Supplier Selection Using an Integrated Decision Making Approach Based on QFD and 2-Tuple Fuzzy Representation

Mehtap Dursun and E. Ertugrul Karsak

Abstract—**Considering its need to trade-off multiple criteria exhibiting vagueness and imprecision, supplier selection is an important multi-criteria decision making problem. Vague and imprecise judgments inherent in numerous features of supplier selection call for using linguistic assessments rather than exact numerical values. In this paper, a novel fuzzy multi-criteria group decision making approach using the quality function deployment (QFD) concept, fusion of fuzzy information and 2-tuple linguistic representation model is developed for supplier selection. The proposed fuzzy decision making approach 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 (BLTS). Then, the collective performance values are transformed into linguistic 2-tuples to rectify the problem of loss of information encountered using other linguistic approaches. The computational procedure of the proposed framework is illustrated through a supplier selection problem reported in an earlier study.**

Index Terms—**Supplier selection, decision support systems, QFD, 2-tuple linguistic representation**

I. Introduction

SUPPLY chain management attempts to reduce supply chain risk and uncertainty, and thus improve customer service, optimize inventory levels, business processes and cycle times, and result in increased competitiveness, customer satisfaction and profitability [1]. Supplier selection is considered as one of the key issues faced by operations and purchasing managers to sharpen the company's competitive advantage. As organizations become more dependent on their suppliers, the consequences of poor decisions on the selection of individual suppliers and the determination of order quantities to be placed with the selected suppliers become more severe [2].

Supplier selection is a popular area of research in purchasing with methodologies ranging from conceptual to empirical and modeling streams. Supplier selection decisions are complicated by the fact that various criteria must be considered in decision making process. Dickson [3] conducted one of the earliest works on supplier selection and identified 23 supplier attributes that managers consider when choosing a supplier.

Most of the research on supplier selection focuses on the quantifiable aspects of the supplier selection decision such as cost, quality, and delivery reliability. However, as firms become involved in strategic partnerships with their suppliers, a new set of supplier selection criteria, which are difficult to quantify, needs to be considered. Fuzzy set theory is an effective tool to deal with uncertainty. In the literature, there are a number of studies that use different fuzzy decision making techniques to evaluate suppliers. Several authors have used fuzzy mathematical programming approaches ([4] - [6]). A number of studies have focused on the use of fuzzy multi-attribute decision making (MADM) techniques for supplier selection process ([7] - [9]). Several papers have proposed the use of 2-tuple fuzzy linguistic representation model ([10], [11]). Lately, few researchers have employed the quality function deployment (QFD) in supplier selection ([12] - [14]).

Although previously reported studies developed approaches for supplier selection process, further studies are necessary to integrate imprecise information into the analysis, regarding the importance of purchased product features, relationship between purchased product features and supplier assessment criteria, and dependencies between supplier assessment criteria. With its need to trade-off multiple criteria exhibiting vagueness and imprecision, supplier selection is a highly important group decision making problem.

In this paper, a fuzzy multi-criteria group decision making approach based on the concepts of QFD, fusion of fuzzy information, and 2-tuple linguistic representation model is proposed. This method identifies how well each supplier characteristic accomplishes meeting the requirements established for the product being purchased by constructing a house of quality, which enables the relationships among the purchased product features and supplier assessment criteria to be considered. Moreover, the method enables the managers to deal with heterogeneous information, and thus, allows for the use of different semantic types by the decision-makers. The proposed decision making approach uses the ordered weighted averaging (OWA) operator to aggregate decision makers' opinions. The OWA operator is a common generalization of the three basic aggregation operators, i.e. *max*, *min*, and the *arithmetic mean*.

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The rest of the paper is organized as follows. The following section provides concise information on QFD. Section III and Section IV present the fusion of fuzzy information approach and 2-tuple fuzzy linguistic representation model, respectively. In Section V, the fuzzy decision making framework is delineated. The application of the fuzzy decision making framework to supplier selection problem is expressed in Section VI. Finally, concluding remarks are given in Section VII.

II. Quality Function Deployment

QFD is a customer-oriented design tool that aims to meet customer needs in a better way and enhance organizational capabilities, while maximizing company goals. QFD aims at delivering value by focusing on prioritized customer needs, translating these into design requirements, and then communicating them throughout the organization in a way to assure that details can be quantified and controlled [15].

The reported benefits of QFD include better products or services that are highly focused and responsive to customer needs (CNs), developed in a shorter period of time with fewer resources. One shall also note the intangible benefits of QFD such as increased customer satisfaction, enhanced multi-disciplined teamwork, and structured basis for improved planning [16].

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 [17]. In this paper, we focus on the first of the four matrices, also called the house of quality (HOQ). The HOQ contains seven elements as depicted in Figure 1.

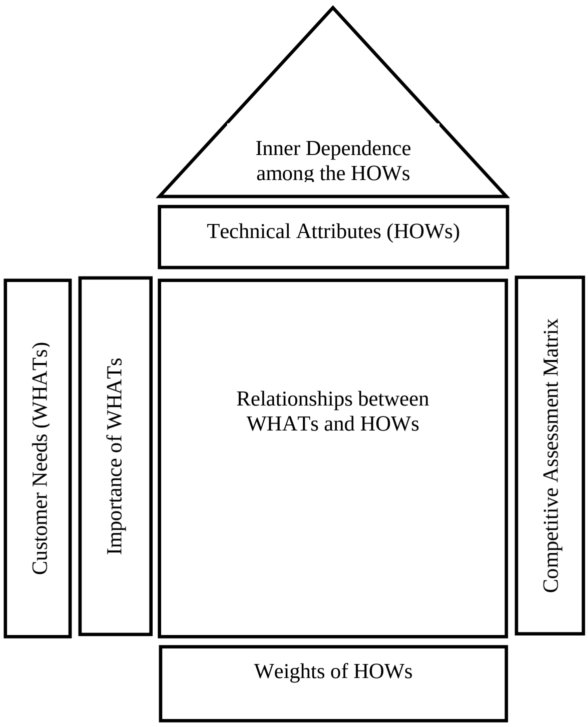

Fig. 1. House of quality.

III. Fusion of Fuzzy Information

Fusion approach of fuzzy information, which was proposed by Herrera, Herrera-Viedma, and Martínez [18] is used to manage information assessed using both linguistic and numerical scales in a decision making problem with multiple information sources. This approach is carried out in two phases:

Phase 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 basic linguistic term set (BLTS), 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 [18]:

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

$$\begin{aligned}
&\tau_{AS_T} = A \rightarrow F(S_T),\\
&\tau_{AS_T}(l_k) = \left\{\left(s_i, \gamma_i^k\right) / i \in \{0,1,...,g\}\right\}, \forall l_k \in A,\\
&\gamma_i^k = \max_y \min\left\{\mu_{l_k}(y), \mu_{s_i}(y)\right\},
\end{aligned} \tag{1}$$

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

Phase 2. Computing the collective performance values: For each alternative, a collective performance value is obtained by means of the aggregation of the aforementioned fuzzy sets on the BLTS that represents the individual performance values assigned to the alternative according to each information source [18]. Therefore, each collective performance value is a new fuzzy set defined on a BLTS. This paper employs the OWA operator, initially proposed by Yager [19], 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 of the criteria to be satisfied. Indeed, the OWA category of operators enables trivial adjustment of the ANDness and ORness degrees embedded in the aggregation [20]. The OWA operator differs from the classical weighted mean in that coefficients are not associated directly with a particular attribute but rather to an ordered position. It encompasses several operators since it can implement different aggregation rules by changing the order weights.

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

$$F(a_1,a_2,...,a_n) = \mathbf{w}\mathbf{b}^T = \sum_{j=1}^{n} w_j b_j, \tag{2}$$

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

To apply the OWA operator for decision making, a crucial issue is to determine its weights. The weights of the OWA operator are calculated using fuzzy linguistic quantifiers, which for a non-decreasing relative quantifier Q, are given by

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

The non-decreasing relative quantifier, Q, is defined as [18]

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

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) given as $(0.3,0.8)$, $(0,0.5)$, and $(0.5,1)$, respectively.

IV. 2-Tuple Fuzzy Linguistic Representation Model

The 2-tuple linguistic model that was presented by Herrera and Martínez [21] 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 [22].

Let $r_1=(s_c,\alpha_1)$ and $r_2=(s_d,\alpha_2)$ be two linguistic variables represented by 2-tuples. The comparison of linguistic information represented by 2-tuples is carried out according to an ordinary lexicographic order as follows [23]:

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

$$\chi : F(S_T) \rightarrow [0,g],$$

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

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

Definition 2 [21]**:** Let $S=\{s_0,s_1,...,s_g\}$ be a linguistic term set and $\beta \in [0,g]$ a value supporting the result of a symbolic aggregation operation, then the 2-tuple that expresses the equivalent information to β is obtained with the following function:

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

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

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

Definition 3 [11, 25]**:** 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 as

$$\bar{x}_l^w\left(\left[(s_1,\alpha_1),(w_1,\alpha_1^w)\right]...\left[(s_n,\alpha_n),(w_n,\alpha_n^w)\right]\right) = \Delta\left(\frac{\sum_{i=1}^{n}\beta_i.\beta_{w_i}}{\sum_{i=1}^{n}\beta_{w_i}}\right) \tag{8}$$

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

V. Fuzzy Decision Making Framework

In this section, a decision making approach that integrates the concepts of QFD, fusion of fuzzy information, and 2-tuple linguistic representation model is developed to address the supplier selection problem. The proposed approach considers the ambiguity resulting from imprecise statements in expressing relative importance of CNs, relationship scores between CNs and TAs, degree of dependencies among TAs, and the ratings of each potential supplier with respect to each TA by using fuzzy set theory. Moreover, 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 of other fuzzy linguistic approaches. The stepwise representation of the fuzzy MCDM framework is as follows:

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 $\tilde{x}_{klz} = (x^1_{klz}, x^2_{klz}, x^3_{klz})$, $\tilde{w}_{lz} = (w^1_{lz}, w^2_{lz}, w^3_{lz})$, and $\tilde{r}_{kk'z} = (r^1_{kk'z}, r^2_{kk'z}, r^3_{kk'z})$, respectively. Convert $\tilde{x}_{klz}$, $\tilde{w}_{lz}$, and $\tilde{r}_{kk'z}$ into the basic linguistic scale S_T by using Eq. (1). The fuzzy assessment vector on S_T, the importance weight vector on S_T, and the degree of dependence vector on S_T, $F(\tilde{x}_{klz})$, $F(\tilde{w}_{lz})$, and $F(\tilde{r}_{kk'z})$ can be represented respectively as

$$F(\tilde{x}_{klz}) = (\gamma(\tilde{x}_{klz}, s_0), \gamma(\tilde{x}_{klz}, s_1), ..., \gamma(\tilde{x}_{klz}, s_6)),\ \forall\, k,l,z \quad (9)$$

$$F(\tilde{w}_{lz}) = (\gamma(\tilde{w}_{lz}, s_0), \gamma(\tilde{w}_{lz}, s_1), ..., \gamma(\tilde{w}_{lz}, s_6)),\ \forall\, l,z \quad (10)$$

and

$$F(\tilde{r}_{kk'z}) = (\gamma(\tilde{r}_{kk'z}, s_0), \gamma(\tilde{r}_{kk'z}, s_1), ..., \gamma(\tilde{r}_{kk'z}, s_6)),\ \forall\, k,k',z \quad (11)$$

In this study, the label set given in Table I is used as the BLTS.

TABLE I
LABEL SET [26]

Label set	Fuzzy number
s_0:	(0,0,0.16)
s_1:	(0,0.16,0.33)
s_2:	(0.16,0.33,0.50)
s_3:	(0.33,0.50,0.66)
s_4:	(0.50,0.66,0.83)
s_5:	(0.66,0.83,1)
s_6:	(0.83,1,1)

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 respectively using Eq. (2) as

$$\tilde{x}_{kl}(s_m) = \varphi_Q(\gamma(\tilde{x}_{kl1}, s_m), \gamma(\tilde{x}_{kl2}, s_m), ..., \gamma(\tilde{x}_{klz}, s_m)),\ \forall k,l,m \quad (12)$$

$$\tilde{w}_l(s_m) = \varphi_Q(\gamma(\tilde{w}_{l1}, s_m), \gamma(\tilde{w}_{l2}, s_m), ..., \gamma(\tilde{w}_{lz}, s_m)),\ \forall l,m \quad (13)$$

and

$$\tilde{r}_{kk'}(s_m) = \varphi_Q(\gamma(\tilde{r}_{kk'1}, s_m), \gamma(\tilde{r}_{kk'2}, s_m), ..., \gamma(\tilde{r}_{kk'z}, s_m)),\ \forall\, k,k',m \quad (14)$$

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 $F(\tilde{r}_{kk'})$ is defined as follows:

$$F(\tilde{x}_{kl}) = (\gamma(\tilde{x}_{kl}, s_0), \gamma(\tilde{x}_{kl}, s_1), ..., \gamma(\tilde{x}_{kl}, s_6)),\ \forall\, k,l \quad (15)$$

$$F(\tilde{w}_l) = (\gamma(\tilde{w}_l, s_0), \gamma(\tilde{w}_l, s_1), ..., \gamma(\tilde{w}_l, s_6)),\ \forall\, l \quad (16)$$

$$F(\tilde{r}_{kk'}) = (\gamma(\tilde{r}_{kk'}, s_0), \gamma(\tilde{r}_{kk'}, s_1), ..., \gamma(\tilde{r}_{kk'}, s_6)),\ \forall\, k,k' \quad (17)$$

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 a linguistic 2-tuple 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. Then, according to Fung et al. [27] and Tang et al. [28], the original relationship measure between the kth TA and the lth CN should be rewritten as

$$\tilde{X}^*_{kl} = \sum_{k'=1}^{K} \tilde{x}_{kk'} D_{k'l} \quad (18)$$

where $\tilde{X}^*_{kl}$ is the actual relationship measure after consideration of the inner dependence among TAs. Note that the correlation matrix **D** is symmetric. A technical attribute has the strongest dependence on itself, i.e. D_{kk} is assigned to be 1. If there is no dependence between the kth and the k'th TAs, then $D_{kk'} = 0$. Benefiting from Eq. (18) the original relationship measure is obtained by 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 weighted average for each TA computed at *Step* 7.

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

VI. ILLUSTRATIVE SUPPLIER SELECTION EXAMPLE

A supplier selection problem addressed in an earlier work by Bevilacqua et al. [12] is used to test the effectiveness of the proposed fuzzy MCDM framework. The problem can be summarized as follows:

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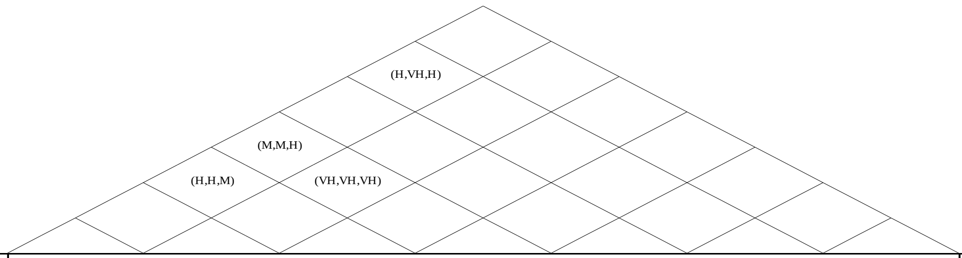

TAs / CNs	EF	IN	SQ	FL	FS	RR	PG	Importance of CNs
Conformity	(VH,H,H)	(VH,VH,VH)	(L,VL,VL)	(M,L,L)	(L,VL,VL)	(H,H,H)	(L,L,L)	(VH,VH,H)
Cost	(M,M,L)	(H,H,M)	(VH,VH,VH)	(L,L,L)	(M,M,M)	(L,L,VL)	(M,M,H)	(M,L,M)
Punctuality	(H,M,H)	(M,M,M)	(L,L,L)	(H,VH,VH)	(L,L,L)	(VH,VH,VH)	(H,H,H)	(H,M,M)
Efficacy	(H,H,VH)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

Fig. 2. House of quality for the supplier selection problem.

The analysis is performed for the selection of clutch plate suppliers for a medium-to-large enterprise that manufactures complete clutch coupling. There are ten suppliers who are in contact with the company. There are six fundamental characteristics (CNs) required of products or services purchased from outside suppliers by the company considered in this study. These can be listed as product conformity, cost, punctuality of deliveries, efficacy of corrective action, availability and customer support, and programming of deliveries. Seven criteria relevant to supplier assessment are identified as "experience of the sector (EF)", "capacity for innovation to follow up the customer's evolution in terms of changes in its strategy and market (IN)", "quality system certification (SQ)", "flexibility of response to the customer's requests (FL)", "financial stability (FS)", "ability to manage orders on-line (RR)", and "geographical position (PG)". The evaluation is conducted by a committee of three decision-makers. The decision-makers used the linguistic variables given in Table II to denote the level of importance of each CN, the impact of each TA on CNs, and the ratings of the suppliers with respect to each TA.

TABLE II
LINGUISTIC TERM SET

Very low (VL)	(0, 0.1, 0.2)
Low (L)	(0.2, 0.3, 0.4)
Medium (M)	(0.4, 0.5, 0.6)
High (H)	(0.6, 0.7, 0.8)
Very high (VH)	(0.8, 0.9, 1)

The inner dependencies among TAs, which were ignored in the supplier selection problem addressed in Bevilacqua et al. [12], were considered in here as shown in Figure 2.

First, the weights of CNs, the fuzzy assessment corresponding the impact of each TA on each CN, and the inner dependencies among TAs are converted into the BLTS employing formulations (9)-(11). Next, by using the linguistic quantifier 'most' and the formulations (3) and (4), the OWA weights for three decision-makers are computed as $\mathbf{w} = (0.067, 0.666, 0.267)$. Then, the weights of CNs, the fuzzy assessment corresponding the impact of each TA on each CN, and the inner dependencies among TAs converted into the BLTS are aggregated employing formulations (12) - (17). The β values of these weights,

TABLE III
PRIORITIZATION OF THE TAS USING THE PROPOSED FRAMEWORK

CNs	Weights of CNs	TAs						
		EF	IN	SQ	FL	FS	RR	PG
Conformity	$(s_5,0.20)$	$(s_3,0.07)$	$(s_4,-0.23)$	$(s_2,0.24)$	$(s_4,-0.26)$	$(s_1,-0.16)$	$(s_4,0.24)$	$(s_2,-0.14)$
Cost	$(s_3,-0.12)$	$(s_3,-0.02)$	$(s_3,0.01)$	$(s_4,0.36)$	$(s_3,-0.12)$	$(s_3,0.01)$	$(s_2,0.21)$	$(s_3,0.01)$
Punctuality	$(s_3,0.14)$	$(s_4,0.07)$	$(s_4,0.04)$	$(s_3,-0.26)$	$(s_4,0.14)$	$(s_2,-0.14)$	$(s_5,-0.20)$	$(s_4,0.18)$
Efficacy	$(s_3,-0.12)$	$(s_4,-0.37)$	$(s_5,0.28)$	$(s_3,-0.06)$	$(s_5,0.07)$	$(s_2,-0.14)$	$(s_4,-0.42)$	$(s_1,-0.16)$
Programming	$(s_2,-0.28)$	$(s_3,0.44)$	$(s_4,-0.45)$	$(s_3,-0.21)$	$(s_4,-0.36)$	$(s_1,-0.16)$	$(s_4,0.18)$	$(s_1,-0.30)$
Availability	$(s_2,0.01)$	$(s_4,-0.22)$	$(s_5,0.20)$	$(s_3,-0.35)$	$(s_5,-0.05)$	$(s_3,0.01)$	$(s_4,0.20)$	$(s_4,0.32)$
2-tuple linguistic weighted average		$(s_3,0.44)$	$(s_4,0.08)$	$(s_3,-0.12)$	$(s_4,0.01)$	$(s_2,-0.22)$	$(s_4,-0.11)$	$(s_2,0.45)$

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ratings, and dependencies are computed and transformed into a linguistic 2-tuple using formulations (5) and (6), respectively. The original relationship measure between TAs and CNs is computed employing Eq. (18) and 2-tuple linguistic weighted average. Then, the 2-tuple linguistic weighted averages for each TA are calculated. The results are shown in Table III.

The ratings of each supplier converted into the BLTS are aggregated and transformed into a linguistic 2-tuple. Finally, the 2-tuple linguistic weighted average for each supplier is calculated and the suppliers are ranked according to the 2-tuple linguistic weighted average score. The ranking order of the suppliers is obtained as Sup 2 $\succ$ Sup 5 $\succ$ Sup 7 $\succ$ Sup 8 $\succ$ Sup 3 $\succ$ Sup 6 $\succ$ Sup 1 $\succ$ Sup 4 $\succ$ Sup 9 $\succ$ Sup 10.

Table IV summarizes the results obtained from the proposed decision algorithm. Supplier 2 is determined as the most suitable supplier, which is followed by supplier 5. While the fuzzy ranking principle of Bevilacqua et al. [12] cannot compare suppliers 1, 9, and 10, the methodology proposed in this study provides a complete ranking of all suppliers. This is due to the minimization of the loss of information by using the 2-tuple fuzzy linguistic representation model.

TABLE IV
RANKING OF THE SUPPLIERS USING THE PROPOSED ALGORITHM

Suppliers	2-tuple linguistic weighted average score	Rank
Sup 1	$(s_2,0.46)$	7
Sup 2	$(s_3,0.32)$	1
Sup 3	$(s_3,-0.24)$	5
Sup 4	$(s_2,0.37)$	8
Sup 5	$(s_3,0.29)$	2
Sup 6	$(s_3,-0.44)$	6
Sup 7	$(s_3,0.22)$	3
Sup 8	$(s_3,-0.08)$	4
Sup 9	$(s_2,0.25)$	9
Sup 10	$(s_2,0.16)$	10

VII. CONCLUSION

In today's competitive environment, comprehensive decision aids for selection of suppliers are essential for the success of a manufacturing firm. In this paper, a fuzzy multi-criteria group decision making algorithm based on the concepts of QFD, fusion of fuzzy information, and 2-tuple linguistic representation model is presented to rectify the problems encountered when using classical decision making methods in supplier selection. The proposed decision framework enables both relationship between purchased product features and supplier assessment criteria, and inner dependencies between supplier assessment criteria to be taken into consideration. The decision making approach presented 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. Moreover, the decision methodology enables managers to deal with heterogeneous information, and thus, allows for the use of different semantic types by decision-makers.

Future research will address the implementation of the proposed methodology in real-world group decision making settings across diverse disciplines that can be represented in HOQ structure.

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