An Integrated QFD-DEA Framework with Imprecise Data for Supplier Selection

E. Ertegrul Karsak and Mehtap Dursun

Abstract—Supplier selection possesses the need to evaluate multiple criteria incorporating vagueness and imprecision with the involvement of a group of experts. This is considered as a crucial multi-criteria group decision making problem. In this paper, a novel fuzzy multi-criteria group decision making approach integrating quality function deployment (QFD), fuzzy weighted average (FWA), and data envelopment analysis (DEA) is developed for supplier selection. The proposed methodology enables to consider the impacts of inner dependence among supplier assessment criteria. The upper and the lower bounds of the weights of supplier assessment criteria are identified by using FWA method that allows for the fusion of imprecise and subjective information expressed as linguistic variables. DEA is implemented for supplier selection utilizing the data from the house of quality (HOQ) and the weights of supplier assessment criteria obtained using FWA. The proposed decision making framework is illustrated using a data set from a previously reported supplier selection problem. The proposed approach is a sound and effective decision aid that considers qualitative as well as quantitative aspects, and thus improves the quality of complex supplier selection decisions.

Index Terms—Data envelopment analysis, decision support systems, fuzzy weighted average, QFD, supplier selection.

I. INTRODUCTION

Supplier selection is considered as one of the essential issues encountered 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 [1].

The classical multi-criteria decision making (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, an integrated group decision making methodology is presented to rectify the problems encountered when using classical decision making methods in supplier selection.

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 [2] 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 ([3] - [5]). A number of studies have focused on the use of fuzzy multi-attribute decision making (MADM) techniques for supplier selection process ([6] - [8]). Lately, few researchers have employed the quality function deployment (QFD) in supplier selection ([9] - [11]).

Data envelopment analysis (DEA) has been actively used in supplier evaluation and selection for more than a decade owing to its capability of handling multiple conflicting factors without the need of eliciting subjective importance weights from the decision-makers ([12]-[14]). One of the major limitations of the use of conventional DEA approach in supplier selection process is the sole consideration of cardinal data. Difficulty in predicting a number of factors considered in supplier selection demand imprecise data to be taken into account as well. Another major limitation is the poor discriminating power of DEA models resulting in a relatively high number of suppliers rated as efficient.

Although previously reported studies developed approaches for supplier selection process, further studies are necessary to account for imprecise information regarding the importance of purchased product features, relationship between purchased product features and supplier assessment criteria, and dependencies between supplier assessment criteria.

In this paper, a fuzzy multi-criteria group decision making approach based on QFD, fuzzy weighted average (FWA), and DEA is proposed. This method identifies how well each supplier attribute 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.

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II. QUALITY FUNCTION DEPLOYMENT

Quality function deployment is a customer-oriented design tool which focuses on developing a holistic systems approach to aid the planning and realization of products or services at a quality level that will meet or exceed customer expectations by bridging the communications gap between the customers and the design team [15]. QFD aims at delivering value by taking into account the customer needs and then deploying this information throughout the development process. The reported benefits of QFD include better products or services that are highly focused and responsive to the customer needs, developed in a shorter period of time with fewer resources.

The key objective of QFD is to translate the desires of customers into design requirements, 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/planning matrices, respectively. The product planning matrix translates customer needs into design requirements; the part deployment matrix translates important design requirements into product/part characteristics; the process planning matrix translates important product/part characteristics into manufacturing operations; the production/planning matrix translates important manufacturing operations into day-to-day operations and controls [16].

In this paper, we focus on the first of the four matrices, also called the house of quality (HOQ). Relationships between customer needs (CNs) and design requirements are defined by answering a specific question corresponding to each cell in the HOQ. In order to incorporate the relationship between design requirements, pairwise comparisons are performed in the area referred as the “roof matrix”.

III. FUZZY WEIGHTED AVERAGE

We will consider the general fuzzy weighted average with \( n \) criteria. Let
\[
\tilde{W}_j = \left\{ w_j, \mu_{\tilde{W}_j}(w_j) \right\} \quad w_j \in W_j, \quad j = 1, 2, ..., n
\]
and
\[
\tilde{X}_{ij} = \left\{ x_{ij}, \mu_{\tilde{X}_{ij}}(x_{ij}) \right\} \quad x_{ij} \in X_{ij}, \quad i = 1, 2, ..., m, \quad j = 1, 2, ..., n
\]
where \( \tilde{W}_j \) denotes the relative importance of criterion \( j \) and \( \tilde{X}_{ij} \) is the rating of alternative \( i \) with respect to criterion \( j \). \( W_j \) and \( X_{ij} \) are the crisp universal sets of the relative importance and the rating, and \( \mu_{\tilde{W}_j} \) and \( \mu_{\tilde{X}_{ij}} \) represent the membership functions of the fuzzy numbers \( \tilde{W}_j \) and \( \tilde{X}_{ij} \), respectively. Then, the fuzzy weighted average is defined as
\[
\tilde{y}_i = \sum_{j=1}^{n} \tilde{W}_j \cdot \tilde{X}_{ij} = \frac{1}{\sum_{j=1}^{n} \tilde{W}_j}, \quad i = 1, 2, ..., m
\]  \hspace{1cm} (3)

Since \( \tilde{W}_j \) and \( \tilde{X}_{ij} \) are fuzzy numbers, the weighted average \( \tilde{y}_i \) is also a fuzzy number. In this paper, the method proposed by Kao and Liu [17] is used for calculating fuzzy weighted average. Kao and Liu [17] approached the problem via mathematical programming technique and developed a pair of fractional programs to find the \( \alpha \)-cut of \( \tilde{y}_i \) based on the extension principle. An outline of the method is provided below.

In order to find the membership function \( \mu_{\tilde{Y}_i} \), one needs to find the right shape function and the left shape function of \( \mu_{\tilde{Y}_i} \), which is equivalent to finding the upper bound \( (Y_i)^U_{\alpha} \) and the lower bound \( (Y_i)^L_{\alpha} \) of \( \tilde{Y}_i \) at the \( \alpha \)-level. Since \( (Y_i)^U_{\alpha} \) and \( (Y_i)^L_{\alpha} \) are respectively the maximum and the minimum of \( \sum_{j=1}^{n} w_j x_{ij} / \sum_{j=1}^{n} w_j \), the upper and the lower bounds of the \( \alpha \)-cut of \( \tilde{Y}_i \) can be solved as
\[
(Y_i)^U_{\alpha} = \max \sum_{j=1}^{n} w_j x_{ij} / \sum_{j=1}^{n} w_j
\]
subject to
\[
(W_j)^L_{\alpha} \leq w_j \leq (W_j)^U_{\alpha}, \quad j = 1, 2, ..., n
\]
\[
(X_{ij})^L_{\alpha} \leq x_{ij} \leq (X_{ij})^U_{\alpha}, \quad i = 1, 2, ..., m, \quad j = 1, 2, ..., n
\]
\[
(Y_i)^L_{\alpha} = \min \sum_{j=1}^{n} w_j x_{ij} / \sum_{j=1}^{n} w_j
\]
subject to
\[
(W_j)^L_{\alpha} \leq w_j \leq (W_j)^U_{\alpha}, \quad j = 1, 2, ..., n
\]
\[
(X_{ij})^L_{\alpha} \leq x_{ij} \leq (X_{ij})^U_{\alpha}, \quad i = 1, 2, ..., m, \quad j = 1, 2, ..., n
\]

It is evident that the maximum and minimum of \( y_i \) must occur at \( (X_{ij})^U_{\alpha} \) and \( (X_{ij})^L_{\alpha} \), respectively. Hence, the variable \( x_{ij} \) in the objective function of formulations (4) and (5) can be replaced by \( (X_{ij})^U_{\alpha} \) and \( (X_{ij})^L_{\alpha} \), respectively. Following the variable substitution of Charnes, Cooper and Rhodes [18], by letting \( t^{-1} = \sum_{j=1}^{n} w_j \) and \( v_j = tw_j \), formulations (4) and (5) can be transformed to the following linear programs:
\[
(Y_i^U)_{\alpha} = \max \sum_{j=1}^{n} v_j (X_{ij}^U)_{\alpha}
\]

subject to
\[
t(W_i^L)_{\alpha} \leq v_j \leq t(W_i^U)_{\alpha}, \quad j = 1, 2, ..., n
\]
\[
\sum_{j=1}^{n} v_j = 1
\]
\[
t, v_j \geq 0, \quad j = 1, 2, ..., n
\]
\[
(Y_i^L)_{\alpha} = \min \sum_{j=1}^{n} v_j (X_{ij}^L)_{\alpha}
\]

subject to
\[
t(W_i^L)_{\alpha} \leq v_j \leq t(W_i^U)_{\alpha}, \quad j = 1, 2, ..., n
\]
\[
\sum_{j=1}^{n} v_j = 1
\]
\[
t, v_j \geq 0, \quad j = 1, 2, ..., n
\]

The \( \alpha \)-cuts of \( \bar{Y}_i \) form the crisp interval \( \left[ (Y_i^L)_{\alpha}, (Y_i^U)_{\alpha} \right] \)

obtained from formulations (6) and (7). The membership function \( \mu_{\bar{Y}_i} \) can be constructed through enumerating different \( \alpha \) values.

IV. DATA ENVENLOPMENT ANALYSIS

Data envelopment analysis is a linear programming based
decision technique designed specifically to measure relative
efficiency using multiple inputs and outputs without a priori
information regarding which inputs and outputs are the most
important in determining an efficiency score. DEA
considers \( n \) decision making units (DMUs) to be evaluated,
where each DMU consumes varying amounts of \( m \) different
inputs to produce \( s \) different outputs.

The relative efficiency of a DMU is defined as the ratio
of its total weighted output to its total weighted input. In
mathematical programming terms, this ratio, which is to be
maximized, forms the objective function for the particular
DMU being evaluated. A set of normalizing constraints is
required to reflect the condition that the output to input ratio
of every DMU be less than or equal to unity. The
mathematical programming problem is then represented as

\[
\begin{align*}
\max E_{j0} &= \sum_{r} u_r y_{r0} \\
\text{subject to} & \sum_{i} v_{i} x_{ij0} \\
& \sum_{r} u_r y_{rj} \leq 1, \quad j = 1, ..., n \\
& u_r, v_i \geq 0, \quad r = 1, ..., s; \quad i = 1, ..., m
\end{align*}
\]

where \( E_{j0} \) is the efficiency score of the evaluated DMU
(\( j_0 \)), \( u_r \) is the weight assigned to output \( r \), \( v_i \) is the weight
assigned to input \( i \), \( y \) denotes amount of output \( r \) produced
by the \( j \)th DMU, \( x_{ij} \) denotes amount of input \( i \) used by the \( j \)th
DMU, and \( \varepsilon \) is an infinitesimal positive number. A DMU
attains a relative efficiency rating of 1 only when
comparisons with other DMUs do not provide evidence of
inefficiency in the use of any input or output.

The fractional program is not used for actual computation
of the efficiency scores due to its intractable nonlinear and
nonconvex properties [18]. Rather, it is transformed to an
ordinary linear program that is computed separately for each
DMU, generating \( n \) sets of optimal weights.

The original DEA models assume that inputs and outputs
are indicated as crisp numbers. Over the past decade, a
number of researchers have published on DEA models
incorporating imprecise data. Kao and Liu [19] developed an
\( \alpha \)-cut based approach to transform a fuzzy DEA model
to a number of crisp DEA models. Since the efficiency
values of DMUs are expressed by membership functions,
the local order of DMUs is obtained by employing fuzzy
number ranking methods that may produce inconsistent
outcomes. Despotis and Smirlis [20] proposed a DEA model
dealing with exact and interval data. Their approach
requires an increase in the number of variables by \( (m + s) (n \) –1), for \( i = 1, ..., m \) and \( r = 1, ..., s \), for each linear
program. Moreover, generalizing their approach to fuzzy
data would be problematic since it is more reasonable to
evaluate DMUs using the same level of \( \alpha \)-cut for each
linear program. Lertworasiriruk et al. [21] have proposed a
possibility approach for solving fuzzy DEA models. Due to
its extremely permissive nature, the possibility approach has a
low discriminating power which often results in several
efficient DMUs at all possibility levels.

In here, a pessimistic DEA formulation based on Karsak
[22] that enables incorporating imprecise data is presented
to address decision problems regarding the evaluation of
relative efficiency of DMUs. Imprecision in inputs and
outputs are taken into account using fuzzy data.

Define \( \tilde{x}_{ij} = \left( x_{ij}, x_{ija}, x_{ijb}, x_{ijc} \right) \), for \( 0 \leq x_{ija} \leq x_{ijb} \leq x_{ijc} \) as
the fuzzy input \( i \) used by the \( j \)th DMU, and
\( \tilde{y}_{rj} = \left( y_{rja}, y_{rjb}, y_{rjc} \right) \) as the fuzzy output \( r \) produced by the
\( j \)th DMU, where \( 0 \leq y_{rja} \leq y_{rjb} \leq y_{rjc} \). Let \( (x_{ij})^L_\alpha \) and
\( (x_{ij})^U_\alpha \) denote the lower and upper bounds of the \( \alpha \)-cut of
the membership function of \( \tilde{x}_{ij} \), and likewise, \( (y_{rj})^L_\alpha \) and
\( (y_{rj})^U_\alpha \) denote the lower and upper bounds of the \( \alpha \)-cut of
the membership function of \( \tilde{y}_{rj} \), respectively. Let \( a_0 = v_r \alpha_r \),
where \( 0 \leq a_0 \leq v_r \). Then, \( \sum_{r} v_{i}(x_{ij})^L_\alpha \) and \( \sum_{r} v_{i}(x_{ij})^U_\alpha \) can be represented as

\[
\sum_{r} v_{i}(x_{ij})^L_\alpha = \sum_{r} v_{i}x_{ij} + a_0(x_{ijb} - x_{ija})
\]

...
\[ \sum_{i} \nu(x_{ij}) = \sum_{i} \nu(x_{ij} - x_{ijb}). \]

Similarly, define \( \mu_r = u_r \cdot \alpha_r \), where \( 0 \leq \mu_r \leq u_r \). Then, \( \sum r \sum u_r (y_{rij})^L \) and \( \sum r \sum u_r (y_{rij})^U \) can be represented respectively as

\[ \sum r \sum u_r (y_{rij})^L = \sum r \sum u_r (y_{rij} + \mu_r (y_{rij} - y_{rij})) \]

\[ \sum r \sum u_r (y_{rij})^U = \sum u_r (y_{rij} - \mu_r (y_{rij} - y_{rij})). \]

Let \( (E_j)^l \) denote the lower bound of the \( \alpha \)-cut of the membership function of the efficiency value for the evaluated DMU \((j)\). Utilizing the substitutions given above, the pessimistic scenario DE model incorporating fuzzy data can be written as follows:

\[ \max \left( (E_j)^l \right) = \sum u_r (y_{rij} + \mu_r (y_{rij} - y_{rij})) \]

subject to

\[ \sum \nu(x_{ijc} - \omega_i (x_{ijb} - x_{ijb})) = 1 \]

\[ \sum u_r (y_{rij} + \mu_r (y_{rij} - y_{rij})) - \sum \nu(x_{ijb} - \omega_i (x_{ijb} - x_{ijb})) \leq 0 \]

\[ \sum u_r (y_{rij} - \mu_r (y_{rij} - y_{rij})) \]

\[ -\sum \nu(x_{ijc} + \omega_i (x_{ijb} - x_{ijb})) \leq 0, \quad j = 1,2,\ldots,m; \quad j \neq j_0 \]

\[ u_r - \beta_r u_p \geq 0, \quad r = 1,\ldots,s; \quad r \neq p \]

\[ u_r - \gamma_r u_p \leq 0, \quad r = 1,\ldots,s; \quad r \neq p \]

\[ \mu_r - u_r \leq 0, \quad r = 1,\ldots,s \]

\[ \omega_i - \gamma_i \leq 0, \quad i = 1,\ldots,m \]

\[ \mu_i \geq 0, \quad r = 1,\ldots,s \]

\[ \omega_i \geq 0, \quad i = 1,\ldots,m \]

\[ u_r \geq \varepsilon > 0, \quad r = 1,\ldots,s \]

\[ v_i \geq \varepsilon > 0, \quad i = 1,\ldots,m \]

where, in addition to the earlier notation introduced for previous formulations, \( \beta_r, \gamma_i \in [0,1] \) represent the lower and upper bounds of the relative importance weights of output \( r \), respectively, and they are normalized in a way that \( \beta_p = \gamma_p = 1 \).

V. FUZZY DECISION MAKING FRAMEWORK

In this section, an integrated decision making approach that utilizes QFD, FWA, and DEA is developed to address the supplier selection problem. The proposed methodology considers the ambiguity resulting from imprecise statements in expressing relative importance of CNs, relationship scores between CNs and supplier attributes (SAs), degree of dependencies among SAs, and the ratings of each potential supplier with respect to each SA by using fuzzy set theory. The stepwise representation of the decision making framework is as follows:

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

Step 2. Construct the decision matrices for each decision-maker that denote the relative importance of CNs, and the fuzzy assessment to determine the CN-SA relationship scores.

Step 3. Let the fuzzy value assigned as the relationship score between the \( k \)th CN (\( k = 1,2,\ldots,K \)) and the \( j \)th SA (\( j = 1,2,\ldots,J \)), and importance weight of the \( k \)th CN for the \( j \)th decision-maker be \( \tilde{x}_{kz} = (x_{k0z}, x_{klz}, \ldots, x_{kcz}) \), and \( \tilde{w}_j = (w_{j0}, w_{j1}, w_{j2}, \ldots, w_{jZ}) \), respectively. Compute the aggregated fuzzy assessment of the relationship scores between the \( j \)th SA and the \( k \)th CN (\( \tilde{x}_{kl} \)), and aggregated importance weight of the \( k \)th CN (\( \tilde{w}_k \)) as follows:

\[ \tilde{x}_{kl} = \sum_{z=1}^{Z} \Omega_z \tilde{x}_{kz} \quad (10) \]

\[ \tilde{w}_k = \sum_{z=1}^{Z} \Omega_z \tilde{w}_z \quad (11) \]

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

Step 4. Construct the inner dependence matrix among the SAs, and compute the original relationship measure between the \( k \)th SA and the \( l \)th SA, \( \tilde{X}_{kl}^{*} \). Let \( D_{kk'} \) denote the degree of dependence of the \( k \)th SA on the \( k' \)th SA. Then, according to Fung et al. [23], the original relationship measure between the \( k \)th SA and the \( l \)th SA should be rewritten as

\[ \tilde{X}_{kl}^{*} = \sum_{k=1}^{K} D_{kk'} \tilde{X}_{kl} \quad (12) \]

where \( \tilde{X}_{kl}^{*} \) is the actual relationship measure after consideration of the inner dependence among SAs. A design requirement has the strongest dependence on itself, i.e. \( D_{kk} \) is assigned to be 1.

Step 5. Calculate the upper and lower bounds of the weight for each SA by employing formulations (6) and (7).

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

Step 7. Aggregate the ratings of suppliers using Eq. (10).

Step 8. Construct the DEA models for supplier selection. The attributes that are to be minimized are viewed as inputs, whereas the ones to be maximized are considered as outputs. The upper and lower bounds of the weights for each SA calculated at Step 5 are used as weight restrictions in the DEA models.
Step 9. Determine the maximum feasible value for $\varepsilon$, which can be computed by maximizing $\varepsilon$ subject to the constraint set of the respective DEA formulation for $j = 1, \ldots, n$, and then by defining $\varepsilon_{\text{max}} = \min_j \{\varepsilon_j\}$.

Step 10. Compute the DEA efficiency scores for the suppliers by employing a pessimistic scenario DEA model. Select the supplier with an efficiency score of 1.

VI. ILLUSTRATIVE SUPPLIER SELECTION EXAMPLE

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

The analysis is performed for the evaluation of ten clutch plate suppliers. There are six fundamental characteristics (CNs) required of products or services purchased from outside suppliers 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 performed by a committee of three decision-makers. The data that are provided in the HOQ depicted in Figure 1 and in Table II consist of assessments of three decision-makers employing linguistic variables represented in Table I.

The aggregated importance of each CN and the aggregated impact of each SA on each CN are obtained by using Eqs. (10) and (11). As equal weights are assigned to each decision-maker in our case, we set $\Omega_1 = \Omega_2 = \Omega_3 = 1/3$. The aggregated impact of each SA on each CN is equivalent to the original relationship measure between SAs and CNs since inner dependencies among the SAs do not exist in Bevilacqua et al. [9].

The upper and lower bounds of the weight of SAs for $\alpha = 0$ are calculated through formulations (6) and (7) as represented in Table III. Since all of the SAs are to be maximized, they are considered as outputs in the DEA formulation, and thus a dummy input with a constant value of 1 is introduced. Using the pertinent data given in Tables II and III, $\varepsilon$ is computed as 0.0171 employing Step 9 of the proposed algorithm. With $\varepsilon = 0.0171$, the efficiency scores of suppliers are calculated using formulation (9). The supplier efficiency scores are provided in Table IV. Supplier 5 (S5) is the only efficient alternative among the candidate suppliers, and thus considered as the most suitable.

<table>
<thead>
<tr>
<th>Suppliers</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>S5</th>
<th>S6</th>
<th>S7</th>
<th>S8</th>
<th>S9</th>
<th>S10</th>
</tr>
</thead>
<tbody>
<tr>
<td>RR (VH,VL,VL)</td>
<td>(VH,VL,VL)</td>
<td>(VH,VL,VL)</td>
<td>(VH,VL,VL)</td>
<td>(L,L,M)</td>
<td>(VH,VH,VH)</td>
<td>(VL,VL,VL)</td>
<td>(VH,VH,VH)</td>
<td>(VH,VH,VH)</td>
<td>(VH,VH,VH)</td>
<td>(VH,VH,VH)</td>
</tr>
</tbody>
</table>

Fig. 1 First house of quality for the supplier selection problem.
DEA circumvents the possibility of selecting a suboptimal and subjective information, to calculate the upper and lower bounds of relationships among the purchased product features and linguistic variables. Second, it is apt to consider the impacts of loss of information that occurs when integrating imprecise method uses FWA method, which rectifies the problem of among supplier selection criteria. Third, the proposed method that identifies the upper and lower bounds of the supply chain through integrating QFD planning, FWA allows for a tradeoff among all types of information within the supplier selection literature. First, the proposed approach advantages compared to other MCDM methods presented in the literature.

### VII. CONCLUSION

In this study, a decision methodology is presented that allows for a tradeoff among all types of information within the supply chain through integrating QFD planning, FWA method that identifies the upper and lower bounds of the weights of supplier selection criteria, and DEA.

The proposed methodology possesses a number of advantages compared to other MCDM methods presented in the literature. First, the proposed approach enables to incorporate imprecise data into the analysis using linguistic variables. Second, it is apt to consider the impacts of relationships among the purchased product features and supplier selection criteria, and also the inner dependence among supplier selection criteria. Third, the proposed method uses FWA method, which rectifies the problem of loss of information that occurs when integrating imprecise and subjective information, to calculate the upper and lower bounds of the weights of supplier selection criteria. Fourth, DEA circumvents the possibility of selecting a suboptimal supplier. Finally, the decision approach presented in here avoids the troublesome fuzzy number ranking process, which may yield inconsistent results for different ranking methods. The implementation of the proposed approach in supplier selection problems using real-world data will be the subject of future research.

### REFERENCES


