
	$(Y_{\text{sup}_8})^U_\alpha$	0.879	0.855	0.830	0.804	0.778	0.750	0.722	0.694	0.665	0.636	0.606
Sup 9	$(Y_{\text{sup}_9})^L_\alpha$	0.241	0.271	0.301	0.329	0.358	0.386	0.415	0.443	0.472	0.501	0.530
	$(Y_{\text{sup}_9})^U_\alpha$	0.817	0.789	0.760	0.731	0.702	0.673	0.644	0.616	0.587	0.558	0.530
Sup 10	$(Y_{\text{sup}_{10}})^L_\alpha$	0.209	0.239	0.270	0.300	0.330	0.360	0.389	0.419	0.448	0.477	0.507
	$(Y_{\text{sup}_{10}})^U_\alpha$	0.805	0.775	0.745	0.714	0.684	0.654	0.624	0.595	0.565	0.536	0.507
Sup 11	$(Y_{\text{sup}_{11}})^L_\alpha$	0.213	0.249	0.286	0.322	0.358	0.394	0.430	0.466	0.502	0.538	0.573
	$(Y_{\text{sup}_{11}})^U_\alpha$	0.886	0.857	0.827	0.797	0.766	0.735	0.703	0.672	0.639	0.606	0.573
Sup 12	$(Y_{\text{sup}_{12}})^L_\alpha$	0.092	0.116	0.141	0.167	0.193	0.219	0.247	0.275	0.304	0.333	0.364
	$(Y_{\text{sup}_{12}})^U_\alpha$	0.742	0.702	0.663	0.624	0.585	0.547	0.510	0.472	0.436	0.400	0.364

In order to demonstrate the robustness of the proposed methodology, the results are compared with those obtained by fuzzy VIKOR, which is a well-known MCDM approach previously used for supplier evaluation as well [11, 12]. The VIKOR method was developed as an MCDM technique to solve a discrete multi-criteria problem with noncommensurable and conflicting criteria [26]. It focuses on ranking and selecting from a set of alternatives in the presence of conflicting criteria, and determines compromise solutions, providing a maximum "group utility" for the "majority" and a minimum of an individual regret for the "opponent". VIKOR introduces the multi-criteria ranking index based on the particular measure of closeness to the ideal solution.

In here, the fuzzy VIKOR method presented in Opricovic [26] is employed to evaluate medical suppliers. To compare the results with those of the proposed decision framework, QFD methodology, which enables to incorporate the relationships between CNs and TAs, and the inner dependencies among TAs, is utilized to compute the weights of TAs. The roof matrix of the HOQ is handled by using the procedure proposed by Fung *et al.* [27]. The ranking of the suppliers is obtained as Sup1~Sup2~Sup7 $\succ$ Sup4 $\succ$ Sup3 $\succ$ Sup6~Sup11 $\succ$ Sup8~Sup9 $\succ$ Sup5~Sup10 $\succ$ Sup12.

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While fuzzy VIKOR identifies suppliers 1, 2 and 7 as the top ranking suppliers, which are in accordance with the proposed approach, the outcomes of fuzzy VIKOR yield indifference between those suppliers. In addition, fuzzy VIKOR results in indifference between suppliers 6 and 11, suppliers 8 and 9 as well as suppliers 5 and 10. One shall note that the fuzzy VIKOR method can neither provide a complete ranking of the suppliers nor identify the best supplier. On the other hand, the proposed decision framework both yields a complete rank order and enables to determine the most suitable supplier.

V. Conclusions

This paper presents a fuzzy multi-criteria group decision making framework to rectify the problems encountered when using traditional decision making methods in supplier selection. It employs the FWA method developed by Wang and Chin [21]; however, it extends their research in several aspects. First, the methodology used in this paper considers QFD planning as a fuzzy multi-criteria group decision making tool and makes use of two interrelated HOQ matrices to evaluate alternative suppliers. In the first HOQ, the characteristics required of products purchased from medical supplies are taken into account as CNs, and the supplier selection criteria are considered as TAs. Then, the lower and upper bounds of the weights of supplier selection criteria are calculated through the FWA method, which enables to rate the importance of TAs in fuzzy environment accurately through α-level sets. In the second HOQ, the FWA method is utilized to compute the lower and upper bounds of the supplier ratings using the weights of supplier selection criteria obtained from the first HOQ. Finally, the rank-order of suppliers is obtained by employing a fuzzy number ranking method based on area measurement, which overcomes the shortcomings of other ranking methods.

It is worth noting that the decision model presented here is not restricted to medical supplier selection and could be applied to a supplier selection problem in another discipline without any difficulty. Future research may concentrate on implementing the proposed decision framework to group decision making problems in real-life across diverse disciplines that can be represented in HOQ structures. Moreover, a user interface can be developed for users who are novice in mathematical programming.

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