

A decision model for selecting appropriate suppliers

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Abstract

The objective of this paper is to present a methodology for selecting decision making units (DMUs) in the presence of undesirable outputs and imprecise data. The proposed model is applied in supplier selection problem. A numerical example demonstrates the application of the proposed method.

Keywords: Data envelopment analysis, Supplier selection, Undesirable outputs, Imprecise data.

1- Introduction

Data Envelopment Analysis (DEA) was proposed by Charnes et al. (1978) as a method for evaluating the relative efficiency of Decision Making Units (DMUs) performing essentially the same task. Each of the units uses multiple inputs to produce multiple outputs. Classical DEA models rely on the assumption that inputs have to be minimized and outputs have to be maximized. However, as Koopmans (1951) discussed earlier, the production process may also generate undesirable outputs like smoke pollution or waste.

Lu and Lo (2007) classified the alternatives for dealing with undesirable outputs in the DEA framework as below. The first is to simply ignore the undesirable outputs. The second is either to treat the undesirable outputs in terms of a non-linear DEA model or to treat the undesirable outputs as outputs and adjust the distance measurement in order to restrict the expansion of the

undesirable outputs (Färe et al., 1989). The third is either to treat the undesirable outputs as inputs or to apply a monotone decreasing transformation (e.g., $1/y^b$, where y^b represents the undesirable output). Seiford and Zhu (2002) have proposed an approach which deals with undesirable outputs in the DEA framework. The approach is invariant to the data transformation within the DEA model.

Undesirable factors have been grown substantially since Färe et al. (1989) firstly introduced a non-linear programming problem for efficiency evaluation in the existence of undesirable factors. Yu and Fan (2006) employed directional graph distance function and DEA approach, which incorporates both desirable and undesirable outputs. They applied the approach to the problem of measuring the cost effectiveness of 24 bus companies in Taiwan. By analyzing the impacts of the non-discretionary input on desirable and undesirable outputs of DMUs, Hua et al. (2007) proposed a non-radial output-oriented DEA model. In the proposed model, they described a new approach of defining reference set that requires reference units operate in a similar environment on average. Amirteimoori et al. (2006) presented a DEA model in which can be used to improve the relative performance via increasing undesirable inputs and decreasing undesirable outputs. For more related researches, please see Jahanshahloo et al. (2004), Hadi Vencheh et al. (2005), Korhonen and Luptacik (2004), Seiford and Zhu (2002), Jahanshahloo et al. (2005), Zhang et al. (2008). To rank DMUs in the presence of undesirable outputs, Liang et al. (2009) proposed an approach. First, they changed the undesirable outputs to be desirable ones by reversing, then they did principal component analysis on the ratios of a single desirable output to a single input. To reduce the dimensionality of data set, the required principal components have been selected from the generated ones according to the given choice principle. Then a linear monotone increasing data transformation was made to the chosen principal components to avoid being negative. Finally, the transformed principal components were treated as outputs into DEA models with a natural Assurance Region (AR). However, the main limitation of their approach is lack of attention to imprecise data.

In most industries the cost of raw materials and component parts constitutes the main cost of a product, such that in some cases it can account for up to 70%. In high technology firms, purchased materials and services represent up to 80% of total product cost. Thus the purchasing department can play a key role in an organization's efficiency and effectiveness because it has a direct effect on cost reduction, profitability and flexibility of a company. Selecting the right

suppliers significantly reduces the purchasing cost and improves corporate competitiveness, which is why many experts believe that the supplier selection is the most important activity of a purchasing department (Ghodsypour and O'Brien, 2001). However, in many supplier selection problems, a supplier produces undesirable outputs, such as Parts Per Million (PPM) of defective parts, in addition to desirable outputs. In the numerical example considered in this paper, suppliers produce not only desirable outputs, such as Number of Bills received from the supplier without errors (NB), but also undesirable outputs, such as PPM. It is thus important to understand the nature of the best-practice technology available to suppliers for turning inputs into desirable and undesirable outputs. Furthermore, it is important to see how individual suppliers measure up to this technology. In other words, evaluation of supplier's efficiency in terms of producing as many desirable outputs and as few undesirable outputs as possible is crucial. Some mathematical programming approaches have been used for supplier selection in the past. A sample of them is presented as below.

Min (1994) considered the qualitative and quantitative factors relevant to international supplier selection under risk and analyzed the various trade-offs among these factors in a multiple criteria environment. Wang et al. (2005a) presented a decision making tool for managers to select suppliers based on the characteristics of outsourced components. Qualitative aspects of the decision were addressed using Analytic Hierarchy Process (AHP). Kameshwaran et al. (2007) developed a multi-attribute e-procurement system for procuring large volume of a single item. Their system is motivated by an industrial procurement scenario for procuring raw material. The procurement scenario demands multi-attribute bids, volume discount cost functions, inclusion of business constraints, and consideration of multiple criteria in bid evaluation. They developed a generic framework for an e-procurement system that meets the above requirements. The bid evaluation problem was formulated as a mixed linear integer multiple criteria optimization problem and goal programming was used as the solution technique. Sha and Che (2006) presented a multi-phase mathematical approach for the design of a complex supply chain network. Their proposed approach is based on the genetic algorithm, the AHP, and the multi-attribute utility theory to satisfy simultaneously the preferences of the suppliers and the customers at each level in the network. To select the best suppliers in the presence of both cardinal and ordinal data, Farzipoor Saen (2007) proposed a method, which is based on Imprecise DEA (IDEA). Farzipoor Saen (in press a) proposed 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. Again, Farzipoor Saen (in press b) proposed a model for ranking suppliers in the presence of weight restrictions, nondiscretionary factors, and cardinal and ordinal data.

To the best of author's knowledge, there is not any reference that discusses supplier selection in the presence of both undesirable outputs and imprecise data. In summary, the contributions of this paper are as below.

- The proposed model considers multiple undesirable outputs for selecting suppliers.
- The proposed model considers imprecise data for selecting suppliers.
- The proposed model considers, for the first time, both undesirable outputs and imprecise data.
- The proposed model selects the suppliers in the existence of both undesirable outputs and imprecise data.

The objective of this paper is to develop a model for selecting suppliers in the presence of both undesirable outputs and imprecise data.

This paper proceeds as follows. In Section 2 the model is proposed. Numerical example and concluding remarks are discussed in Sections 3 and 4, respectively.

2- Proposed model

Imprecise data implies that some data are known only to the extent that the true values lie within prescribed bounds while other data are known only in terms of ordinal relations.

There have been conducted some researches on IDEA in the past. A number of them are Athanassopoulos and Podinovski (1997), Wang et al. (2005b), Cooper et al. (1999), Cooper et al. (2001a), Cooper et al. (2001b), Despotis and Smirlis (2002) and Zhu (2003). However, none of them discussed undesirable outputs. Here, to select DMUs in the presence of both undesirable outputs and imprecise data, a model is developed.

Assume that there are n homogeneous DMUs, each consuming m inputs and producing p outputs. The outputs corresponding to indices $1, 2, \dots, k$ are desirable and the outputs corresponding to indices $k+1, k+2, \dots, p$ are undesirable outputs. It is preferred to produce

desirable outputs as much as possible and not to produce undesirable outputs. Let $\mathbf{X} \in \mathfrak{R}_+^{m \times n}$ and $\mathbf{Y} \in \mathfrak{R}_+^{p \times n}$ be the matrices, consisting of non-negative elements, containing the observed input and output measures for the DMUs. The vector of inputs consumed by DMU $_j$, is denoted by \mathbf{x}_j (the j th column of \mathbf{X}). The quantity of input i consumed by DMU $_j$ is denoted by x_{ij} . A similar notation is used for outputs. DMU $_o$ is the DMU under consideration.

The fractional form of multiplier Additive model is as below¹.

$$\begin{aligned}
 & \max \quad \sum_{r=1}^p \mu_r y_{ro} - \sum_{i=1}^m v_i x_{io} \\
 & \text{s.t.} \\
 & \quad \frac{\sum_{r=1}^p \mu_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1, \quad j = 1, 2, \dots, n \quad (1) \\
 & \quad \mu_r \geq 1 \quad r = 1, 2, \dots, p \\
 & \quad v_i \geq 1 \quad i = 1, 2, \dots, m
 \end{aligned}$$

where μ_r is the weight given to r th output and v_i is the weight given to i th input. j_o is the DMU under evaluation (usually denoted by DMU $_o$). In this paper, the idea for considering undesirable outputs is based on presenting all outputs as a weighted sum, but using negative weights for undesirable outputs.

¹ Additive model was developed by Charnes et al. (1985).

$$\begin{aligned}
& \max \sum_{r=1}^k \mu_r y_{ro} - \sum_{s=k+1}^p \mu_s y_{so} - \sum_{i=1}^m v_i x_{io} \\
& \text{s.t.} \\
& \frac{\sum_{r=1}^k \mu_r y_{rj} - \sum_{s=k+1}^p \mu_s y_{sj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1, \quad j = 1, 2, \dots, n \quad (2) \\
& \mu_r \geq 1 \quad r = 1, 2, \dots, k \\
& \mu_s \geq 1 \quad s = k+1, k+2, \dots, p \\
& v_i \geq 1 \quad i = 1, 2, \dots, m
\end{aligned}$$

where μ_r and μ_s are the weights given to desirable outputs and undesirable outputs, respectively.

At this juncture, to select the efficient suppliers, a new model that considers both undesirable outputs and imprecise data is proposed. The final efficiency score for each DMU (supplier) will be characterized by an interval bounded by the best lower bound efficiency and the best upper bound efficiency of each DMU. The model is based on the interval arithmetic.

Let

$$\frac{\sum_{r=1}^k \mu_r y_{rj} - \sum_{s=k+1}^p \mu_s y_{sj}}{\sum_{i=1}^m v_i x_{ij}} \quad j = 1, 2, \dots, n \quad (3)$$

be the efficiency of DMU_j. According to the operation rules on interval data, there is

$$\begin{aligned}
& \frac{\sum_{r=1}^k \mu_r [y_{rj}^L, y_{rj}^U] - \sum_{s=k+1}^p \mu_s [y_{sj}^L, y_{sj}^U]}{\sum_{i=1}^m v_i [x_{ij}^L, x_{ij}^U]} \\
&= \frac{\sum_{r=1}^k \mu_r y_{rj}^L, \sum_{r=1}^k \mu_r y_{rj}^U - \sum_{s=k+1}^p \mu_s y_{sj}^L, \sum_{s=k+1}^p \mu_s y_{sj}^U}{\sum_{i=1}^m v_i x_{ij}^L, \sum_{i=1}^m v_i x_{ij}^U} \\
&= \frac{\sum_{r=1}^k \mu_r y_{rj}^L, \sum_{r=1}^k \mu_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L, \sum_{i=1}^m v_i x_{ij}^U} - \frac{\sum_{s=k+1}^p \mu_s y_{sj}^L, \sum_{s=k+1}^p \mu_s y_{sj}^U}{\sum_{i=1}^m v_i x_{ij}^L, \sum_{i=1}^m v_i x_{ij}^U} \\
&= \frac{\sum_{r=1}^k \mu_r y_{rj}^L}{\sum_{i=1}^m v_i x_{ij}^L}, \frac{\sum_{r=1}^k \mu_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^U} - \frac{\sum_{s=k+1}^p \mu_s y_{sj}^L}{\sum_{i=1}^m v_i x_{ij}^L}, \frac{\sum_{s=k+1}^p \mu_s y_{sj}^U}{\sum_{i=1}^m v_i x_{ij}^U} \quad j = 1, 2, \dots, n \\
& \tag{4}
\end{aligned}$$

It is obvious that equation (4) should be an interval number. In order to measure the upper and lower bounds of the efficiency of DMU_o , the following pair of fractional programming models for DMU_o is constructed:

$$\begin{aligned}
& \text{Max} \quad \sum_{r=1}^k \mu_r y_{ro}^U - \sum_{s=k+1}^p \mu_s y_{so}^U - \sum_{i=1}^m v_i x_{io}^L \\
& \text{s.t.} \\
& \frac{\sum_{r=1}^k \mu_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} - \frac{\sum_{s=k+1}^p \mu_s y_{sj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \leq 1, \quad j=1, \dots, n \quad (5) \\
& \mu_r, \mu_s, v_i \geq 1 \quad \square r, s, i
\end{aligned}$$

$$\begin{aligned}
& \text{Max} \quad \sum_{r=1}^k \mu_r y_{rj}^L - \sum_{s=k+1}^p \mu_s y_{sj}^L - \sum_{i=1}^m v_i x_{ij}^U \\
& \text{s.t.} \\
& \frac{\sum_{r=1}^k \mu_r y_{rj}^U}{\sum_{i=1}^m v_i x_{ij}^L} - \frac{\sum_{s=k+1}^p \mu_s y_{sj}^U}{\sum_{i=1}^m v_i x_{ij}^L} \leq 1, \quad j=1, \dots, n \quad (6) \\
& \mu_r, \mu_s, v_i \geq 1 \quad \square r, s, i
\end{aligned}$$

Using Charnes-Cooper transformation, the above pair of fractional programming models can be simplified as the following equivalent linear programming models:

$$\begin{aligned}
& \text{Max} \quad \sum_{r=1}^k \mu_r y_{ro}^U - \sum_{s=k+1}^p \mu_s y_{so}^U - \sum_{i=1}^m v_i x_{io}^L \\
& \text{s.t.} \\
& \sum_{r=1}^k \mu_r y_{rj}^U - \sum_{s=k+1}^p \mu_s y_{sj}^U - \sum_{i=1}^m v_i x_{ij}^L \leq 0, \quad j=1, \dots, n \quad (7) \\
& \mu_r, \mu_s, v_i \geq 1 \quad \square r, s, i
\end{aligned}$$

$$\begin{aligned}
& \text{Max} \quad \sum_{r=1}^k \mu_r y_{rj}^L - \sum_{s=k+1}^p \mu_s y_{sj}^L - \sum_{i=1}^m v_i x_{ij}^U \\
& \text{s.t.} \\
& \sum_{r=1}^k \mu_r y_{rj}^U - \sum_{s=k+1}^p \mu_s y_{sj}^U - \sum_{i=1}^m v_i x_{ij}^L \leq 0, \quad j=1, \dots, n \quad (8) \\
& \mu_r, \mu_s, v_i \geq 1 \quad \square r, s, i
\end{aligned}$$

where the objective value of Model (7) stands for the best possible relative efficiency achieved by DMU_o , when all the DMUs are in the state of best production activity, while the objective value of Model (8) stands for the lower bound of the best possible relative efficiency of DMU_o . They constitute a possible best relative efficiency interval.

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

Definition 1. A DMU, DMU_o , is said to be DEA efficient if its best possible upper bound efficiency be zero, otherwise, it is said to be DEA inefficient.

Therefore, one unified approach that deals with imprecise data and undesirable outputs in a direct manner has been introduced.

Now, the method of transforming ordinal preference information into interval data is discussed, so that the interval DEA models presented in this paper can still work properly even in these situations (Wang et al., 2005b).

Suppose some input and/or output data for DMUs are given in the form of ordinal preference information. There may exist strong ordinal preference information such as $y_{rj} > y_{rf}$ or $x_{ij} > x_{if}$, which can be further expressed as $y_{rj} \geq \chi_r y_{rf}$ and $x_{ij} \geq \eta_i x_{if}$, where $\chi_r > 1$ and $\eta_i > 1$ are the parameters on the degree of preference intensity provided by decision maker. At this point, consider the transformation of ordinal preference information about the output y_{rj} ($j=1, \dots, n$) for example. The ordinal preference information about input and undesirable output data can be converted in the same way. For strong ordinal preference data, the resultant permissible interval for each \hat{y}_{rj} can be derived as follows:

$$\hat{y}_{rj} \square [\sigma_r \chi_r^{n-j}, \chi_r^{1-j}] \quad j = 1, \dots, n \quad \text{with} \quad \sigma_r \leq \chi_r^{1-n}. \quad (9)$$

where σ_r is a small positive number reflecting the ratio of the possible minimum of $\{y_{rj} | j=1, \dots, n\}$ to its possible maximum. It can be approximately estimated by the decision maker. It is referred as the ratio parameter for convenience.

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 Models (7) and (8).

In the meantime, the outcome of the Model (7) is an efficiency score equal to zero for efficient DMUs and less than zero for inefficient DMUs.

In the next section, a numerical example is presented.

3- Numerical Example

The data set for this example is partially taken from Farzipoor Saen (2008) and contains specifications on 18 suppliers (DMUs). The cardinal input considered is Total Cost of shipments (TC). The desirable output utilized in the study is Number of Bills received from the supplier without errors (NB). NB will serve as the bounded output. The undesirable output is Parts Per Million (PPM) of defective parts. Supplier Reputation (SR) is included as a qualitative input. 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 utilized to evaluate suppliers. In an application of this methodology, decision makers must carefully identify appropriate inputs and outputs to be used in the decision making process. Table 1 depicts the supplier's attributes.

Table 1. Related attributes for 18 suppliers

Supplier No. (DMU)	Inputs		Desirable output	Undesirable output
	TC (1000 \$) x_{1j}	SR* x_{2j}	NB y_{1j}	PPM y_{2j}
1	253	5	[50, 65]	1
2	268	10	[60, 70]	5.3
3	259	3	[40, 50]	4.6
4	180	6	[100, 160]	30
5	257	4	[45, 55]	30
6	248	2	[85, 115]	30
7	272	8	[70, 95]	30
8	330	11	[100, 180]	13.8
9	327	9	[90, 120]	4
10	330	7	[50, 80]	30
11	321	16	[250, 300]	26.4
12	329	14	[100, 150]	25.8
13	281	15	[80, 120]	25.8
14	309	13	[200, 350]	21.9
15	291	12	[40, 55]	9
16	334	17	[75, 85]	7
17	249	1	[90, 180]	6.3
18	216	18	[90, 150]	28.8

* Ranking such that 18 \equiv highest rank, ..., 1 \equiv lowest rank ($x_{2,18} > x_{2,16} \dots > x_{2,17}$)

Suppose the preference intensity parameter and the ratio parameter about the strong ordinal preference information are given (or estimated) as $\eta_2 = 1.12$ and $\sigma_2 = 0.01$, respectively. Using the transformation technique described in previous section, an interval estimate for SR of each supplier can be derived, which is shown in the Table 2.

Table 2. Interval estimate for the 18 suppliers after the transformation of ordinal preference information

Supplier No. (DMU)	SR
1	[.01574, .22917]
2	[.02773, .40388]
3	[.01254, .1827]
4	[.01762, .25668]
5	[.01405, .20462]
6	[.0112, .16312]
7	[.02211, .32197]
8	[.03106, .45235]
9	[.02476, .36061]
10	[.01974, .28748]
11	[.05474, .79719]
12	[.04363, .63552]
13	[.04887, .71178]
14	[.03896, .56743]
15	[.03479, .50663]
16	[.0613, .89286]
17	[.01, .14564]
18	[.06866, 1]

Therefore, all the input and output data are now transformed into interval numbers and can be evaluated using proposed models. Table 3 reports the results of efficiency assessments for the 18 suppliers obtained by using proposed Models (7) and (8).

Based on the definition 1, suppliers 1, 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. Although suppliers 1, 14, and 17 have the possibility to be DEA efficient, due to the differences in the lower bound efficiencies, their performances are in fact different. The remaining 15 suppliers with relative efficiency scores of less than zero are considered to be inefficient.

Table 3. The efficiency interval for the 18 suppliers

Supplier No. (DMU)	Efficiency Interval
1	[-88, 0]
2	[-218, -207]
3	[-227, -217]
4	[-121, -57]
5	[-258, -238]
6	[-208, -155]
7	[-249, -217]
8	[-256, -175]
9	[-218, -135]
10	[-330, -289]
11	[-117, -67]
12	[-275, -225]
13	[-244, -204]
14	[-150, 0]
15	[-268, -252]
16	[-272, -262]
17	[-170, 0]
18	[-169, -108]

4- Concluding Remarks

To select the best suppliers, this paper has proposed a methodology for dealing with undesirable outputs in the presence of imprecise data.

The problem considered in this research is at initial stage of investigation and further studies can be done based on the results of this paper. One of them is as follow.

This study used the proposed model for supplier selection. It seems that more fields (e.g. technology selection, personnel selection, market selection, etc) can be applied.

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