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Supplier Selection Based on a Combination of QFD and DEA with Ambiguous Data

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A B S T R A C T

The assessment and selection of the supplier is an important issue, which includes not only quantitative criteria, but also qualitative factors with combination of ambiguity and inaccuracy. The proposed method uses the house of quality (HOQ) to assess the implications of internal dependencies among the supplier's assessment criteria. The upper and lower bounds of the weights associated with the supplier's assessment criteria are determined by adopting a fuzzy method (i.e., fuzzy weight average (FWA)), which allows for the integration of obscure and subjective information as linguistic variables. The vague DEA method for choosing the supplier is utilized by applying the weights of the supplier's assessment criteria (derived from FWA), which is obtained using the obtained HOQ data. In this study, the proposed framework is implemented through a case study in a factory.

Keywords: Supplier Selection, QFD, DEA.

INTRODUCTION

The performance of suppliers is crucial in terms of cost, quality, and delivery and service goals. The assessment and selection of suppliers is considered as one of the important issues that are being considered by manufacturers and purchasing managers in the supply chain in order to improve the competitive position among large companies(Dursun & Karsak, 2013; Karsak & Dursun, 2015; Lima-Junior & Carpinetti, 2016).

As the need for better management emerged in choosing a better supplier in the supply chain, companies felt the need for a systematic approach to avoid the consequences of poor decision makers' choices. The key advantage of correct performance in supplier selection is accelerating competition. In order to get ahead in competition, higher levels of integration are needed by suppliers and customers (Hatami-Marbini, Ebrahimnejad, & Lozano, 2017; Kao & Liu, 2000).

Supplier selection, with different methods ranging from conceptual to empirical and modeling, is a subject of interest in researches(Zimmer, Fröhling, & Schultmann, 2016). The decision about supplier selection is complex and this indicates the fact that different measures should be taken into consideration (Azadi, Jafarian, Farzipoor Saen, & Mirhedayatian, 2015; Ding, Dong, Bi, & Liang, 2015; Saen, 2006).

One of the first tasks is done in the direction of supplier selection, and the identification of 23 supplier attributes that managers examine when selecting a supplier. Several studies emphasize

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the importance of different criteria in supplier selection; criteria such as price, quality, delivery and performance (Ebrahimi, Tavana, Rahmani, & Santos-Arteaga, 2018; Mahdiloo, Saen, & Lee, 2015; Shirouyehzad, Lotfi, Aryanezhad, & Dabestani, 2011).

There is a need for strong evaluation models that effectively combine different criteria for choosing the supplier of the product. The involvement of different criteria in the decision making process has made sophisticated supplier assessment and decision making in this regard (Kanagaraj, Ponnambalam, & Jawahar, 2016; Mohammady Garfamy, 2006; Visani, Barbieri, Di Lascio, Raffoni, & Vigo, 2016).

The classic multi-criteria decision-making methods that consider deterministic or stochastic processes fail to effectively address issues related to supplier selection (of fuzzy, imprecision, etc.) in the real world. And from this fourth set, it should be considered, and that is, in conjunction with the supplier selection methods, it needs to be considered vague or qualitative (Charnes & Cooper, 1962; Das, Edalatpanah, & Mandal, 2018; Zionts, 1968).

Achieving these goals depends on the relationship between product attributes and supplier selection criteria, away from the acquisition of the real non - real terms of independence of these criteria. As a result, building a quality house that is not only able to examine the relationship between products attributes and the company's evaluation criteria, it can also consider the criteria for supplier selection. This is necessary to determine the required specifications of the supplier to purchase the desired product(Kannan & Tan, 2002).

First, a proposed framework is used to identify the characteristics of the product purchased to meet the needs of the company and subsequently to establish (or:) meet the criteria for assessing the relevant supplier. Quality function deployment (QFD) is a useful tool for creating better output that is highly focused on the needs of customers and is highly responsive to their needs(Amin & Razmi, 2009; Karsak & Dursun, 2015). The QFD ensures that the supplier's assessment criteria are in line with the characteristics required for the products purchased. In this paper, we first focus on four matrices in the QFD and then on the HOQ. The data envelopment analysis (DEA) framework was then calculated using the weights of the supplier's assessment criteria using the fuzzy weighted average (FWA). Using the information obtained from the HOQ and the supplier's credentials, we act according to the criteria of the supplier's assessment criteria to identify the best supplier among the other suppliers (Arikan, 2013; Awasthi, Govindan, & Gold, 2018).

METHODOLOGY

Many studies on supplier selection have included aspects of this assessment, such as: cost, quality, and reliability of delivery (product or service). However, companies that deal with their suppliers with different cooperative strategies; the new set of supplier selection criteria, which is difficult to quantify, should be taken into account. Fuzzy theory is an effective tool for solving uncertainty model in supplier selection. In this research, we introduce a number of studies that use different fuzzy decision making techniques for supplier selection. Our focus is on research which has recently and specifically applied to the supplier selection theory after 2006, when a significant volume of them has used the fuzzy collection theory in supplier selection(Karsak *, 2004).

Recently, researchers have developed the QFD function and used it in the selection of the supplier. In many of these studies, QFD has been implemented in combination with fuzzy hierarchical analysis (AHP). HOQ recognizes the product features purchased to meet the needs of customers. In the future, potential suppliers will be examined against the selection criteria of the supplier. A two-stage decision-making model is proposed for supplier management, including the selection, evaluation, and development of the supplier. The QFD and AHP combinations for ranking and, subsequently, the selection of supplier suppliers (under an environment with multiple natural criteria). The combination of QFD and AHP was used to evaluate suppliers in this research to select vendors in the pharmaceutical company and to use fuzzy AHP to determine weight and importance in QFD (Liu *, 2005).

Data envelopment analysis (DEA) has been used in the assessment of suppliers for more than a decade. Since 2006, a surge in the use of data envelopment analysis (DEA) has been used as a way to choose commodity suppliers. In this study, DEA is used to measure the performance of suppliers based on the concept of total cost ownership for selection of technology suppliers in situations where involuntary factors exist from the perspective of suppliers(Chan, Kumar, Tiwari, Lau, & Choy, 2008).

It is used as a contribution to make decision in line with the selection of commodity suppliers. Given the control of multiple conflicting factors, regardless of the need to extract the importance and weight of decision - makers (without the need, the importance and weight of criteria from decision makers), on the other hand, a number of factors that are considered ambiguous and also weak in DEA model will result in a relatively high number of suppliers as effective suppliers, and this is one of the major constraints in DEA's conventional approach. Although the initial work in this method has been developed in line with supplier selection process, however, for vague or ambiguous information about the importance of product attributes, the relationship between characteristics purchased and supplier evaluation criteria also requires more studies. In this paper, the fuzzy multi-criteria group decision-making approach has been developed based on QFD and DEA. This method identifies each attribute or attribute of the supplier in relation to the requirements specified for the product; this is done by the HOQ. HOQ not only is capable of examining the relationship between product characteristics and supplier assessment criteria, but also the intermediate internal affinities of supplier assessment criteria. The FWA method is used to determine the upper and lower bounds of the weight of the supplier's choice of the goods. Finally, the best supplier of the goods is used through the imprecise DEA method, which includes limits on weighting (the weight of the supplier of the goods) (Charnes, Cooper, & Rhodes, 1978).

Expansion of quality performance

QFD as a strategic design tool that focuses on developing systems with a holistic approach, and that services and services can be delivered to a level of quality beyond the expectations of customers by bridging the gap between customers and the design team. QFD enables companies to prevent exposure to customers ' complaints (by the issue of quality). It is necessary to assess the decisions at the beginning of the product design fuzzy to change and develop it, as it minimizes the changes over the construction process(C.-M. Chen, 2009).

Data envelopment analysis

The data envelopment analysis is designed based on a decision - making technique based on the technical decision - making technique. Specially to measure the associated performance using inputs and multiple outputs without prior information or only with the consideration that the inputs and outputs are important in determining an efficient score(Shemshadi, Shirazi, Toreihi, & Tarokh, 2011).

RESULT

General DEA

Data Envelopment Analysis examines the decision-making unit for evaluation; each unit assumes the decision making various rates of different input m for different output s. The efficiency of a decision maker is defined as the root of its total output weights to its total input weights. The mathematical programming problem is given:

$$\max E_{j0} = \frac{\sum_r u_r y_{rj0}}{\sum_i \nu_r x_{ij0}}$$

subject to:

$$\max E_{j0} = \frac{\sum_r u_r y_{rj}}{\sum_i \nu_r x_{ij}} \le 1;\ j = 1, \ldots, m \quad u_r, \upsilon_i \ge \varepsilon > 0,\ r = 1, \ldots, s;\ i = 1, \ldots, m \tag{1}$$

Where E_{j0} is the efficiency score of the decision making unit evaluation (j_0); u_r is the specified weight for output r; v_i is the specified weight for input; y_{rj} denotes the output of r that is generated by the j decision unit; x_{ij} implies the amount of input i used by the j decision unit(Bhattacharya, Geraghty, & Young, 2010).

The scope of the methodology of data envelopment analysis

The traditional models of data envelopment analysis that assume inputs and outputs as crisp numbers. Over the past decade, a number of researchers have published data envelopment analysis models that combine vague data with each other. These vague DEA models have improved the traditional DEA by enabling risk control, uncertainty and inaccuracy. Development of an approach based on a reduction of α to convert a fuzzy model into a number of DEA models. Since the performance value of decision units is influenced by functional members, a rating order of decision units will be taken from decision - making units by selecting fuzzy numbers - rating methods that may generate conflicting results(Chan & Kumar, 2007).

In this research, a pessimistic formulation of the DEA, based on the Karzak research, allows the combination of ambiguous data presented to be used to address decision-making problems in assessing the relative efficiency of decision-making units. The inaccuracy of input and output from fuzzy data is taken.

$\tilde{x}_{ij}=(x_{ija},\ x_{ijb},\ x_{ijc});0\le x_{ija}\le x_{ijb}\le x_{ijc}$

input i from DMU_j.

$y_{ij}=(y_{ija},y_{ijb},y_{ijc});0\le y_{ija}\le y_{ijb}\le y_{ijc}$

Output i from DMU_j.

$\left(x_{ij}\right)_\alpha^u$ and $\left(x_{ij}\right)_\alpha^l$ are the upper and lower bounds of the α cut, the membership function x_{ij}, and $\left(y_{ij}\right)_\alpha^l$ and $\left(y_{ij}\right)_\alpha^u$ are the upper and lower bounds of the α cut, from the membership function y_{ij}.

$\omega_i = \upsilon_i.\alpha_i$ where $0\le\omega_i\le \upsilon_i$ then, $\sum_i \upsilon_i \left(x_{ij}\right)_\alpha^l$ and, $\sum_i \upsilon_i \left(x_{ij}\right)_\alpha^u$ can be shown:

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

$$\sum_i \nu_i \left(x_{ij}\right)_\alpha^u = \sum_i \nu_i x_{ijc} + \omega_i \left(x_{ijc} - x_{ijb}\right),$$

Similarly $\mu_r = u_r.\alpha_r$ which $0 \le \mu_r \le u_r$ 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 as follows:

$$\sum_i u_r \left(x_{rj}\right)_\alpha^l = \sum_i u_r x_{rja} + \mu_r \left(x_{ijb} - x_{ija}\right),$$
$$\sum_i u_r \left(x_{rj}\right)_\alpha^u = \sum_i u_r x_{rjc} + \mu_r \left(x_{ijc} - x_{ijb}\right),$$

Where $\left(E_{j0}\right)^l$ is the lower bound α-cut, from the function-membership function value of the DMU$_{j0}$ evaluation?. After applying changes to model number one, the pessimistic scenario model of data envelopment analysis, combined with fuzzy data, is as follows:

Model (2):

$$\max\left(E_{j0}\right)^l = \sum_r u_r y_{rj_0a} + \mu_r\left(y_{rj0b} - y_{rj0a}\right)$$

$$\text{subject to:}$$

$$\sum_r \nu_r x_{ij_0c} + \omega_i\left(x_{ij0c} - x_{rj0b}\right) = 1$$
$$\sum_r \nu_r x_{ij_0a} + \mu_r\left(x_{rj0b} - x_{rj0a}\right) - \sum_r \nu_r x_{ij_0c} + \omega_i\left(x_{rj0c} - x_{rj0b}\right) \le 0$$
$$\sum_r u_r x_{rjc} + \mu_r\left(x_{rj_c} - x_{rjb}\right) - \sum_r \nu_i x_{ija} + \omega_i\left(x_{rj_b} - x_{rj_a}\right) \le 0 \quad j = 1, 2, ..., n; j \ne j_0$$
$$u_r - \beta_r u_h \ge 0 \quad r = 1, ..., s; r \ne h$$
$$u_r - \gamma_r u_h \ge 0 \quad r = 1, ..., s$$
$$\omega_i - \nu_i \le 0, i = 1, ..., m$$
$$\mu_r \ge 0, \ r = 1, ..., s$$
$$\omega_i \ge 0, i = 1, ..., m$$
$$u_r \ge \varepsilon > 0, \ \ r = 1, ..., s$$
$$\nu_i \ge \varepsilon > 0 \quad i = 1, ..., m \tag{2}$$

In addition to the above symbols, β_r, $\gamma_r \in [0,1]$ represents the upper and lower bounds of the relative weight of the output r. The above model n times are solved for calculating the relative efficiency of all DMUs(Bevilacqua, Ciarapica, & Giacchetta, 2006).

Determine the boundary (range) for weights

When the relative weight of customer needs, and the interactions between customer needs and technical characteristics, and the interdependence between technical characteristics, as fuzzy numbers, fuzzy weighted average, is a suitable tool for calculating the general priorities of technical characteristics. In this paper, the methodology proposed by Wang and Chin, which is used to generate normal fuzzy importance calibration, is used for technical characteristics. According to Wasserman's study, the relationship between customer needs and product characteristics should be normalized. Otherwise, the importance of technical features cannot be properly ranked. This is also valid for fuzzy relations; therefore, other methods that do not normalize fuzzy relations between customer requirements and technical characteristics may produce wrong results. Using a fuzzy account is not suitable for fuzzy normalization or for FWA calculation, or because fuzzy math operations support normal fuzzy relations and FWAs, and is broader than those that are real.

Wang and China's method, the Score points the importance of technical features in a fuzzy environment accurately through the collection of α levels. This method is summarized as follows: W_p represents the relative weight of the customer's request P; X_{pr} indicates the fuzzy relation between the requirement p and the r feature; ρ_{kr} represents the degree of dependence of the k-th property on the r-th property. $[(W_p)_\alpha{}^l,\ (W_p)\ _\alpha{}^u]$ and $[(X_{pr})_\alpha{}^l,\ (X_{pr})_\alpha{}^u]$ and $[(\rho_{kr})_\alpha{}^l,\ (\rho_{kr})_\alpha{}^u]$, respectively, as a set of α levels of fuzzy relative weights and Fuzzy relations and fuzzy correlations are considered. The normalized fuzzy relations are calculated as follows:

$$\tilde{X}'_{pr} = \frac{\sum_{k=1}^{s} \tilde{X}_{pk}\tilde{\rho}_{kr}}{\sum_{\substack{l=1\\ l\neq r}}^{s} \tilde{X}_{pk}\tilde{\rho}_{kl} + \sum_{k=1}^{s} \tilde{X}_{pk}\tilde{\rho}_{kr}}, p = 1, 2, ..., s; \tag{3}$$

Equation (3) can be rewritten for each p and r using a set of α levels by two nonlinear programming models.

$$\left(\tilde{X}'_{pr}\right)_\alpha^U = \text{Max} \frac{\sum_{k=1}^{s} X_{pk} \left(\rho_{kr}\right)_\alpha^L}{\sum_{\substack{l=1\\ l\neq r}}^{s} \sum_{k=1}^{s} X_{pk} \left(\rho_{kr}\right)_\alpha^L + \sum_{k=1}^{s} X_{pk} \left(\rho_{kr}\right)_\alpha^U}$$

$$\text{subject to:}$$

$$\left(X_{pk}\right)_\alpha^L \leq X_{pk} \leq \left(X_{pk}\right)_\alpha^U, k = 1, 2, ..., s$$

$$\left(\tilde{X}'_{pr}\right)_\alpha^U = \text{Max} \frac{\sum_{k=1}^{s} X_{pk} \left(\rho_{kr}\right)_\alpha^U}{\sum_{\substack{l=1\\ l\neq r}}^{s} \sum_{k=1}^{s} X_{pk} \left(\rho_{kr}\right)_\alpha^L + \sum_{k=1}^{s} X_{pk} \left(\rho_{kr}\right)_\alpha^U} \tag{4}$$

$$\text{subject to:}$$

$$\left(X_{pk}\right)_\alpha^L \leq X_{pk} \leq \left(X_{pk}\right)_\alpha^U, k = 1, 2, ..., s \tag{5}$$

$$t^{-1} = \sum_{\substack{l=1\\ l\neq r}}^{s} \sum_{k=1}^{s} X_{pk} \left(\rho_{kl}\right)_\alpha^U + \sum_{k=1}^{s} X_{pk} \left(\rho_{kr}\right)_\alpha^L, \quad z_{pk} = tX_{pk}, \quad k = 1, 2, ..., s \tag{6}$$

$$\delta^{-1} = \sum_{\substack{l=1\\ l\neq r}}^{s} \sum_{k=1}^{s} X_{pk} \left(\rho_{kl}\right)_\alpha^L + \sum_{k=1}^{s} X_{pk} \left(\rho_{kr}\right)_\alpha^U, \quad \varnothing_{pk} = \delta X_{pk}, \quad k = 1, 2, ..., s \tag{7}$$

Using the definitions presented above, Equations 4 and 5 can be written as two linear programming models:

$$\left(\tilde{X}'_{pr}\right)_\alpha^L = \text{Min} \sum_{k=1}^{s} Z_{pk} \left(\rho_{kr}\right)_\alpha^L$$

$$\text{subject to:}$$

$$\sum_{k=1}^{s} Z_{pk} \left(\left(\rho_{kr}\right)_\alpha^L + \sum_{\substack{l=1\\ l\neq r}}^{s} \left(\rho_{kl}\right)_\alpha^U \right) = 1$$

$$\left(X_{pk}\right)_\alpha^L t \leq Z_{pk} \leq \left(X_{pk}\right)_\alpha^U t, \quad k = 1, 2, ..., s, \quad t > 0 \tag{8}$$

$$\left(\tilde{X}'_{pr}\right)^{U}_{\alpha} = \mathrm{Max}\sum_{k=1}^{s} \varnothing_{pk}\left(\rho_{kr}\right)^{U}_{\alpha}$$
$$\text{subject to:}$$
$$\sum_{k=1}^{s} \varnothing_{pk}\left(\left(\rho_{kr}\right)^{U}_{\alpha} + \sum_{\substack{l=1 \\ l\neq r}}^{s}\left(\rho_{kl}\right)^{L}_{\alpha}\right) = 1$$
$$\left(X_{pk}\right)^{L}_{\alpha}\delta \leq \varnothing_{pk} \leq \left(X_{pk}\right)^{U}_{\alpha}\delta,\quad k=1,2,\ldots,s,\quad \delta > 0 \tag{9}$$

t and δ and ∅δ are decision variables. By solving these two programming models for each α level, the normalized fuzzy correlation matrix $X' = (X'_{pr})_{q\times s}$ can be obtained. When normal fuzzy relations are produced, the fuzzy weighted average of the normal fuzzy correlation can be formulated as follows:

$$\tilde{\Theta}_r = \sum\nolimits_{p=1}^{q} \tilde{W}_p \tilde{X}'_{pr} \Big/ \sum\nolimits_{p=1}^{q} \tilde{W}_p,\ r = 1,2,\ldots,s \tag{10}$$

And from the upper and lower bounds of α from Θ_r can be solved:

$$\left(\tilde{\Theta}_r\right)^{L}_{\alpha} = \min \sum\nolimits_{p=1}^{q} \tilde{W}_p \left(\tilde{X}'_{pr}\right)^{L}_{\alpha} \Big/ \sum\nolimits_{p=1}^{q} \tilde{W}_p$$
$$\text{subject to:}$$
$$\left(W_p\right)^{L}_{\alpha} \leq w_p \leq \left(W_p\right)^{U}_{\alpha},\ p=1,2,\ldots,q \tag{11}$$

$$(\square_r)^{U}_{\alpha} = \max \tilde{\Theta}_r = \sum\nolimits_{p=1}^{q} \tilde{W}_p \left(\tilde{X}'_{pr}\right)^{U}_{\alpha} \Big/ \sum\nolimits_{p=1}^{q} w_p$$
$$\text{subject to:}$$
$$\left(W_p\right)^{L}_{\alpha} \leq w_p \leq \left(W_p\right)^{U}_{\alpha},\ p=1,2,\ldots,q \tag{12}$$

Charnz and Cooper to the variable of variation change with $\lambda^{-1} = \Sigma w_p{}^q p = 1$ and $\eta_p = \lambda wp$ with the equations (11 (and) 12), can be converted to the following linear programs; for determining the upper and lower bounds $\alpha = 0$:

$$\beta_r = \min \sum_{p=1}^{q} \eta_p \left(X'_{pr}\right)^{L}_{\alpha}$$
$$\text{subject to:}$$
$$\lambda\left(W_p\right)^{L}_{\alpha} \leq \eta_p \leq \lambda\left(W_p\right)^{U}_{\alpha},\quad p=1,2,\ldots q$$
$$\sum_{p=1}^{q} \eta_p = 1$$
$$\lambda,\eta \geq 0,\quad p=1,2,\ldots.,q \tag{13}$$

$$\gamma_r = \max \sum_{p=1}^{q} \eta_p \left(X'_{pr}\right)^{U}_{\alpha}$$
$$\lambda\left(W_p\right)^{L}_{\alpha} \leq \eta_p \leq \lambda\left(W_p\right)^{U}_{\alpha},\quad p=1,2,\ldots q$$
$$\sum_{p=1}^{q} \eta_p = 1$$
$$\lambda,\eta \geq 0,\quad p=1,2,\ldots.,q \tag{14}$$

Fuzzy decision-making framework

In this section, a decision-making approach has been developed using DEA and QFD to solve supplier selection issues. The QFD assures us that the supplier's assessment criteria are consistent with those of the product being purchased. Technical features that are used in HOQ are known as "Supplier Features" (SAs). The ambiguous method of generating ambiguous expressions in expressing the relative importance of customer needs, scores between customer needs and supplier features, the degree of dependency between supplier features, and the credibility of each potential supplier, with regard to each supplier's feature, using the fuzzy set theory, Considers. The step-by-step steps in this decision framework are shown in Figure 1 (C.-T. Chen, Lin, & Huang, 2006).

Step 1: Formation of a committee of decision makers from the expert Z (ζ = 1, 2, ... Z). Identify the features that the product purchased must meet, in order to meet the company's requirements and the criteria for the supplier's assessment (SAs).

Step 2: Set up decision matrix for each decision maker that represents the relative importance of customer needs (CNs); fuzzy evaluation to determine the scores of the CN and SA relationships; and the degree of dependency between SAs.

Step 3: The assigned fuzzy value as the weight and importance of the CN_p, (P = 1,2, ..., q) for the ζ-th decision maker, the scores for the relationship between p-th CN, and SA_r, (r = 1,2, ..., s, for the decision maker ζ and the degree of dependence SA_k, on SA_r, for the decision-maker ζ, $W_{p\zeta} = (W_{p\zeta}W_p, W_{p\zeta}W_p, W_{p\zeta}W_p)$, $X_{pr\zeta} = (X_{pr\zeta}X_{pr}, X_{pr\zeta}X_{pr}, X_{pr\zeta}X_{pr})$ and $\rho_{rp\zeta} = (\rho_{kr\zeta a}, \rho_{kr\zeta b}, \rho_{kr\zeta b})$, respectively. The calculation of the total weight of the CN, pM (Wp), the fuzzy sum assessment of the scores of the relationships between the CN_p and SA_r (X_{pr}), and the sum of the degree of dependence of SA_k, and SA_r (ρ_{rp}) is as follows:

$$\tilde{W}_p = \sum_{\zeta=1}^{z} \Omega_\zeta \tilde{W}_{p\zeta} \tag{15}$$

$$\tilde{X}_{pr} = \sum_{\zeta=1}^{z} \Omega_\zeta \tilde{X}_{pr\zeta} \tag{16}$$

$$\tilde{\rho}_{kr} = \sum_{\zeta=1}^{z} \Omega_\zeta \tilde{\rho}_{kr\zeta} \tag{17}$$

Where $\Omega_\zeta \in [0,1]$ represents the decision weight of ζ and $\Sigma\Omega_{\zeta=1} z_\zeta = 1$.

Step 4: Calculate the upper and lower bounds of the weight, for SA, using the equations.

Step 5: Set up a decision matrix for each decision maker, representing the credibility of each supplier with respect to each SA.

Step 6: Calculate the fuzzy value assigned as the supplier's rating j (j = 1, 2, ..., n) with respect to SA, r for the decision maker ζ, $y_{rj\zeta} = (X_{rj\zeta a}, X_{rj\zeta b}, X_{rj\zeta b})$. The total amount of the j-provider's favor, according to SA_r (y_{rj}):

$$\tilde{y}_{rj} = \sum_{\zeta=1}^{z} \Omega_\zeta \tilde{y}_{rj\zeta} \tag{18}$$

In step 3, Ω_ζ is defined. Total suppliers' rates are used in Equation 18.

Building quality house

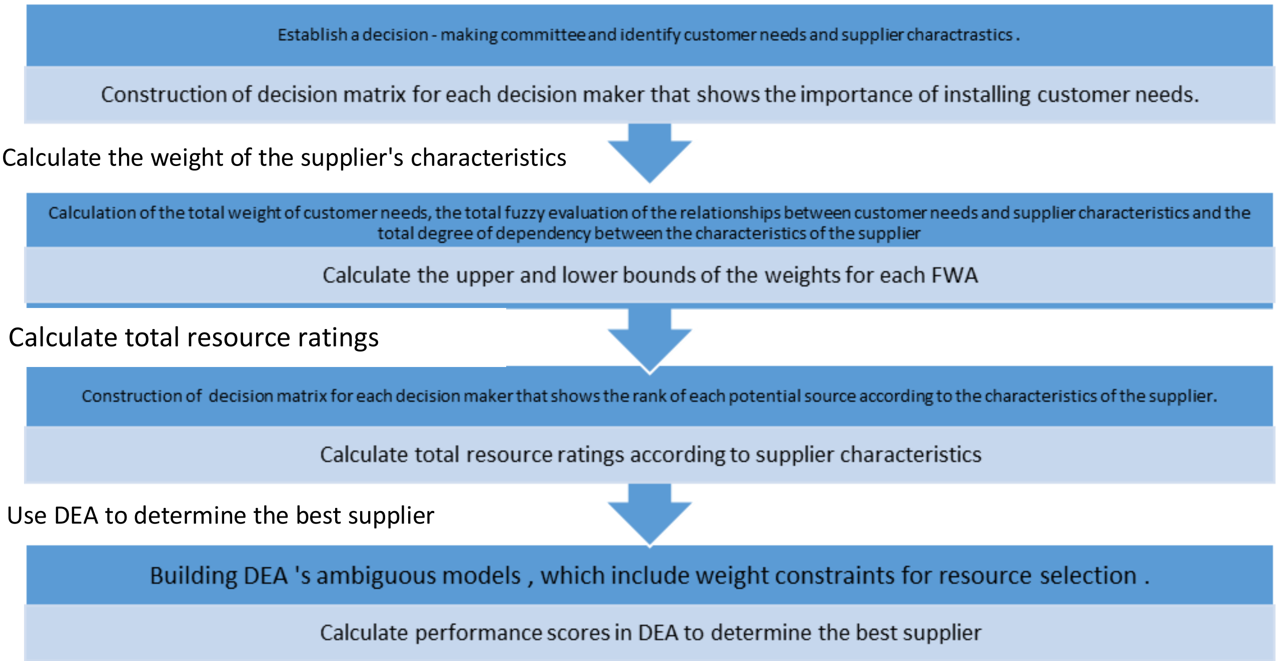

Figure 1. Proposed source chart for selection method

Step 7: Construction of DEA Models to Select Supplier. Minimal features are seen as inputs, while those that have reached the maximum are seen as outputs. The upper and lower bounds for the weights of each SA, as calculated in step 6, are used as weight limits in the DEA model(C.-T. Chen et al., 2006).

Step 8: Determine the maximum practical value for ε, which can be achieved by maximizing ε in the set of constraints of the DEA formula for j = 1…, n and then defining $\varepsilon max = min_j\ (\varepsilon_j)$.

Step 9: Calculate DEA Productivity Scores, for suppliers using a pessimistic DEA formula scenario with weight limitation. Select a supplier with a productivity score of 1.

CONCLUSION

In this study, a decision making method that allows for the trading of all types of information within the chain through the integration of QFD and DEA programming is provided. The weight of the criterion of supplier selection is determined in a manner that both sets out the goals established, such as cost, quality, product matching, etc., determined by the relevant supplier benchmark and internal dependence among those criteria.

The FWA method is used to identify the high and low points of the weight of supplier selection criteria. The proposed QFD-DEA positivist integration that falsifies the false data allows us to make a new decision-making approach for choosing the supplier with the former use in the literature related to it, is our best knowledge of this field. Using QFD is able to integrate product requirements by its users and

The supplier's detection criterion is inherent in the degree of dependency from the supplier's metric to the use of quality home. The decision-makers' opinions to identify the importance of the supplier's metric to accomplishing the goals set, such as cost, quality, product matching, etc., are based on the simple application of the FWA method.

The proposed methodology yields a number of comparisons with other MCDM methods in the supplier selection literature. First, the proposed approach is able to incorporate incorrect data for analysis by using linguistic variables. Second, it is appropriate to examine both the effects of the relationship between the characteristics of the products purchased and the criteria for choosing the supplier and the internal affinities of the supplier selection criteria. Third, this developed approach uses the FWA method, which corrects the lack of information that occurs when personal and incorrect information is integrated, which calculates the high and low weight of the supplier selection criteria. Fourth, data envelopment analysis censures the feasibility of choosing an optimal supplier. Fifth, the unique flexible weight of the data envelopment analysis, the use of a set of weights for a supplier criterion that would be unacceptable in the real world would be abandoned.

However, limited weights, as much as the DEA model's pessimistic scenario, specifically improves the power of DEA differentiation. Finally, the ranking of fuzzy numbers to identify the most suitable supplier is usually needed when a fuzzy theory set is used to model uncertainty in the choice of supplier. The decision approach presented here favors the process of ranking the number of hard fuzzy numbers that may have results that are used to differ if the number of fuzzy numbers is different with ranking methods. The implementation of the proposed approach in supplier selection problems is used in industries different from real-world data based on individual futures research. Additionally, a user-friendly relationship can be developed for decision-makers who are new to decision-making analysis techniques.

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