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

E. Ertugrul 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, and 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.

Manuscript received March 18, 2013. This work was financially supported by Galatasaray University Research Fund under Grant 12.402.001.

E. E. Karsak is with Industrial Engineering Department, Galatasaray University, Ortakoy, Istanbul 34357, Turkey (fax: +90-212-259-5557; e-mail: ekarsak@gsu.edu.tr).

M. Dursun is with Industrial Engineering Department, Galatasaray University, Ortakoy, Istanbul 34357, Turkey (fax: +90-212-259-5557; e-mail: mdursun@gsu.edu.tr).

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.

ISBN: 978-988-19251-0-7
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

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/operation 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/operation 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

$$\widetilde{W}_j = \left\{ \left(w_j, \mu_{\widetilde{W}_j}\left(w_j\right)\right) \middle| w_j \in W_j \right\}, \quad j = 1,2,...,n \tag{1}$$

and

$$\tilde{X}_{ij} = \left\{ \left(x_{ij}, \mu_{\tilde{X}_{ij}}\left(x_{ij}\right)\right) \middle| x_{ij} \in X_{ij} \right\}, \; i = 1,2,...,m, \; j = 1,2,...,n \tag{2}$$

where $\widetilde{W}_j$ denotes the relative importance of criterion j and $\widetilde{X}_{ij}$ 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 $\mu_{\widetilde{W}_j}$ and $\mu_{\widetilde{X}_{ij}}$ represent the membership functions of the fuzzy numbers $\widetilde{W}_j$ and $\widetilde{X}_{ij}$, respectively. Then, the fuzzy weighted average is defined as

$$\widetilde{Y}_i = \sum_{j=1}^{n} \widetilde{W}_j \widetilde{X}_{ij} \Big/ \sum_{j=1}^{n} \widetilde{W}_j, \quad i = 1,2,...,m \tag{3}$$

Since $\widetilde{W}_j$ and $\widetilde{X}_{ij}$ are fuzzy numbers, the weighted average $\widetilde{Y}_i$ 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 α-cut of $\widetilde{Y}_i$ based on the extension principle. An outline of the method is provided below.

In order to find the membership function $\mu_{\widetilde{Y}_i}$, one needs to find the right shape function and the left shape function of $\mu_{\widetilde{Y}_i}$, which is equivalent to finding the upper bound $\left(Y_i\right)_\alpha^U$ and the lower bound $\left(Y_i\right)_\alpha^L$ of $\widetilde{Y}_i$ at the α-level. Since $\left(Y_i\right)_\alpha^U$ and $\left(Y_i\right)_\alpha^L$ are respectively the maximum and the minimum of $\sum_{j=1}^{n} w_j x_{ij} \Big/ \sum_{j=1}^{n} w_j$, the upper and the lower bounds of the α-cut of $\widetilde{Y}_i$ can be solved as

$$\begin{aligned} \left(Y_i\right)_\alpha^U &= \max \sum_{j=1}^{n} w_j x_{ij} \Big/ \sum_{j=1}^{n} w_j \\ \text{subject to} & \\ & \left(W_j\right)_\alpha^L \le w_j \le \left(W_j\right)_\alpha^U, \quad j = 1,2,...,n \\ & \left(X_{ij}\right)_\alpha^L \le x_{ij} \le \left(X_{ij}\right)_\alpha^U, \; i = 1,2,...,m, \; j = 1,2,...,n \end{aligned} \tag{4}$$

$$\begin{aligned} \left(Y_i\right)_\alpha^L &= \min \sum_{j=1}^{n} w_j x_{ij} \Big/ \sum_{j=1}^{n} w_j \\ \text{subject to} & \\ & \left(W_j\right)_\alpha^L \le w_j \le \left(W_j\right)_\alpha^U, \; j = 1,2,...,n \\ & \left(X_{ij}\right)_\alpha^L \le x_{ij} \le \left(X_{ij}\right)_\alpha^U, \; i = 1,2,...,m, \; j = 1,2,...,n \end{aligned} \tag{5}$$

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

ISBN: 978-988-19251-0-7
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

$$\left(Y_i\right)_\alpha^U = \max \sum_{j=1}^{n} v_j \left(X_{ij}\right)_\alpha^U$$

subject to

$$t\left(W_j\right)_\alpha^L \le v_j \le t\left(W_j\right)_\alpha^U,\ j=1,2,...,n \tag{6}$$

$$\sum_{j=1}^{n} v_j = 1$$

$$t, v_j \ge 0,\ j=1,2,...,n$$

$$\left(Y_i\right)_\alpha^L = \min \sum_{j=1}^{n} v_j \left(X_{ij}\right)_\alpha^L$$

subject to

$$t\left(W_j\right)_\alpha^L \le v_j \le t\left(W_j\right)_\alpha^U,\ j=1,2,...,n \tag{7}$$

$$\sum_{j=1}^{n} v_j = 1$$

$$t, v_j \ge 0,\ j=1,2,...,n$$

The α-cuts of $\widetilde{Y}_i$ form the crisp interval $\left[(Y_i)_\alpha^L, (Y_i)_\alpha^U\right]$ obtained from formulations (6) and (7). The membership function $\mu_{\tilde{Y}_i}$ can be constructed through enumerating different α values.

IV. Data Envelopment 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

$$\max E_{j_0} = \frac{\sum_r u_r y_{rj_0}}{\sum_i v_i x_{ij_0}}$$

subject to (8)

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \le 1,\ j = 1, ..., n$$

$$u_r, v_i \ge \varepsilon > 0,\ r = 1,\dots, s;\ i = 1, \dots, m$$

where E_{j_0} 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_{rj} denotes amount of output r produced by the jth DMU, x_{ij} denotes amount of input i used by the jth DMU, and ε 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 α–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, a rank 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 $i = 1, \dots, m$ and $r = 1, \dots, s$, 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 α–cut for each linear program. Lertworasirikul 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 $\tilde{x}_{ij} = \left(x_{ija}, x_{ijb}, x_{ijc}\right)$, for $0 \le x_{ija} \le x_{ijb} \le x_{ijc}$ as the fuzzy input i used by the jth DMU, and $\tilde{y}_{rj} = \left(y_{rja}, y_{rjb}, y_{rjc}\right)$ as the fuzzy output r produced by the jth DMU, where $0 \le y_{rja} \le y_{rjb} \le y_{rjc}$. Let $\left(x_{ij}\right)_\alpha^L$ and $\left(x_{ij}\right)_\alpha^U$ denote the lower and upper bounds of the α-cut of the membership function of $\tilde{x}_{ij}$, and likewise, $\left(y_{rj}\right)_\alpha^L$ and $\left(y_{rj}\right)_\alpha^U$ denote the lower and upper bounds of the α-cut of the membership function of $\tilde{y}_{rj}$, respectively. Let $\omega_i = v_i \cdot \alpha_i$, where $0 \le \omega_i \le v_i$. Then, $\sum_i v_i\left(x_{ij}\right)_\alpha^L$ and $\sum_i v_i\left(x_{ij}\right)_\alpha^U$ can be represented as

$$\sum_i v_i\left(x_{ij}\right)_\alpha^L = \sum_i v_i x_{ija} + \omega_i\left(x_{ijb} - x_{ija}\right),$$

ISBN: 978-988-19251-0-7
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

$$\sum_i v_i\left(x_{ij}\right)_\alpha^U = \sum_i v_i x_{ijc} - \omega_i\left(x_{ijc} - x_{ijb}\right).$$

Similarly, define $\mu_r = u_r \cdot \alpha_r$, where $0 \le \mu_r \le u_r$. Then, $\sum_r u_r\left(y_{rj}\right)_\alpha^L$ and $\sum_r u_r\left(y_{rj}\right)_\alpha^U$ can be represented respectively as

$$\sum_r u_r\left(y_{rj}\right)_\alpha^L = \sum_r u_r y_{rja} + \mu_r\left(y_{rjb} - y_{rja}\right),$$

$$\sum_r u_r\left(y_{rj}\right)_\alpha^U = \sum_r u_r y_{rjc} - \mu_r\left(y_{rjc} - y_{rjb}\right).$$

Let $\left(E_{j_0}\right)^L$ denote the lower bound of the α-cut of the membership function of the efficiency value for the evaluated DMU (j_0). Utilizing the substitutions given above, the pessimistic scenario DEA model incorporating fuzzy data can be written as follows:

$$\max\left(E_{j_0}\right)^L = \sum_r u_r y_{rj_0a} + \mu_r\left(y_{rj_0b} - y_{rj_0a}\right)$$

subject to (9)

$$\sum_i v_i x_{ij_0c} - \omega_i\left(x_{ij_0c} - x_{ij_0b}\right) = 1$$

$$\sum_r u_r y_{rj_0a} + \mu_r\left(y_{rj_0b} - y_{rj_0a}\right) - \sum_i v_i x_{ij_0c} - \omega_i\left(x_{ij_0c} - x_{ij_0b}\right) \le 0$$

$$\sum_r u_r y_{rjc} - \mu_r\left(y_{rjc} - y_{rjb}\right)$$

$$-\sum_i v_i x_{ija} + \omega_i\left(x_{ijb} - x_{ija}\right) \le 0,\ j = 1,2,...,n;\ j \ne j_0$$

$$u_r - \beta_r u_p \ge 0, \quad r = 1,\ldots,s; r \ne p$$

$$u_r - \gamma_r u_p \le 0, \quad r = 1,\ldots,s; r \ne p$$

$$\mu_r - u_r \le 0, \quad r = 1,\ldots,s$$

$$\omega_i - v_i \le 0, \quad i = 1,\ldots,m$$

$$\mu_r \ge 0, \quad r = 1,\ldots,s$$

$$\omega_i \ge 0, \quad i = 1,\ldots,m$$

$$u_r \ge \varepsilon > 0, \quad r = 1,\ldots,s$$

$$v_i \ge \varepsilon > 0, \quad i = 1,\ldots,m$$

where, in addition to the earlier notation introduced for previous formulations, $\beta_r, \gamma_r \in [0,1]$ 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 $(z = 1,2,...,Z)$. 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 lth CN $(l = 1,2,...,L)$ and the kth SA $(k = 1,2,...,K)$, and importance weight of the lth CN for the zth decision-maker be $\tilde{x}_{klz} = \left(x_{klza}, x_{klzb}, x_{klzc}\right)$, and $\tilde{w}_{lz} = \left(w_{lza}, w_{lzb}, w_{lzc}\right)$, respectively. Compute the aggregated fuzzy assessment of the relationship scores between the kth SA and the lth CN $\left(\tilde{x}_{kl}\right)$, and aggregated importance weight of the lth CN $\left(\tilde{w}_l\right)$ as follows:

$$\tilde{x}_{kl} = \sum_{z=1}^{Z} \Omega_z \tilde{x}_{klz} \tag{10}$$

$$\tilde{w}_l = \sum_{z=1}^{Z} \Omega_z \tilde{w}_{lz} \tag{11}$$

where $\Omega_z \in [0,1]$ denotes the weight of the zth 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 kth SA and the lth CN, $\tilde{X}_{kl}^*$. Let $D_{kk'}$ denote the degree of dependence of the kth SA on the k'th SA. Then, according to Fung et al. [23], the original relationship measure between the kth SA and the lth CN should be rewritten as

$$\tilde{X}_{kl}^* = \sum_{k'=1}^{K} D_{kk'} \tilde{x}_{k'l} \tag{12}$$

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.

Customer Needs \ Supplier Attributes	EF	IN	SQ	FL	FS	RR	PG	Importance of Customer Needs
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. 1 First house of quality for the supplier selection problem.

Step 9. Determine the maximum feasible value for ε, which can be computed by maximizing ε subject to the constraint set of the respective DEA formulation for j = 1, …, n, and then by defining $\varepsilon_{\max} = \min_j \left(\varepsilon_j\right)$.

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.

TABLE I
Linguistic term set [9]

Very low (VL)	(0, 1, 2)
Low (L)	(2, 3, 4)
Medium (M)	(4, 5, 6)
High (H)	(6, 7, 8)
Very high (VH)	(8, 9, 10)

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 α = 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, ε is computed as 0.0171 employing Step 9 of the proposed algorithm. With ε = 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 II
Ratings of suppliers with respect to SAs [9]

	Suppliers									
SAs	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
EF	(M,L,M)	(H,H,H)	(L,M,VL)	(M,M,L)	(VH,VH,VH)	(H,VH,VH)	(VL,L,VL)	(L,L,H)	(M,M,M)	(H,H,H)
IN	(L,M,L)	(H,M,M)	(VH,H,VH)	(H,H,H)	(VH,VH,VH)	(L,VL,L)	(M,M,M)	(M,H,M)	(H,H,H)	(VL,L,VL)
SQ	(M,L,M)	(M,M,H)	(VH,VH,H)	(VL,VL,L)	(VL,VL,VL)	(M,M,L)	(VH,VH,VH)	(H,H,H)	(M,M,L)	(M,M,H)
FL	(M,M,H)	(VH,VH,H)	(L,L,L)	(VL,VL,L)	(H,H,H)	(M,M,M)	(H,VH,VH)	(VL,VL,L)	(L,H,L)	(L,L,VL)
FS	(M,M,M)	(VH,VH,VH)	(L,L,L)	(H,H,H)	(M,M,L)	(H,H,VH)	(L,L,L)	(H,H,H)	(VL,VL,VL)	(VH,VH,H)
RR	(VL,L,L)	(VL,L,VL)	(VL,L,L)	(VL,VL,VL)	(L,L,M)	(VL,VL,VL)	(M,M,H)	(VH,VH,VH)	(VL,VL,L)	(VL,VL,M)
PG	(VL,M,L)	(L,L,M)	(VL,L,VL)	(VH,H,H)	(VL,VL,M)	(VL,VL,L)	(L,M,L)	(VL,VL,L)	(VL,VL,L)	(VL,VL,M)

ISBN: 978-988-19251-0-7
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

TABLE III
UPPER AND LOWER BOUNDS OF THE WEIGHT OF SAs FOR $\alpha = 0$

EF	$(Y_{EF})_\alpha^L$	5.488
	$(Y_{EF})_\alpha^U$	7.861
IN	$(Y_{IN})_\alpha^L$	6.201
	$(Y_{IN})_\alpha^U$	8.806
SQ	$(Y_{SQ})_\alpha^L$	2.217
	$(Y_{SQ})_\alpha^U$	4.919
FL	$(Y_{FL})_\alpha^L$	4.434
	$(Y_{FL})_\alpha^U$	7.364
FS	$(Y_{FS})_\alpha^L$	1.817
	$(Y_{FS})_\alpha^U$	4.317
RR	$(Y_{RR})_\alpha^L$	4.95
	$(Y_{RR})_\alpha^U$	7.739
PG	$(Y_{PG})_\alpha^L$	2.915
	$(Y_{PG})_\alpha^U$	5.938

TABLE IV
EFFICIENCY VALUES FOR THE SUPPLIERS

Suppliers	Efficiency values
S1	0.679
S2	0.982
S3	0.746
S4	0.727
S5	1.000
S6	0.726
S7	0.860
S8	0.892
S9	0.673
S10	0.677

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 supplier selection 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

[1] L. Boer, E. Labro, and P. Morlacchi, “A review of methods supporting supplier selection,” European Journal of Purchasing & Supply Management, vol. 7, pp. 75-89, 2001.
[2] G. Dickson, “An analysis of vendor selection systems and decisions,” Journal of Purchasing, vol. 2, pp. 28-41, 1966.
[3] A. Amid, S.H. Ghodsypour, and C. O’Brien, “Fuzzy multiobjective linear model for supplier selection in a supply chain,” Int J Prod Econ, vol. 104, pp. 394-407, 2006.
[4] C. Araz, P.M. Özfırat, and I. Özkarahan, “An integrated multicriteria decision-making methodology for outsourcing management,” Computers & Operations Research, vol. 34, pp. 3738-3756, 2007.
[5] A. Amid, S.H. Ghodsypour, and C. O’Brien, “A weighted additive fuzzy multiobjective model for the supplier selection problem under price breaks in a supply chain,” Int J Prod Econ, vol. 121, pp. 323-332, 2009.
[6] C.T. Chen, C.T. Lin, and S.F. Huang, “A fuzzy approach for supplier evaluation and selection in supply chain management,” Int J Prod Econ, vol. 102, pp. 289-301, 2006.
[7] A. Awasthi, S.S. Chauhan, and S.K. Goyal, “A fuzzy multicriteria approach for evaluating environmental performance of suppliers,” Int J Prod Econ, vol. 126, pp. 370-378, 2010.
[8] S. Vinodh, R. A. Ramiya, and S. G. Gautham, “Application of fuzzy analytic network process for supplier selection in a manufacturing organization,” Expert Syst Appl, vol. 38, pp. 272-280, 2011.
[9] M. Bevilacqua, F.E. Ciarapica, and G. Giacchetta, “A fuzzy-QFD approach to supplier selection,” Journal of Purchasing & Supply Management, vol. 12, pp. 14-27, 2006.
[10] S.H. Amin, and J. Razmi, “An integrated fuzzy model for supplier management: A case study of ISP selection and evaluation,” Expert Syst Appl, vol. 36, pp. 8639-8648, 2009.
[11] A. Bhattacharya, J. Geraghty, and P. Young, “Supplier selection paradigm: An integrated hierarchical QFD methodology under multiple-criteria environment,” Applied Soft Computing, vol. 10, pp. 1013-1027, 2010.
[12] C.A. Weber, “A data envelopment analysis approach to measuring vendor performance,” Supply Chain Management, vol. 1, no. 1, pp. 28-39, 1996.
[13] J. Liu, F-Y. Ding, and V. Lall, “Using data envelopment analysis to compare suppliers for supplier selection and performance improvement,” Supply Chain Management, vol. 5, no. 3, pp. 143-150, 2000.
[14] S. Talluri, and J. Sarkis, “A model for performance monitoring of suppliers,” Int J Prod Res, vol. 40, no. 16, pp. 4257-4269, 2002.
[15] E.E. Karsak, “Fuzzy multiple objective decision making approach to prioritize design requirements in quality function deployment,” Int J Prod Res, vol. 42, pp. 3957-3974, 2004.
[16] M.L. Shillito, Advanced QFD – Linking Technology to Market and Company Needs, Wiley, New York 1994.
[17] C. Kao, and S.T. Liu, “Fractional programming approach to fuzzy weighted average,” Fuzzy Sets Syst, vol. 120, pp. 435-444, 2001.
[18] A. Charnes, W.W. Cooper, and E. Rhodes, “Measuring the efficiency of decision making units,” Eur J Oper Res, vol. 2, pp. 429-444, 1978.
[19] C. Kao, and S.T. Liu, “Fuzzy efficiency measures in data envelopment analysis,” Fuzzy Sets Syst, vol. 113, pp. 427-437, 2000.
[20] D.K. Despotis, and Y.G. Smirlis, “Data envelopment analysis with imprecise data,” Eur J Oper Res, vol. 140, pp. 24-36, 2002.
[21] S. Lertworasirikul, S-C. Fang, J.A. Joines, and H.L.W. Nuttle, “Fuzzy data envelopment analysis (DEA): A possibility approach,” Fuzzy Sets Syst, vol. 139, pp. 379-394, 2003.
[22] E.E. Karsak, “Using data envelopment analysis for evaluating flexible manufacturing systems in the presence of imprecise data”, Int J Adv Manuf Tech, vol. 35, no. 9-10, pp. 867-874, 2008.
[23] R.Y.K. Fung, J. Tang, Y. Tu, and D. Wang, “Product design resources optimization using a non-linear fuzzy quality function deployment model,” Int J Prod Res, vol. 40, pp. 585-599, 2002.

ISBN: 978-988-19251-0-7
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)