A Fuzzy Decision Model for Strategic Evaluation of Medical Suppliers

Mehtap Dursun and E. Ertugrul Karsak

***Abstract*— Numerous distinct attributes considered for supplier selection such as delivery, reliability, and experience exhibit vagueness and imprecision. Fuzzy set theory appears as an essential tool to provide a decision framework that incorporates imprecise judgments inherent in the supplier selection process. This paper aims to develop a fuzzy multi-criteria group decision making technique that makes use of the quality function deployment (QFD) methodology for supplier evaluation and selection. The proposed decision framework initially identifies the features that the purchased product should possess to meet the company's requirements, and then it seeks to determine the relevant supplier assessment criteria while also considering the impacts of inner dependence among them. A house of quality (HOQ) matrix, which translates purchased product features into supplier assessment criteria, is built to determine the desired levels of supplier assessment criteria. Finally, supplier alternatives are ranked by a distance-based method. The application of the developed methodology is demonstrated through a case study for evaluation of medical suppliers.**

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

I. Introduction

SUPPLY chain management involves coordinating the flows of materials and information between suppliers, manufacturers and customers, and implementing product postponement and mass customization in the supply chain [1]. 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. A well-selected set of suppliers makes a strategic difference to an organization's ability to reduce costs and improve quality of its end products. As a result, an effective supplier selection process is a crucial element in a company's quality success or failure. Earlier studies on supplier selection were traced back to 1960s. Based on a survey of 273 purchasing managers, Dickson [2] conducted one of the earliest works on supplier selection and identified 23 supplier attributes that managers consider when choosing a supplier. Results of this study indicated that the supplier selection and evaluation is a multi-criteria process in nature; that is, typically more than one criterion need to be considered and evaluated in selecting suppliers and monitoring their performance. Furthermore, Weber et al. [3] noted that 47 of the 74 articles discussed more than one criterion. This demonstrates the inherent multi-criteria nature of many supplier selection decisions. Thus, with its need to trade-off multiple criteria, supplier selection is nowadays considered as a highly important multi-criteria decision making (MCDM) problem.

Most of the existing research on supplier selection considers only quantifiable aspects of the supplier selection decision. However, several factors such as incomplete information, qualitative criteria and imprecision preferences are not taken into account in the decision making process. These criteria are subjective factors that are difficult to quantify. Supplier selection that requires considering multiple conflicting criteria incorporating vagueness and imprecision with the involvement of a group of experts is an important multi-criteria group decision making problem. The fuzzy set theory is a viable decision aid that enables to account for the inherent imprecision and vagueness in criteria values.

In light of the multi-criteria nature of supplier selection process, it would appear that the application of MCDM techniques to the supplier selection 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. Sarkis and Talluri [4] illustrated the use of ANP for supplier selection. Chan [5] proposed an AHP based approach, which considers the interactions among the supplier selection criteria. Chain of interaction was developed to determine the relative interactions. Haq and Kannan [6] compared the results obtained by employing AHP and fuzzy AHP to the supplier selection process of a tire manufacturing company. Chen and Wang [7] 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. Jolai et al. [8] suggested a two-phase approach for supplier selection and order allocation problem under fuzzy environment. In the first phase, a fuzzy MADM approach based on TOPSIS was employed to obtain the overall ratings of alternative suppliers. In the second phase, a multi-objective mixed integer linear programming model was constructed to determine the quantity of each product that should be allocated to each supplier. Lin et al. [9] proposed a decision support system based on the integration of AHP and gray relational analysis for supplier selection. Lin et al. [10]

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modeled a green purchasing system by applying the ANP and linear programming methods. The ANP is used to provide the solution for green supplier selection and linear programming is employed for the problem of order allocation for each vendor. Wu et al. [11] employed fuzzy TOPSIS to select the most appropriate supplier. Recently, You et al. [12] proposed an extended VIKOR method for supplier selection with interval 2-tuple linguistic information.

Over the past decade, a few researchers have employed QFD in supplier selection. Bevilacqua et al. [13] 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. [14] proposed a supplier selection methodology based on QFD and data mining techniques. Data mining techniques were utilized to find out quality requirements correlated to customer categories, product usage patterns, and frequent fault patterns in order to select the proper combination of suppliers. Ho et al. [15] developed a combined QFD and AHP approach to measure the performance of alternative suppliers. Dursun and Karsak [16] integrated QFD and fuzzy weighted average for supplier selection process. In a recent work, Karsak and Dursun [17] developed a fuzzy multi-criteria group decision making approach that makes use of QFD, fusion of fuzzy information and 2-tuple linguistic representation model for supplier selection.

The objective of this study is to propose a fuzzy multi-criteria group decision making methodology based on QFD. A house of quality (HOQ) matrix, which translates purchased product features into supplier assessment criteria is built, and supplier alternatives are ranked by a distance-based method. The proposed methodology is a group decision making tool that enables to account for imprecise data using fuzzy set theory. Furthermore, 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.

The rest of the paper is organized as follows: In the following section, a concise treatment of the basic concepts of QFD is presented. Section 3 outlines the developed methodology and provides a stepwise representation of the proposed fuzzy decision making approach. In Section 4, the proposed decision framework is implemented for evaluating medical suppliers of a private hospital in Istanbul. Finally, concluding remarks are provided in Section 5.

II. QUALITY FUNCTION DEPLOYMENT

Quality function deployment (QFD) is a crucial product development method dedicated to translating customer requirements into activities to develop products and services [18]. QFD was originally proposed, through a well structured framework of analyzing the needs of the customer, to develop products with higher quality to meet or exceed customer expectations. Hence, the primary functions of QFD are product development, quality management, and customer needs analysis. Later, QFD's functions have been expanded to wider fields such as design, planning, decision-making, engineering, management, teamwork, timing, and costing.

The basic concept of QFD is to translate the desires of customers into technical attributes (TAs), and subsequently into parts characteristics, process plans and production requirements. In order to establish these relationships, QFD usually requires four matrices each corresponding to a stage of the product development cycle. These are product planning, part deployment, process planning, and production/operation planning matrices, respectively. The product planning matrix translates customer needs (CNs) into 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 [19]. In this paper, our focus is on the first and the most widely used of the four matrices, also called the HOQ. Relationships between CNs and TAs and among the TAs are defined by answering a specific question corresponding to each cell in HOQ.

The elements of the HOQ can be briefly described as follows:

(1) CNs: They are also known as voice of the customer, customer attributes, customer requirements or demanded quality. The initial step in constructing the HOQ includes determining, clarifying, and specifying the customer's needs.

(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. They are used to determine how well the company satisfies the CNs [20].

(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 [20].

(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 [21].

(5) Competitive assessment matrix: Understanding how customers rate the competition can be a tremendous competitive advantage. This matrix contains the idea of how the company's product or service rates in relation to its competitors. Thus, relative position of the company's product can be assessed in terms of CNs.

(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.

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III. Proposed Fuzzy Decision Making Algorithm

This section outlines a fuzzy multi-criteria group decision making approach based on QFD. The proposed algorithm builds an HOQ matrix, which translates purchased product features into supplier assessment criteria, to determine the desired levels of supplier assessment criteria. Finally, supplier alternatives are ranked by a distance-based method.

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

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

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

Step 3. Let the fuzzy value assigned as the importance weight of the ith CN, relationship score between the ith CN $(i=1,2,...,m)$ and the jth TA $(j=1,2,...,n)$, degree of dependence of the kth TA on the jth TA, and rating of the pth supplier $(p=1,2,...,P)$ with respect to the jth TA for the zth decision-maker be $\tilde{W}_{iz}=\left(W_{iz}^1,W_{iz}^2,W_{iz}^3\right)$, $\tilde{X}_{ijz}=\left(X_{ijz}^1,X_{ijz}^2,X_{ijz}^3\right)$, $\tilde{r}_{kjz}=\left(\rho_{kjz}^1,\rho_{kjz}^2,\rho_{kjz}^3\right)$, and $\tilde{y}_{pjz}=\left(y_{pjz}^1,y_{pjz}^2,y_{pjz}^3\right)$, respectively. Compute the aggregated importance weight of the ith CN $(\tilde{W}_i)$, aggregated fuzzy assessment of the relationship scores between the ith CN and the jth TA $(\tilde{X}_{ij})$,aggregated degree of dependence of the kth TA on the jth TA $(\tilde{r}_{kj})$, and aggregated rating of the pth supplier with respect to the jth TA $(\tilde{y}_{pj})$ using arithmetic mean operator.

Step 4. Calculate the normalized fuzzy relationships for α=0 and α=1 as

$$\left(\tilde{X}'_{ij}\right)_\alpha^L=\min\sum_{k=1}^{n}q_{ik}\left(r_{kj}\right)_\alpha^L$$

subject to

$$\sum_{k=1}^{n}q_{ik}\left(\left(r_{kj}\right)_\alpha^L+\sum_{\substack{l=1\\l\neq j}}^{n}\left(r_{kl}\right)_\alpha^U\right)=1 \tag{1}$$

$$\left(X_{ik}\right)_\alpha^L t\le q_{ik}\le\left(X_{ik}\right)_\alpha^U t,\quad k=1,2,...,n$$

$$t>0$$

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

subject to

$$\sum_{k=1}^{n}u_{ik}\left(\left(r_{kj}\right)_\alpha^U+\sum_{\substack{l=1\\l\neq j}}^{n}\left(r_{kl}\right)_\alpha^L\right)=1 \tag{2}$$

$$\left(X_{ik}\right)_\alpha^L s\le u_{ik}\le\left(X_{ik}\right)_\alpha^U s,\quad k=1,2,...,n$$

$$s>0$$

where t, s, q_{ik}, and u_{ik} are decision variables. The normalization procedure is required to correctly rate the TAs.

Step 5. Calculate the weight of each criteria $\tilde{\psi}_j=\left(\psi_j^1,\psi_j^2,\psi_j^3\right)$ for α=0 and α=1 using

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

subject to

$$\lambda\left(W_i\right)_\alpha^L\le v_i\le\lambda\left(W_i\right)_\alpha^U,\quad i=1,2,...,m \tag{3}$$

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

$$\lambda,v_i\ge 0$$

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

subject to

$$\lambda\left(W_i\right)_\alpha^L\le v_i\le\lambda\left(W_i\right)_\alpha^U,\quad i=1,2,...,m \tag{4}$$

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

$$\lambda,v_i\ge 0$$

where λ and v_i are decision variables. This approach enables the fusion of imprecise and subjective information expressed as linguistic variables or fuzzy numbers and rectifies the problem of loss of information.

Step 6. Calculate distances from the ideal and the anti-ideal solutions (D_p^* and D_p^-, respectively) for each alternative as

$$D_p^*=\sum_{j=1}^{n}\frac{1}{2}\left\{\max\left(\psi_j^1\left|y_{pj}^1-1\right|,\psi_j^3\left|y_{pj}^3-1\right|\right)+\psi_j^2\left|y_{pj}^2-1\right|\right\} \tag{5}$$

$$D_p^-=\sum_{j=1}^{n}\frac{1}{2}\left\{\max\left(\psi_j^1\left|y_{pj}^1-0\right|,\psi_j^3\left|y_{pj}^3-0\right|\right)+\psi_j^2\left|y_{pj}^2-0\right|\right\} \tag{6}$$

Step 7. Calculate the ranking index (RI) of the pth supplier:

$$RI_p=\frac{D_p^-}{D_p^-+D_p^*} \tag{7}$$

Step 8. Rank the suppliers according to RI_p values in descending order. Identify the alternative with the highest RI_p as the best supplier.

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IV. STRATEGIC SUPPLIER EVALUATION USING THE PROPOSED APPROACH

A case study conducted in a private hospital in Istanbul is presented for demonstrating the application of the proposed decision making method [22]. 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)”. The hospital is currently in contact with 12 suppliers.

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.

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. The results are presented in Fig. 1 and in Table 2.

Using formulations (1)-(4) the weights of each TA are calculated as in Table 3.

TABLE III
WEIGHTS OF EACH TA.

TAs	Importance Weights
TA_1	(0.0328, 0.0814, 0.1633)
TA_2	(0.0515, 0.1122, 0.1900)
TA_3	(0.0499, 0.1029, 0.1893)
TA_4	(0.0527, 0.1070, 0.1926)
TA_5	(0.0647, 0.1172, 0.1878)
TA_6	(0.0882, 0.1400, 0.2203)
TA_7	(0.0607, 0.1202, 0.1917)
TA_8	(0.0914, 0.1429, 0.2226)
TA_9	(0.0281, 0.0762, 0.1507)

The distances from the ideal and the anti-ideal solutions for each alternative and the ranking index of each alternative are computed employing Eqs. (5)-(7) as in Table 4.

TABLE IV
RANKING OF SUPPLIERS.

Suppliers	D_p^*	D_p^-	RI_p	Rank
Sup 1	0.2279	1.2035	0.8408	1
Sup 2	0.2830	1.1573	0.8035	3
Sup 3	0.3196	1.1094	0.7763	5
Sup 4	0.3044	1.1172	0.7859	4
Sup 5	0.4323	0.9523	0.6878	8
Sup 6	0.3203	1.1068	0.7756	6
Sup 7	0.2428	1.1941	0.8310	2
Sup 8	0.4058	0.9902	0.7093	7
Sup 9	0.4491	0.9301	0.6744	10
Sup 10	0.4825	0.8977	0.6504	11
Sup 11	0.4437	0.9684	0.6858	9
Sup 12	0.6804	0.7028	0.5081	12

TABLE II
AGGREGATED RATINGS OF SUPPLIERS WITH RESPECT TO TAs

	TA_1	TA_2	TA_3	TA_4	TA_5	TA_6	TA_7	TA_8	TA_9
Sup 1	(0.750,1,1)	(0.417,0.667,0.917)	(0.583,0.833,1)	(0.750,1,1)	(0.583,0.833,1)	(0.750,1,1)	(0.583,0.833,1)	(0.333,0.583,0.833)	(0.167,0.417,0.667)
Sup 2	(0.417,0.667,0.917)	(0.583,0.833,1)	(0.500,0.750,0.971)	(0.417,0.667,0.917)	(0.583,0.833,1)	(0.667,0.917,1)	(0.500,0.750,1)	(0.417,0.667,0.917)	(0.083,0.333,0.583)
Sup 3	(0.167,0.417,0.667)	(0.667,0.917,1)	(0.583,0.833,1)	(0.167,0.417,0.667)	(0.333,0.583,0.833)	(0.500,0.750,1)	(0.667,0.917,1)	(0.333,0.583,0.833)	(0.583,0.833,1)
Sup 4	(0.167,0.417,0.667)	(0.667,0.917,1)	(0.667,0.917,1)	(0.167,0.417,0.667)	(0.500,0.750,0.971)	(0.667,0.917,1)	(0.667,0.917,1)	(0.417,0.667,0.917)	(0.167,0.417,0.667)
Sup 5	(0.167,0.417,0.667)	(0.417,0.667,0.917)	(0.667,0.917,1)	(0.333,0.583,0.833)	(0.250,0.500,0.750)	(0.167,0.417,0.667)	(0.583,0.833,1)	(0.083,0.333,0.583)	(0.167,0.417,0.667)
Sup 6	(0.500,0.750,1)	(0.333,0.583,0.833)	(0.667,0.917,1)	(0.583,0.833,1)	(0.417,0.667,0.917)	(0.250,0.500,0.750)	(0.667,0.917,1)	(0.417,0.667,0.917)	(0.083,0.333,0.583)
Sup 7	(0.583,0.833,1)	(0.333,0.583,0.833)	(0.667,0.917,1)	(0.417,0.667,0.917)	(0.500,0.750,1)	(0.750,1,1)	(0.583,0.833,1)	(0.583,0.833,1)	(0.167,0.417,0.667)
Sup 8	(0.167,0.417,0.667)	(0.167,0.417,0.667)	(0.667,0.917,1)	(0.083,0.333,0.583)	(0.333,0.583,0.833)	(0.250,0.500,0.750)	(0.667,0.917,1)	(0.333,0.583,0.833)	(0.583,0.833,1)
Sup 9	(0.167,0.417,0.667)	(0.333,0.583,0.833)	(0.417,0.667,0.917)	(0.250,0.500,0.750)	(0.250,0.500,0.750)	(0.333,0.583,0.833)	(0.333,0.583,0.833)	(0.167,0.417,0.667)	(0.250,0.500,0.750)
Sup 10	(0.083,0.333,0.583)	(0.167,0.417,0.667)	(0.417,0.667,0.917)	(0.333,0.583,0.833)	(0.333,0.583,0.833)	(0.250,0.500,0.750)	(0.250,0.500,0.750)	(0.250,0.500,0.750)	(0.167,0.417,0.667)
Sup 11	(0.167,0.417,0.667)	(0.083,0.333,0.583)	(0.417,0.667,0.917)	(0.083,0.333,0.583)	(0.083,0.333,0.583)	(0.417,0.667,0.917)	(0.583,0.833,1)	(0.417,0.667,0.917)	(0.667,0.917,1)
Sup 12	(0,0.083,0.333)	(0,0.083,0.333)	(0.500,0.750,1)	(0.083,0.333,0.583)	(0.417,0.667,0.917)	(0.250,0.500,0.750)	(0,0.167,0.417)	(0.083,0.333,0.583)	(0.083,0.250,0.500)

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

Technical Attributes / Customer Needs	TA_1	TA_2	TA_3	TA_4	TA_5	TA_6	TA_7	TA_8	TA_9	Importance of Customer Needs
CN_1	(0.667,0.917,1)	(0,0,0.250)	(0.667,0.917,1)	(0.667,0.917,1)	(0.583,0.833,1)	(0.583,0.833,1)	(0.250,0.500,0.750)	(0.583,0.833,1)	(0.583,0.833,1)	(0.583,0.833,1)
CN_2	(0.583,0.833,1)	(0,0.083,0.333)	(0,0,0.250)	(0.583,0.833,1)	(0.750,1,1)	(0.750,1,1)	(0.250,0.500,0.750)	(0.750,1,1)	(0,0.167,0.417)	(0.583,0.833,1)
CN_3	(0.167,0.417,0.667)	(0.167,0.417,0.667)	(0,0.167,0.417)	(0.667,0.917,1)	(0.750,1,1)	(0.667,0.917,1)	(0.167,0.417,0.667)	(0.583,0.833,1)	(0,0.083,0.333)	(0.750,1,1)
CN_4	(0,0.083,0.333)	(0,0.167,0.417)	(0,0.167,0.417)	(0.417,0.667,0.917)	(0.583,0.833,1)	(0.583,0.833,1)	(0.583,0.833,1)	(0.583,0.833,1)	(0.083,0.333,0.583)	(0.667,0.917,1)
CN_5	(0,0.083,0.333)	(0.083,0.333,0.583)	(0,0.167,0.417)	(0.333,0.583,0.833)	(0.667,0.917,1)	(0.667,0.917,1)	(0.583,0.833,1)	(0.500,0.750,0.971)	(0.333,0.583,0.833)	(0.417,0.667,0.917)

Fig. 1. Aggregated importance of CNs, aggregated impact of TAs on CNs, and aggregated degree of dependence of TAs.

The rank order of the suppliers is Sup 1 $\succ$ Sup 7 $\succ$ Sup 2 $\succ$ Sup 4 $\succ$ Sup 3 $\succ$ Sup 6 $\succ$ Sup 8 $\succ$ Sup 5 $\succ$ Sup 11 $\succ$ Sup 9 $\succ$ Sup 10 $\succ$ Sup 12. According to the results of the analysis, supplier 1 is determined as the most suitable supplier, which is followed by supplier 7, and then by suppliers 2 and 4. Suppliers 10 and 12 are ranked at the bottom of the list due to late delivery time, inadequate experience in the sector, unsatisfactory earlier business relationships, and improper geographical location. We have been informed that the hospital was previously working with suppliers 1, 2 and 7 based on their own evaluation system. Thus, the results reveal the robustness of the proposed methodology and promote its use as a decision aid for imminent supplier selection situations.

V. Conclusions

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. As supplier selection requires considering multiple conflicting criteria subject to information imperfection with the involvement of a group of experts, it is an important multi-criteria group decision making problem. The classical MCDM methods that consider deterministic or random processes cannot effectively deal with supplier selection problems since fuzziness, imprecision and interaction coexist in real-world. In this paper, a fuzzy multi-criteria group decision making framework is presented to rectify the problems encountered when using classical decision making methods in supplier selection.

The contributions of this research to supplier selection can be summarized as follows. The proposed method is a group decision making process, which enables the group to identify and better appreciate the differences and similarities of their judgments, and is apt to incorporate imprecise data into the analysis using fuzzy set theory. Moreover, the developed methodology enables 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.

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 fuzzy group decision-making approach appears as a sound alternative to existing methods.

One shall also note that the MCDM approach proposed in here for evaluating medical suppliers is a general purpose decision making methodology and can be easily programmed. Hence, implementing the decision framework presented here for real-world group decision making problems in other disciplines that can be represented using HOQ matrices may be the focus of future research.

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