Supplier Selection by the Pair of Nondiscretionary Factors-Imprecise Data Envelopment Analysis Models

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Abstract

Discretionary models for evaluating the efficiency of suppliers assume that all criteria are discretionary, i.e., controlled by the management of each supplier and varied at its discretion. These models do not assume supplier selection in the conditions that some factors are nondiscretionary. The objective of this paper is to propose a new pair of Nondiscretionary Factors-Imprecise Data Envelopment Analysis (NF-IDEA) models for selecting the best suppliers in the presence of nondiscretionary factors and imprecise data. A numerical example demonstrates the application of the proposed method.

Keywords: Nondiscretionary factors, Imprecise data envelopment analysis, Supplier selection

Introduction

Supplier selection models are based on cardinal data with less emphasis on ordinal data. However, with the widespread use of manufacturing philosophies such as Just-In-Time (JIT), emphasis has shifted to the simultaneous consideration of cardinal and ordinal data in supplier selection process. On the other hand, discretionary models for evaluating the efficiency of suppliers assume that all criteria are discretionary, i.e., controlled by the management of each supplier and varied at its discretion. Thus, failure of a supplier to produce maximal output levels with minimal input consumption results in a decreased efficiency score. In any realistic situation, however, there may exist exogenously fixed or nondiscretionary criteria that are beyond the control of a management. In an analysis of a network of fast food restaurants, Banker and Morey (1986) illustrate the impact of exogenously determined inputs that are not controllable. In their study, each of the 60 restaurants in the fast food chain consumes six inputs to produce three outputs. The three outputs (all controllable) correspond to breakfast, lunch, and dinner sales. Only two of the six inputs, expenditures for supplies and expenditures for labor, are discretionary. The other four inputs (age of store, advertising level, urban/rural location, and presence/absence of drive-in capability) are beyond the control of the individual restaurant manager. Their analysis clearly demonstrates the value of accounting for the nondiscretionary character of these inputs explicitly in the Data Envelopment Analysis (DEA) models they employ; the result is identification of a considerably enhanced opportunity for targeted savings in the controllable inputs and targeted increases in the outputs. In the case of supplier selection, distance and supply variety are generally considered nondiscretionary criterion.

Weber (1996) applied DEA in supplier evaluation for an individual product and demonstrated the advantages of applying DEA to such a system. In Weber's study, six vendors supplying an item to a baby food manufacturer were evaluated. Significant reductions in costs, late deliveries, and rejected materials can be achieved if inefficient vendors can become DEA efficient.

When suppliers are compared for their overall performances, an aggregate evaluation relevant to the considerations of a purchasing firm needs to be conducted. Such an overall performance evaluation of suppliers should be based on performance measures for all part types supplied to the purchasing company. A potential use of an overall performance evaluation of suppliers is to provide benchmarking data for reducing the number of suppliers, which in turn results in benefits including reduction in costs of parts and order processing, and better partnership with suppliers.

This paper depicts the supplier selection process through an Imprecise Data Envelopment Analysis (IDEA) model, while allowing for the incorporation of nondiscretionary factors. The objective of this paper is to propose a new pair of Nondiscretionary Factors-Imprecise Data Envelopment Analysis (NF-IDEA) models for selecting the best suppliers in the presence of nondiscretionary factors and imprecise data.

Literature review

Some mathematical programming approaches have been used for supplier selection in the past. Zeng et al, (2006) considered a simplified partner selection problem which takes into account only the bid cost, the bid completion time of subprojects, and the due date of the project. They modeled the problem as a nonlinear integer programming problem and proved that the decision problem of the partner selection problem is NP-complete. Then they analysed some properties of the partner selection problem and construct a branch and bound algorithm.

Hajidimitriou and Georgiou (2002) presented a quantitative model, based on the Goal Programming (GP) technique, which uses appropriate criteria to evaluate potential candidates and leads to the selection of the optimal partner (supplier). Çebi and Bayraktar (2003) proposed an integrated model for supplier selection. In their model, supplier selection problem has been structured as an integrated Lexicographic Goal Programming (LGP) and Analytic Hierarchy Process (AHP) model including both quantitative and qualitative conflicting factors. Karpak et al, (2001) presented one of the "user-friendly" multiple criteria decision support systems-Visual Interactive Goal programming (VIG). VIG facilitates the introduction of a decision support vehicle that helps improve the supplier selection decisions. To take into account both cardinal and ordinal data in supplier selection, Wang et al, (2004) developed an integrated AHP and Preemptive Goal Programming (PGP) based methodology.

However, one of the GP problems arises from a specific technical requirement. After the purchasing managers specify the goals for each selected criterion (e.g., amount of price, quality level, etc), they must decide on a preemptive priority order of these goals, i.e., determining in which order the goals will be attained. Frequently such a priori input might not produce an acceptable solution and the priority structure may be altered to resolve the problem once more. In this fashion, it may be possible to generate a solution iteratively that finally satisfies the Decision Maker (DM). Unfortunately, the number of potential priority reorderings may be very large. A supplier selection problem with five factors has up to 120 priority reorderings. Going through such a laborious process would be costly and inefficient.

Sha and Che (2006) presented a multi-phased mathematical approach called the Hybrid Multi-phased-based Genetic Algorithm (HMGA) for network design of supply chain. From the point of view of network design, the important issues are to find suitable and quality companies, and to decide upon an appropriate production/distribution strategy. It is based on various methodologies that embrace Genetic Algorithms (GAs), AHP, and the Multi-Attribute Utility Theory (MAUT) to simultaneously satisfy the preferences of suppliers and customers at each level of the supply chain network. Bayazit (2006) provided a good insight into the use of the Analytic Network Process (ANP) that is a multiple criteria decision making methodology in evaluating supplier selection problems. Dulmin and Mininno (2003) presented a proposal for applying a decision model to the final vendor-rating phase of a process of supplier selection. Their model uses a Multiple Criteria Decision Aid (MCDA) technique (PROMETHEE 1 and 2), with a high-dimensional sensitivity analysis approach. They tried to explain how an outranking method and PROMETHEE/GAIA techniques, provides powerful tools to rank alternatives and analysed the relations between criteria or between DMs. Bhutta and Huq (2002) illustrated Total Cost of Ownership (TCO) and AHP approaches and provided a comparison. They concluded that TCO is better suited to those situations where cost is of high priority and detailed cost data are available to make comparisons. In the case of AHP, it is better suited to solve and decide between suppliers when several conflicting goals exist and, though cost may be an important factor, it is not the overriding one.

However, AHP has two main weaknesses. First subjectivity of AHP is a weakness. Second AHP could not include interrelationship within the criteria in the model.

Chen et al, (2006) presented a fuzzy decision making approach to deal with the supplier selection problem in supply chain system. They used linguistic values to assess the ratings and weights for the criteria. These linguistic ratings can be expressed in trapezoidal or triangular fuzzy numbers. Then, a hierarchy Multiple Criteria Decision Making (MCDM) model based on fuzzy sets theory is proposed to deal with the supplier selection problems in the supply chain system. According to the concept of the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), a closeness coefficient is defined to determine the ranking order of all suppliers by calculating the distances to the both Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) simultaneously.

Choy et al, (2002) presented an Intelligent Supplier Management Tool (ISMT) using the Case-Based Reasoning (CBR) and Neural Network (NN) techniques to select and benchmark suppliers. Choy and Lee (2003) suggested an intelligent Generic Supplier Management Tool (GSMT) using the CBR technique for outsourcing to suppliers and automating the decision making process when selecting them. Choy et al, (2004) discussed an Intelligent Supplier Relationship Management System (ISRMS) integrating a company's Customer Relationship Management (CRM) system, Supplier Rating System (SRS) and Product Coding System (PCS) by the CBR technique to select preferred suppliers during the New Product Development (NPD) process. In order to develop a flexible data access framework, and to support the partner selection activity, the combination of OnLine Analytical Processing (OLAP), and CBR was proposed by Lau et al, (2005).

Lee et al, (2003) proposed a High-Quality-Supplier Selection (HQSS) model to deal with supplier selection problems in supply chain management. In selecting a supplier, quality management factors are considered first, and then price, delivery, etc. Linn et al, (2006) proposed a new approach to supplier selection using a Capability index and Price Comparison (CPC) chart. The CPC chart integrates the process capability and price information of multiple suppliers and presents them in a single chart for the management to make supplier selection decisions.

All the aforementioned literature relied on some form of procedures that assigns weights to various performance measures. The primary problem associated with arbitrary weights is that they are subjective, and it is often a difficult task for the DM to accurately assign numbers to preferences. It is a daunting task for the DM to assess weighting information as the number of performance criteria increased. Therefore, a more robust mathematical technique that does not demand too much and too precise information, i.e., ordinal preferences instead of cardinal weights, from the DM can strengthen the supplier evaluation process. To this end, Weber (1996) demonstrated how DEA can be used to evaluate vendors on multiple criteria and identified benchmark values which can then be used for this purpose. Weber et al, (2000) presented an approach for evaluating the number of vendors to employ in a procurement situation using Multi-Objective Programming (MOP) and DEA. The approach advocates developing vendor-order quantity solutions (referred to as supervendors) using MOP and then evaluating the efficiency of these supervendors on multiple criteria using DEA. Recently, to select the best suppliers in the presence of both cardinal and ordinal data, Farzipoor Saen (2007) proposed an innovative method, which is based on IDEA. However, he did not consider the weights restrictions.

However, all the aforementioned references are based on complete discretion of decision making criteria (factors) and do not consider supplier selection in the presence of both imprecise data and nondiscretionary factors.

To the best of author's knowledge, there is not any reference that deals with supplier selection in the conditions that nondiscretionary factor and imprecise data are present.

Proposed model for supplier selection

DEA formulations proposed by Charnes et al, (1978) (CCR model) and developed by Banker et al, (1984) (BCC model) is an approach for evaluating the efficiencies of Decision Making Units (DMUs). This evaluation is generally assumed to be based on a set of cardinal (quantitative) output and input factors. In many real world applications (especially supplier selection problems), however, it is essential to take into account the existence of ordinal (qualitative) factors when rendering a decision on the performance of a DMU. Very often, it is the case that for a factor such as supplier reputation, one can, at most, provide a ranking of the DMUs from best to worst relative to this attribute. The capability of providing a more precise, quantitative measure reflecting such a factor is generally beyond the realm of reality. In some situations, such factors can be legitimately quantified, but very often such quantification may be superficially forced as a modeling convenience. In situations such as that described, the data for certain influence factors (inputs and outputs) might better be represented as rank positions in an ordinal, rather than numerical sense. Refer again to the supplier reputation example. In certain circumstances, the information available may permit one to provide a complete rank ordering of the DMUs on such a factor. Therefore, the data may be imprecise.

Recently, Wang et al, (2005) developed a new pair of interval DEA models for dealing with imprecise data such as interval data, ordinal preference information, fuzzy data and their mixture. Compared with the IDEA model developed by Cooper et al, (1999), Cooper et al, (2001a), and Cooper et al, (2001b), their interval DEA models are much easier to understand and more convenient to use. Also, compared with the interval DEA models developed by Despotis and Smirlis (2002), their interval DEA models utilise a fixed and unified production frontier as a benchmark to measure the efficiencies of all DMUs, which makes their models more rational and more reliable. Moreover, the means by which they treat ordinal preference information also seems more reasonable than the way Zhu (2003) did. However, Wang et al, (2005) did not consider nondiscretionary factors.

In this section, a new pair of NF-IDEA models is proposed that can overcome the shortcoming mentioned above, to consider nondiscretionary factors of the suppliers (DMUs) while ordinal and cardinal data are present. The final efficiency score for each DMU will be characterised by an interval bounded by the best lower bound efficiency and the best upper bound efficiency of each DMU.

Suppose that there are n DMUs to be evaluated. Each DMU consumes m inputs to produce s outputs. In particular, DMU_j consumes amounts $X_j = \{x_{ij}\}$ of inputs (i=1, …, m) and produces amounts $Y_j = \{y_{rj}\}$ of outputs (r=1, …, s). Without loss of generality, it is assumed that all the input and output data x_{ij} and y_{rj} (i=1, …, m; r=1, …, s; j=1, …, n) cannot be exactly obtained due to the existence of uncertainty. They are only known to lie within the upper and lower bounds represented by the intervals $[x_{ij}^L, x_{ij}^U]$ and $[y_{rj}^L, y_{rj}^U]$, where $x_{ij}^L > 0$ and $y_{rj}^L > 0$.

In order to deal with such an uncertain situation, the following pair of linear programming models have been developed to generate the upper and lower bounds of interval efficiency for each DMU (Wang et al, 2005):

$$
\begin{aligned}
& Max\theta_{jo}^{U} = \sum_{r=1}^{s} u_r y_{rj_o}^{U} \\
& s.t. \\
& \qquad \sum_{i=1}^{m} v_i x_{ij_o}^{L} = 1, \\
& \qquad \sum_{r=1}^{s} u_r y_{rj}^{U} - \sum_{i=1}^{m} v_i x_{ij}^{L} \le 0, \qquad j = 1, \cdots, n, \\
& \qquad u_r, v_i \ge \varepsilon \qquad \forall r, i.
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
& Max\theta_{jo}^{L} = \sum_{r=1}^{s} u_r y_{rj_o}^{L} \\
& s.t. \\
& \qquad \sum_{i=1}^{m} v_i x_{ij_o}^{U} = 1, \\
& \qquad \sum_{r=1}^{s} u_r y_{rj}^{U} - \sum_{i=1}^{m} v_i x_{ij}^{L} \le 0, \qquad j = 1, \cdots, n, \\
& \qquad u_r, v_i \ge \varepsilon \qquad \forall r, i.
\end{aligned} \tag{2}
$$

where j_o is the DMU under evaluation (usually denoted by $\mathrm{DMU_o}$); u_r and v_i are the weights assigned to the outputs and inputs; θ_{jo}^{U} stands for the best possible relative efficiency achieved by $\mathrm{DMU_o}$ when all the DMUs are in the state of best production activity, while θ_{jo}^{L} stands for the lower bound of the best possible relative efficiency of DMU_o. They constitute a possible best relative efficiency interval $\left[\theta_{jo}^{L}, \theta_{jo}^{U}\right]$. ε is the non-Archimedean infinitesimal.

In order to judge whether a DMU is DEA efficient or not, the following definition is given.

Definition 1. A DMU, $\mathrm{DMU_o}$, is said to be DEA efficient if its best possible upper bound efficiency $\theta_{jo}^{U*} = 1;$ otherwise, it is said to be DEA inefficient if $\theta_{jo}^{U*} < 1.$

Now, to demonstrate how to consider nondiscretionary factors in the model, the new pair of NF-IDEA models is proposed. The envelopment formulation (dual problem) of Models (1) and (2) becomes

$$
\begin{aligned}
& Min c_{jo}^{U} = \theta_o - \varepsilon \sum_{i=1}^{m} s_i^- - \varepsilon \sum_{r=1}^{s} s_r^+ , \\
& s.t. \\
& \qquad \sum_{j=1}^{n} y_{rj}^{U} \lambda_j - s_r^+ = y_{rjo}^{U} \qquad r = 1, \cdots, s, \\
& \qquad x_{ijo}^{L} \theta_o - \sum_{j=1}^{n} x_{ij}^{L} \lambda_j - s_i^- = 0 \qquad i = 1, \cdots, m, \\
& \qquad \theta_o \qquad \text{free}, \\
& \qquad \lambda_j \geq 0 \qquad j = 1, \cdots, n, \\
& \qquad s_i^- \geq 0 \qquad i = 1, \cdots, m, \\
& \qquad s_r^+ \geq 0 \qquad r = 1, \cdots, s.
\end{aligned}
\tag{3}
$$

$$
\begin{aligned}
& Min c_{jo}^{L} = \theta_o - \varepsilon \sum_{i=1}^{m} s_i^- - \varepsilon \sum_{r=1}^{s} s_r^+ , \\
& s.t. \\
& \qquad \sum_{j=1}^{n} y_{rj}^{U} \lambda_j - s_r^+ = y_{rjo}^{L} \qquad r = 1, \cdots, s, \\
& \qquad x_{ijo}^{U} \theta_o - \sum_{j=1}^{n} x_{ij}^{L} \lambda_j - s_i^- = 0 \qquad i = 1, \cdots, m, \\
& \qquad \theta_o \qquad \text{free}, \\
& \qquad \lambda_j \geq 0 \qquad j = 1, \cdots, n, \\
& \qquad s_i^- \geq 0 \qquad i = 1, \cdots, m, \\
& \qquad s_r^+ \geq 0 \qquad r = 1, \cdots, s.
\end{aligned}
\tag{4}
$$

where $\theta_o, \lambda_j, s_i^-$, and s_r^+ are the dual variables. θ_o is the radial input shrinkage factor (eventually to become efficiency measure) and $\lambda = \{\lambda_j\}$ is the vector of DMU loadings, determining "best practice" for the DMU being evaluated. c_{jo}^{U} stands for the best possible relative efficiency achieved by

DMU$_o$ when all the DMUs are in the state of best production activity, while c_{jo}^L stands for the lower bound of the best possible relative efficiency of DMU$_o$. They constitute a possible best relative efficiency interval $\left[c_{jo}^L, c_{jo}^U\right]$. The variable s_r^+ is shortfall amount of output *r* and s_i^- is excess amount of input *i*. From the duality theory in linear programming, for an inefficient DMU$_o$, $\lambda_j^* > 0$ in the optimal dual solution implies that DMU$_j$ is a unit of the peer group. A peer group of an inefficient DMU$_o$ is defined as the set of DMUs that reach the efficiency score of 1 using the same set of weights that result in the efficiency score of DMU$_o$. It is the existence of this collection of DMUs that forces the DMU$_o$ to be inefficient.

Now, the model that considers both imprecise data and nondiscretionary factors is introduced. Suppose that the input variables may be partitioned into subsets of discretionary (D) and nondiscretionary (N) variables. Thus,

$$I = \{1,2,...,m\} = I_D \cup I_N, \quad I_D \cap I_N = \Phi$$

The pair of NF-IDEA models is then finally given by

$$Minc_{jo}^{U} = \theta_o - \varepsilon \sum_{i \in D} s_i^- - \varepsilon \sum_{r=1}^{s} s_r^+,$$

$$s.t.$$

$$\begin{aligned}
&\sum_{j=1}^{n} y_{rj}^{U} \lambda_j - s_r^+ = y_{rjo}^{U} && r = 1, \cdots, s, \\
&x_{ijo}^{L} \theta_o - \sum_{j=1}^{n} x_{ij}^{L} \lambda_j - s_i^- = 0 && i \in D, \\
&x_{ijo}^{L} - \sum_{j=1}^{n} x_{ij}^{L} \lambda_j - s_i^- = 0 && i \in N, \\
&\theta_o && \text{free}, \\
&\lambda_j \geq 0 && j = 1, \cdots, n, \\
&s_i^- \geq 0 && i \in D, \\
&s_i^- = 0 && i \in N, \\
&s_r^+ \geq 0 && r = 1, \cdots, s.
\end{aligned} \tag{5}$$

$$Minc_{jo}^{L} = \theta_o - \varepsilon \sum_{i \in D} s_i^- - \varepsilon \sum_{r=1}^{s} s_r^+,$$

$$s.t.$$

$$\begin{aligned}
&\sum_{j=1}^{n} y_{rj}^{U} \lambda_j - s_r^+ = y_{rjo}^{L} && r = 1, \cdots, s, \\
&x_{ijo}^{U} \theta_o - \sum_{j=1}^{n} x_{ij}^{L} \lambda_j - s_i^- = 0 && i \in D, \\
&x_{ijo}^{U} - \sum_{j=1}^{n} x_{ij}^{L} \lambda_j - s_i^- = 0 && i \in N, \\
&\theta_o && \text{free}, \\
&\lambda_j \geq 0 && j = 1, \cdots, n, \\
&s_i^- \geq 0 && i \in D, \\
&s_i^- = 0 && i \in N, \\
&s_r^+ \geq 0 && r = 1, \cdots, s.
\end{aligned} \tag{6}$$

It is to be noted that the θ_o to be minimised appears only in the constraints for which $i \in D$, whereas the constraints for which $i \in N$ operate only indirectly (as they should) because the input levels x_{ijo} are not subject to managerial control. Therefore this is recognised by entering all $x_{ijo}, \quad i \in N$ at their fixed (observed) value. Note that the slacks $s_i^-, \quad i \in N$ are omitted from the objective function. Hence these nondiscretionary inputs do not enter directly into the efficiency measures being optimised in (5) and (6). They can, nevertheless, affect the efficiency evaluations by virtue of their presence in the constraints. For models (5) and (6), it is not relevant to minimise the proportional decrease in the entire input vector. Such minimisation should be determined only with respect to the subvector that is composed of discretionary inputs.

In order to judge whether a DMU is DEA efficient or not, the following definition is given.

Definition 2. A DMU, DMU$_o$, is said to be DEA efficient if its best possible upper bound efficiency $c_{jo}^{U*} = 1$; otherwise, it is said to be DEA inefficient if $c_{jo}^{U*} < 1$.

Therefore, one unified approach that deals with all aspects of the imprecise data and nondiscretionary factors in a direct manner has been introduced.

Now, the method of transforming ordinal preference information into interval data is discussed, so that the pair of NF-IDEA models presented in this paper can still work properly even in these situations.

Suppose some input and/or output data for DMUs are given in the form of ordinal preference information. Usually, there may exist three types of ordinal preference information: (1) strong ordinal preference information such as $y_{rj}>y_{rk}$ or $x_{ij}>x_{ik}$, which can be further expressed as $y_{rj} \geq \chi_r y_{rk}$ and $x_{ij} \geq \eta_i x_{ik}$, where $\chi_r > 1$ and $\eta_i > 1$ are the parameters on the degree of preference intensity provided by decision maker; (2) weak ordinal preference information such as $y_{rp} \geq y_{rq}$ or $x_{ip} \geq x_{iq}$; (3) indifference relationship such as $y_{rl} = y_{rt}$ or $x_{il} = x_{it}$. Since a DEA model has the property of unitinvariance, the use of scale transformation to ordinal preference information does not change the original ordinal relationships and has no effect on the efficiencies of DMUs. Therefore, it is possible to conduct a scale transformation to every ordinal input and output index so that its best ordinal datum is less than or equal to unity and then give an interval estimate for each ordinal datum.

Now, consider the transformation of ordinal preference information about the output y_{rj} ($j=1,\ldots, n$) for example. The ordinal preference information about input and other output data can be converted in the same way.

For weak ordinal preference information $y_{r1} \geq y_{r2} \geq \cdots \geq y_{rn}$, we have the following ordinal relationships after scale transformation:

$$1 \geq \hat{y}_{r1} \geq \hat{y}_{r2} \geq \cdots \geq \hat{y}_{rn} \geq \sigma_r ,$$

where σ_r is a small positive number reflecting the ratio of the possible minimum value $\{y_{rj} | j=1,\ldots, n\}$ to its possible maximum value. As well, it can be approximately estimated by the decision maker. It is referred as the ratio parameter for convenience. The resultant permissible interval for each $\hat{y}_{rj}$ is given by

$$\hat{y}_{rj} \in [\sigma_r, 1], \qquad j = 1, \cdots, n.$$

For strong ordinal preference information $y_{r1} > y_{r2} > \cdots > y_{rn}$, there is the following ordinal relationships after scale transformation:

$$1 \geq \hat{y}_{r1}, \qquad \hat{y}_{rj} \geq \chi_r \hat{y}_{r,j+1} \quad (j = 1, \cdots, n-1) \qquad \text{and} \qquad \hat{y}_{rn} \geq \sigma_r ,$$

where χ_r is a preference intensity parameter satisfying χ_r >1 provided by the decision maker and σ_r is the ratio parameter also provided by the decision maker. The resultant permissible interval for each $\hat{y}_{rj}$ can be derived as follows:

$$\hat{y}_{rj} \in [\sigma_r \chi_r^{n-j}, \chi_r^{1-j}], \qquad j = 1, \cdots, n \quad \text{with} \quad \sigma_r \leq \chi_r^{1-n}.$$

Finally, for an indifference relationship, the permissible intervals are the same as those obtained for weak ordinal preference information.

Through the scale transformation above and the estimation of permissible intervals, all the ordinal preference information is converted into interval data and can thus be incorporated into the pair of NF-IDEA models.

In the next section, a numerical example is presented.

Numerical example

The data set for this example is partially taken from Farzipoor Saen (2007) and contains specifications on 18 suppliers (DMUs). In particular, this example is used to show how ordinal and bounded data, as well as nondiscretionary factors, can be combined into the one unified approach provided by NF-IDEA. The cardinal inputs considered are Total Cost of shipments (TC) and Distance (D). D is generally considered as a nondiscretionary input variable. Supplier Reputation (SR) is included as a qualitative input while Number of Bills received from the supplier without errors (NB) will serve as the bounded data output. SR is an intangible factor that is not usually explicitly included in evaluation model for supplier. This qualitative variable is measured on an ordinal scale so that, for instance, reputation of supplier 18 is given the highest rank, and supplier 17, the lowest. Note that, the measures selected in this paper are not exhaustive by any means, but are some general measures that can be utilised to evaluate suppliers. In an application of this methodology, DMs must carefully identify appropriate inputs and outputs to be used in the decision making process. The second and third column of Table 1 depicts the inputs and output of suppliers.

Suppose the preference intensity parameter and the ratio parameter about the strong ordinal preference information are given (or estimated) as $\eta_3 = 1.12$ and $\sigma_3 = 0.01$, respectively. To show the transformation technique described in previous section, interval estimate for supplier 1 is calculated as follows:

$$\hat{x}_{31} \in \left[\sigma_3 \eta_3^{n-j},\ \ \eta_3^{1-j}\right] = \left[.01(1.12)^{18-14},\ \ 1.12^{1-14}\right] = \left[.01574,\ \ .22917\right]$$

The interval estimate for SR of each supplier is shown in the fourth column of Table 1. Therefore, all the input and output data are now transformed into interval numbers and can be evaluated using the pair of NF-IDEA models. Applying Models (5) and (6), the efficiency scores of suppliers (DMUs) and peer groups of suppliers have been presented in the fifth and sixth column of Table 1, respectively. Samples of Models (5) and (6) for supplier 1 have been presented in Appendix. The positive non-Archimedean infinitesimal, ε, has been set to 0.0001.

Based on the definition 2, suppliers 4, 6, 11, 14, and 17 have the possibility to be DEA efficient. If they are able to use the minimum inputs to produce the maximum outputs, they are DEA efficient (efficient in scale); otherwise, they are not DEA efficient. The remaining 13 suppliers with relative efficiency scores of less than 1 are considered to be inefficient. Therefore, DM can choose one or more of these efficient suppliers. Also, the last column of Table 1 provides peer groups for inefficient suppliers. The peer groups serve as a benchmark to use in seeking improvements for inefficient suppliers.

Conclusion

The decision of selecting the best supplier from a wide supplier base is an unstructured, complicated and time-consuming problem. The literature review clearly indicates that the supplier selection problem is a multi-criteria decision making process. The supplier selection criteria are of two types: cardinal (quantitative) and ordinal (qualitative).

This study has demonstrated the use of advanced DEA modeling for measuring how well suppliers perform on multiple criteria relative to other suppliers competing in the same marketplace. The approach allows the buyer to evaluate effectively each supplier's performance relative to the performance of the "best suppliers" in the marketplace, through calculation of DEA efficiency measures.

This paper has introduced a new pair of NF-IDEA models and employed it for supplier selection. The approach presented in this paper has some distinctive benefits.

- The proposed model does not demand weights from the DM.
- Supplier selection is a straightforward process carried out by proposed model.
- The proposed model considers cardinal and ordinal data for supplier selection.
- The proposed model considers nondiscretionary factors for supplier selection.
- The proposed model deals with imprecise data in a direct manner.
- Nondiscretionary factors and imprecise data are considered simultaneously.
- An application of the methodology has been performed on a set of data retrieved from the information of 18 suppliers.

The problem considered in this study is at initial stage of investigation and much further researches can be done based on the techniques of this paper. Some of them are as follows:

Similar research can be repeated for suppliers ranking in the presence of both imprecise data and nondiscretionary factors. Another practical extension to the methodology includes the case that some of the suppliers are slightly non-homogeneous. One of the assumptions of all the classical models of DEA is based on complete homogeneity of DMUs (suppliers), whereas this assumption in many real applications cannot be generalised. In other words, some inputs and/or outputs are not common for all the DMUs occasionally. Therefore, there is a need for a model that deals with these conditions.

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Appendix

Model (5) for supplier 1:

$$
\begin{aligned}
&\min c_1^U = \theta - .0001(s_1^- + s_3^- + s^+)\\
&s.t.\\
&65\lambda_1 + 70\lambda_2 + 50\lambda_3 + \cdots + 85\lambda_{16} + 180\lambda_{17} + 150\lambda_{18} - s^+ = 65\\
&253\theta - 253\lambda_1 - 268\lambda_2 - 259\lambda_3 - \cdots - 334\lambda_{16} - 249\lambda_{17} - 216\lambda_{18} - s_1^- = 0\\
&.01574\theta - .01574\lambda_1 - .02773\lambda_2 - .01254\lambda_3 - \cdots - .0613\lambda_{16} - .01\lambda_{17} - .06866\lambda_{18} - s_3^- = 0\\
&249\theta - 249\lambda_1 - 643\lambda_2 - 714\lambda_3 - \cdots - 795\lambda_{16} - 689\lambda_{17} - 913\lambda_{18} - s_2^- = 0\\
&\theta \qquad \textit{free}\\
&\lambda_j \geq 0 \qquad j = 1, \ldots, 18\\
&s_1^-, s_3^- \geq 0\\
&s_2^- = 0\\
&s^+ \geq 0
\end{aligned}
$$

Model (6) for supplier 1:

$$
\begin{aligned}
&\min c_1^L = \theta - .0001(s_1^- + s_3^- + s^+)\\
&s.t.\\
&65\lambda_1 + 70\lambda_2 + 50\lambda_3 + \cdots + 85\lambda_{16} + 180\lambda_{17} + 150\lambda_{18} - s^+ = 50\\
&253\theta - 253\lambda_1 - 268\lambda_2 - 259\lambda_3 - \cdots - 334\lambda_{16} - 249\lambda_{17} - 216\lambda_{18} - s_1^- = 0\\
&.22917\theta - .01574\lambda_1 - .02773\lambda_2 - .01254\lambda_3 - \cdots - .0613\lambda_{16} - .01\lambda_{17} - .06866\lambda_{18} - s_3^- = 0\\
&249\theta - 249\lambda_1 - 643\lambda_2 - 714\lambda_3 - \cdots - 795\lambda_{16} - 689\lambda_{17} - 913\lambda_{18} - s_2^- = 0\\
&\theta \qquad \textit{free}\\
&\lambda_j \geq 0 \qquad j = 1, \ldots, 18\\
&s_1^-, s_3^- \geq 0\\
&s_2^- = 0\\
&s^+ \geq 0
\end{aligned}
$$

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Table 1. Inputs, output, transformed ordinal data, and efficiency interval for the 18 suppliers

Supplier No. (DMU)	Inputs			Output	Transformed ordinal data	Efficiency interval	Peer group
	TC x_{1j}	D (km) x_{2j}	SR* x_{3j}	NB y_{1j}	SR		
1	253	249	5	[50, 65]	[.016, .229]	[.187, .312]	4,14,17
2	268	643	10	[60, 70]	[.028, .404]	[.248, .278]	4,14,17
3	259	714	3	[40, 50]	[.013, .183]	[.272, .546]	4
4	180	1809	6	[100, 160]	[.018, .257]	[.994, 1]	N/A
5	257	238	4	[45, 55]	[.014, .205]	[.167, .273]	4,14,17
6	248	241	2	[85, 115]	[.011, .163]	[.303, 1]	N/A
7	272	1404	8	[70, 95]	[.022, .322]	[.508, .613]	4
8	330	984	11	[100, 180]	[.031, .452]	[.328, .576]	4,14,17
9	327	641	9	[90, 120]	[.025, .361]	[.277, .424]	4,14,17
10	330	588	7	[50, 80]	[.020, .287]	[.177, .329]	4,17
11	321	241	16	[250, 300]	[.055, .797]	[.821, 1]	N/A
12	329	567	14	[100, 150]	[.044, .636]	[.293, .416]	4,14
13	281	567	15	[80, 120]	[.049, .712]	[.286, .401]	4,14
14	309	967	13	[200, 350]	[.039, .567]	[.609, 1]	N/A
15	291	635	12	[40, 55]	[.035, .507]	[.216, .217]	4
16	334	795	17	[75, 85]	[.061, .893]	[.248, .272]	4,14
17	249	689	1	[90, 180]	[.010, .146]	[.369, 1]	N/A
18	216	913	18	[90, 150]	[.067, 1]	[.455, .679]	4,14

* Ranking such that 18 ≡ highest rank,…, 1 ≡ lowest rank ($x_{3,18} > x_{3,16} \ldots > x_{3,17}$)