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# A new model for ranking suppliers in the presence of both undesirable and non-discretionary outputs

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# A new model for ranking suppliers in the presence of both undesirable and non-discretionary outputs


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**Abstract:** Data envelopment analysis (DEA) can be used for supplier selection problem due to its multiple criteria nature. In suppliers' evaluation, there might be some factors, which are beyond the control of their management, that are needed to be modelled in an appropriate way. Also, there are some situations in which some factors are undesirable and they are favourable to be decreased. The aim of this paper is to propose a model for evaluation of suppliers' performance in the presence of both undesirable and non-discretionary outputs. This model can rank efficient suppliers by a super-efficiency DEA model. A numerical example has sought to demonstrate that the proposed model is actually applicable.



**Keywords:** supplier selection; undesirable output; non-discretionary output; super-efficiency.

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## 1 Introduction

Supply chain management (SCM) is widely used by pioneer companies for improvement of their competitiveness strength. Chopra and Meindl (2001) declare that supply chain comprises all the stages which satisfy customer's desideratum whether directly or indirectly. These stages include suppliers, manufacturers, transporters, warehouses, distributors, retailers and the customers. Furthermore, among all the activities performed to manage the supply chain, suppliers' evaluation plays a crucially important role. Every decision made in the supply chain is directly affected by the evaluation and selection of the suppliers. To increase competitive advantage, improve end-user satisfaction by high-quality products, reduce purchasing costs and in general, enhance the efficiency of supply chain, it is essential to select right suppliers (Kumar et al., 2004; Ordoobadi and Wang, 2011; Noorizadeh et al., 2013; Choudhary and Shankar, 2013). Since equal up to

70% of the product cost is composed by the raw materials and component parts (Ghodsypour and O'Brien, 1998), purchasing managers play a key role in reducing the final products costs by selecting good suppliers.

On the other hand, benchmarking is a managerial tool that can be used in the process of suppliers' evaluation. Evaluation of suppliers enables companies to distinguish efficient and inefficient suppliers in comparison with each other. After recognition of inefficient suppliers, overall efficiency of supply chain can be increased by benchmarking from efficient suppliers. Benchmarking provides a means of determining how well a business unit or organisation is performing in comparison to similar units. This provides a broader perspective for the use of performance measure as well as a measure of 'best practice' (Parker, 2000).

The rest of this paper proceeds as follows. In Section 2, literature review is presented. Section 3, introduces the model which selects the suppliers. Numerical example and concluding remarks are discussed in Sections 4 and 5, respectively.

## 2 Literature review

To select the vendors, Weber and Current (1993) used a multi-objective programming problem. Weber (1996) used data envelopment analysis (DEA) to evaluate vendors and to find benchmark values for each inefficient vendor. Mohammady Garfamy (2006) using the data for a hypothetical firm, applied DEA and total cost of ownership (TCO) concept to compare and select the suppliers. To evaluate distribution centres performance trends, Ross and Droge (2002) applied windows analysis using four years data. To select the best suppliers, Vokurka et al. (1996) integrated expert system technology with a decision-support framework. They also incorporated subjective judgements of purchasing experts into their expert system. Using a scoring method and fuzzy expert systems approach, Kwong et al. (2002) carried out suppliers' assessment. To select suppliers and assign the optimal amount order quantities, which should be bought from each supplier, Özgen et al. (2008) proposed a combination of the analytic hierarchy process (AHP) and a multi-objective possibilistic linear programming (MOPLP). Choudhary and Shankar (2013) proposed an integer linear programming approach for joint decision-making of multi-period procurement lot-sizing, supplier selection, and carrier selection problem. They believe that proposed model is able to simultaneously determine the timings of procurement, lot-sizes, suppliers and carriers in an appropriate way.

Ertay et al. (2011) used an integrated method based on fuzzy AHP and ELECTRE III to build a decision support system for supplier evaluation and selection in the presence of quantitative and qualitative criteria. Labib (2011) compared fuzzy logic and AHP to support the decision of the selection of the appropriate supplier. Mishra et al. (2012) suggested a combination of the multi-attribute decision-making (MADM), fuzzy sets theory and VIKOR method to select suppliers. Azadi et al. (2013) applied a goal directed benchmarking theory for benchmarking and selecting suppliers in an uncertain environment and in the presence of fuzzy data.

Lasch and Janker (2005) used multivariate analysis for suppliers rating purpose. Ndubisi et al. (2005) applied a multiple regression model for supplier selection. Considering the assumptions that the suppliers cannot supply perfect quality items, the capacity of suppliers is limited, the amount of demand is predicted, and the buyer has a maximum storage capacity in each period, Rezaei and Davoodi (2008) solved the supplier selection problem. Ustun and Demirtas (2008) considered time horizon and a number of tangible and intangible criteria in their proposed two-stage method for supplier selection problem. They also determined suppliers optimum order allocations using the proposed approach.

Noorizadeh et al. (2013) applied DEA cross-efficiency evaluation for suppliers ranking in the presence of non-discretionary inputs in order to complete ranking of suppliers and avoiding from unrealistic weighting schemes. Mahdiloo et al. (2012) developed an algorithm for ranking suppliers in the presence of volume discount offers in terms of multiple criteria in the context of cross-efficiency evaluation. To select the suppliers, Farzipoor Saen (2010) incorporated both undesirable outputs and imprecise data into a single DEA model. However, he did not consider non-discretionary outputs in his model.

In the case of undesirable outputs, examples from different areas can be found in Yaisawarng and Klein (1994), Färe et al. (1989, 1996), Pittman (1983), Korhonen and Luptacik (2004), Mahdiloo et al. (2011) and Barros et al. (2012). Yang and Pollitt (2009) incorporated undesirable outputs as well as non-discretionary inputs simultaneously into a DEA model and analysed the performance of Chinese coal-fired power plants. Although they took into account undesirable outputs and non-discretionary inputs, their model cannot give a complete ranking among all decision-making units (DMUs) and there may exist lack of discrimination among efficient DMUs. Golany and Roll (1989), and Bowlin (1998) argued that the lack of discrimination power occurs when there are insufficient DMUs or the number of inputs and outputs is too high relative to the number of DMUs. Therefore, our paper differentiates itself from Yang and Pollitt (2009) from two aspects. Firstly, we consider undesirable outputs as well as non-discretionary ones in supplier selection context. Secondly, our model can rank all efficient DMUs.

To the best of knowledge of authors, there is no paper to evaluate suppliers in the presence of both undesirable and non-discretionary outputs. The proposed model ranks all DMUs applying super-efficiency concept. The objective of this paper is to propose a model dealing with both undesirable and non-discretionary outputs via super-efficiency model for ranking the suppliers. The contributions of this paper are as below:

1 Proposed model considers undesirable outputs. In many cases, there are situations in which some outputs are allowed to be decreased. Take for instance, defective parts detected by buyer, which are undesirable outputs, are favourable to decrease.

2 Proposed model considers non-discretionary outputs.

3 Proposed model discusses the evaluation of suppliers' performance in the presence of both undesirable and non-discretionary outputs and also can rank efficient suppliers by applying super-efficiency DEA model. Therefore, proposed model does not suffer from lack of discrimination power.

## 3 Proposed model

DEA was first developed by Charnes et al. (1978) as a non-parametric programming technique to evaluate the relative efficiency of homogenous DMUs. The weighted sum of outputs divided by the weighted sum of inputs is defined as the efficiency score of each DMU (Liu et al., 2000). In DEA, producing more outputs and consuming fewer inputs is generally considered as a measure of efficiency. However, when some outputs are undesirable, DMUs with more desirable outputs relative to less undesirable outputs and inputs are supposed to be efficient (Cooper et al., 2007). To select suppliers, in this paper, defective parts per million (PPM) is considered as an undesirable output.

**Table 1** Nomenclatures

| | |
|---|---|
| $\mathrm{DMU}_o$ | The decision-making unit under investigation |
| $j = 1, \ldots, n$ | Collection of DMUs |
| $r = 1, \ldots, k$ | The set of desirable outputs |
| $i = 1, \ldots, m$ | The set of inputs |
| $s = k + 1, \ldots, p$ | The set of undesirable outputs |
| $y_{ro}^{g}$ | The $r^{\text{th}}$ desirable output of the $\mathrm{DMU}_o$ |
| $x_{io}$ | The $i^{\text{th}}$ input of the $\mathrm{DMU}_o$ |
| $y_{so}^{b}$ | The $s^{\text{th}}$ undesirable output of the $\mathrm{DMU}_o$ |
| $\mu_r^g$ | The weight for $r^{\text{th}}$ desirable output |
| $v_i$ | The weight for $i^{\text{th}}$ input |
| $\mu_s^b$ | The weight for $s^{\text{th}}$ undesirable output |
| $\mu_{rD}^{g}$ | The weight for $r^{\text{th}}$ desirable and discretionary output |
| $\mu_{rF}^{g}$ | The weight for $r^{\text{th}}$ desirable and non-discretionary output |
| $y_{r_i}^{g}$ | The $r^{\text{th}}$ desirable output of $\mathrm{DMU}_j$ |
| $x_{ij}$ | The $i^{\text{th}}$ input of $\mathrm{DMU}_j$ |
| $y_{s_i}^{b}$ | The $s^{\text{th}}$ undesirable output of $\mathrm{DMU}_j$ |
| $\theta$ | Efficiency measure for $\mathrm{DMU}_o$ |
| $s_r^g$ | Shortages in $r^{\text{th}}$ desirable output |
| $s_i^-$ | Excesses in $i^{\text{th}}$ input |
| $s_s^b$ | Excesses in $s^{\text{th}}$ undesirable output |
| $\lambda_j$ | Reference weights associated with $\mathrm{DMU}_j$ |
| $O_D^o$ | The set of discretionary and desirable outputs |
| $O_F^g$ | The set of non-discretionary and desirable outputs |
| $\varepsilon$ | Defined as an infinitesimal constant (a non-Archimedean quantity) |

Model (1) is based on fractional Charnes, Cooper, and Rhodes (CCR) (Charnes et al., 1978) model. Following Korhonen and Luptacik (2004) and also Yang and Pollitt (2009), undesirable outputs are incorporated into Model (1) like inputs. Briefly, the applied notations have been addressed in the nomenclature (Table 1).

$$
\begin{aligned}
&\max\ h_A = \frac{\sum_{r=1}^{k} \mu_r^g y_{ro}^g}{\sum_{i=1}^{m} v_i x_{io} + \sum_{s=k+1}^{p} \mu_r^b y_{so}^b} \\
&\text{s.t.} \qquad \frac{\sum_{r=1}^{k} \mu_r^g y_{rj}^g}{\sum_{i=1}^{m} v_i x_{ij} + \sum_{s=k+1}^{p} \mu_r^b y_{sj}^b} \le 1, \quad j = 1, 2, \ldots, n, \\
&\mu_r^g \ge \varepsilon, \qquad r = 1, 2, \ldots, k, \\
&v_i \ge \varepsilon, \qquad i = 1, 2, \ldots, m, \\
&\mu_s^b \ge \varepsilon, \qquad s = k+1, \ldots, p \\
&\varepsilon > 0 \text{ (non-Archimedean).}
\end{aligned}
\tag{1}
$$

Using a standard technique proposed by Charnes et al. (1978), Model (1) can be converted into a linear programming problem as follows:

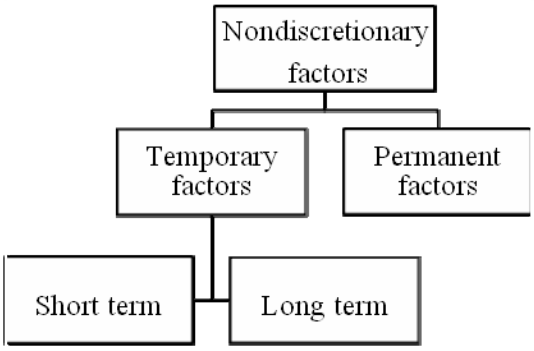
$$
\begin{aligned}
&\max\ h_B = \sum_{r=1}^{k} \mu_r^g y_{ro}^g \\
&\text{s.t.} \qquad \sum_{i=1}^{m} v_i x_{io} + \sum_{s=k+1}^{p} \mu_s^b y_{so}^b = 1, \\
&\qquad \sum_{r=1}^{k} \mu_r^g y_{rj}^g - \sum_{s=k+1}^{p} \mu_s^b y_{sj}^b - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j = 1, 2, \ldots, n, \\
&\qquad \mu_r^g \ge \varepsilon, \qquad r = 1, 2, \ldots, k, \\
&\qquad v_i \ge \varepsilon, \qquad i = 1, 2, \ldots, m, \\
&\qquad \mu_s^b \ge \varepsilon, \qquad s = k+1, \ldots, p, \\
&\qquad \varepsilon > 0 \text{ (non-Archimedean).}
\end{aligned}
\tag{2}
$$

Therefore, Model (2) is a linear multiplicative CCR model which can treat undesirable outputs. Model (3) is the dual (envelopment) form of Model (2). This model suggests improvement targets for inefficient DMUs to become efficient.

$$
\begin{aligned}
&\min\ h_C = \theta - \varepsilon\left(\sum_{r=1}^{k} s_r^g + \sum_{i=1}^{m} s_i^- + \sum_{s=k+1}^{p} s_s^b\right) \\
&\text{s.t.} \qquad \sum_{j=1}^{n} y_{rj}^g \lambda_j - s_r^g = y_{ro}^g, \qquad r = 1, 2, \ldots, k, \\
&\qquad \sum_{j=1}^{n} x_{ij} \lambda_j - \theta x_{io} + s_i^- = 0, \quad i = 1, 2, \ldots, m, \\
&\qquad \sum_{j=1}^{n} y_{sj}^b \lambda_j - \theta y_{so}^b + s_s^b = 0, \quad s = k+1, \ldots, p \\
&\qquad \lambda_j > 0, \qquad j = 1, 2, \ldots, n, \\
&\qquad s_i^- \ge 0, \qquad i = 1, 2, \ldots, m, \\
&\qquad s_r^g \ge 0, \qquad r = 1, 2, \ldots, k, \\
&\qquad s_s^b \ge 0, \qquad s = k+1, \ldots, p, \\
&\qquad \varepsilon > 0 \text{ (non-Archimedean).}
\end{aligned}
\tag{3}
$$

Supply variety is one of the criteria used in this paper for supplier selection problem. Liu et al. (2000) considered this factor as a non-discretionary output. It might be asked why this factor should be considered as a non-discretionary factor? In order to clarify the issue, Figure 1 depicts the different kinds of non-discretionary factors including temporary and permanent factors. The temporary factors refer to those factors that can be controlled by the DMU after a short period of time. For example, despite the fact that suppliers can increase supply variety by spending too much expenses, it is impossible for them to increase it in short-term. Therefore, we call these kinds of factors as temporary and short-term non-discretionary factors. Moreover, there are some other factors that are not under control of managers in short-term and it takes long time of the suppliers to change these types of factors. The suppliers' distance from the buyer is an explicit example for this kind of temporary and long-term non-discretionary factor. Permanent non-discretionary factors refer to those which by no means can be controlled by the DMU. For instance, in the efficiency evaluation of farming lands, amount of rain as an input, is out of the control permanently.

**Figure 1** Different kinds of non-discretionary factors




Therefore, to incorporate undesirable output (PPM) and non-discretionary output (supply variety) into a single model simultaneously, Model (4) is developed that is based on Banker and Morey's (1986) idea for the inclusion of non-discretionary outputs in DEA models.

$$
\begin{aligned}
&\min h_D = \theta - \varepsilon\left(\sum_{\substack{r=1\\ r\in O_D}}^{k} s_r^g + \sum_{i=1}^{m} s_i^- + \sum_{s=k+1}^{p} s_s^b\right) \\
&\text{s.t.} \quad \sum_{j=1}^{n} y_{rj}^g \lambda_j - s_r^g = y_{ro}^g, && r = 1, 2, \ldots, k, \quad r \in O_D^g \cup O_F^g, \\
&\qquad \sum_{j=1}^{n} x_{ij}\lambda_j - \theta x_{io} + s_i^- = 0, && i = 1, 2, \ldots, m, \\
&\qquad \sum_{j=1}^{n} y_{sj}^b \lambda_j - \theta y_{so}^b + s_s^b = 0, && s = k+1, \ldots, p \\
&\qquad \lambda_j \ge 0, && j = 1, 2, \ldots, n, \\
&\qquad s_i^- \ge 0, && i = 1, 2, \ldots, m, \\
&\qquad s_r^g \ge 0, && r = 1, 2, \ldots, k, \quad r \in O_D^g \cup O_F^g, \\
&\qquad s_s^b \ge 0, && s = k+1, \ldots, p \\
&\qquad \varepsilon > 0, \text{ (non-Archimedean).}
\end{aligned} \tag{4}
$$

where $\lambda$ is intensity vector, determining 'best practice' for the DMU$_o$. The variable $s_r^g$ addresses shortages in desirable outputs. $s_i^-$ and $s_s^b$ correspond to excesses in inputs and undesirable outputs, respectively. The DMU$_o$ is efficient in the presence of both undesirable outputs and non-discretionary outputs, if and only if $h_d$ = 1, i.e., $\theta$ = 1, $s_r^g = 0$, $s_i^- = 0$, and $s_s^b = 0$. Notice that the slack $s_r^g$, $r \in O_F^g$ are omitted from the objective function. Since the levels of non-discretionary outputs are not subject to managerial control, these have nothing to do with minimising the efficiency score of DMU$_o$ by the entire output vector's slacks. Such a minimisation should be determined only with respect to the slacks which are composed of discretionary outputs. From another point of view, to ensure that no priority is given to any slack associated with non-discretionary outputs, these slacks are eliminated from the objective function. This property can be shown in the Model (5) which is the dual form of Model (4).

$$
\begin{aligned}
\max\ h_E = {} & \sum\nolimits_{r \in O_D} \mu_{rD}^g y_{ro}^g + \sum\nolimits_{r \in O_F} \mu_{rF}^g y_{ro}^g \\
\text{s.t.} \quad & \sum\nolimits_{i=1}^{m} v_i x_{io} + \sum\nolimits_{s=k+1}^{p} \mu_s^b y_{so}^b = 1 \\
& \left( \sum\nolimits_{r \in O_D} \mu_{rD}^g y_{rj}^g + \sum\nolimits_{r \in O_F} \mu_{rF}^g y_{rj}^g \right) \\
& - \left( \sum\nolimits_{i=1}^{m} v_i x_{ij} + \sum\nolimits_{s=k+1}^{p} \mu_s^b y_{sj}^b \right) \le 0, \quad j = 1, \ldots, n \\
& v_i \ge \varepsilon \qquad i = 1, \ldots, m \\
& \mu_s^b \ge \varepsilon \qquad s = k+1, \ldots, p \\
& \mu_{rD}^g \ge \varepsilon \qquad r = 1, \ldots, k \\
& \mu_{rF}^g \ge 0 \qquad r = 1, \ldots, k
\end{aligned}
\tag{5}
$$

As is seen above, in the case the slacks associated with the non-discretionary outputs would not be omitted from the objective function of Model (4), $\mu_{rF}^g$ will be greater than or equal to $\varepsilon$ instead of $\mu_{rF}^g \ge 0$ in Model (5).

Hence, these non-discretionary outputs do not enter directly into the efficiency measures being optimised in the objective function of Model (4). They can, nevertheless, affect the efficiency evaluations by virtue of their presence in the constraints. Outcome of Model (4) is an efficiency score equal to one to efficient DMUs and less than one to inefficient DMUs.

Although Models (4) and (5) can give a complete ranking of inefficient DMUs, they are not able to rank efficient DMUs thoroughly. Lack of discrimination among the efficient suppliers is a problem that might be occurred when DEA method is employed to select the suppliers. In particular, this problem happens when there are not sufficient suppliers or the number of inputs and outputs is too high relative to the number of suppliers. The model proposed by Anderson and Petersen (1993) has the advantages of the basic DEA models and also allows differentiating among the efficient units. In this model, to construct the new efficiency frontier, the dataset related to DMU$_o$ is excluded from the reference set. The exclusion of an efficient DMU might change the efficiency frontier. Now each efficient DMU has a super-efficiency score greater than or equal to

100%, which is derived by the distance of efficient DMU due to the new frontier. This technique has been termed 'super-efficiency analysis'.

At this juncture, in order to derive the complete ranking of suppliers, we incorporate both undesirable and non-discretionary outputs in a super-efficiency DEA model.

$$
\begin{aligned}
&\min h_F = \theta - \varepsilon \left( \sum_{\substack{r=1 \\ r \in O_D}}^{k} s_r^g + \sum_{i=1}^{m} s_i^- + \sum_{s=k+1}^{p} s_s^b \right) \\
&\text{s.t.} \quad \sum_{\substack{j=1 \\ j \neq 0}}^{n} y_{rj}^g \lambda_j - s_r^g = y_{ro}^g, \qquad r = 1, 2, \ldots, k, \qquad r \in O_D^g \cup O_F^g, \\
&\qquad \sum_{\substack{j=1 \\ j \neq 0}}^{n} x_{ij} \lambda_j - \theta x_{io} + s_i^- = 0, \qquad i = 1, 2, \ldots, m, \\
&\qquad \sum_{\substack{j=1 \\ j \neq 0}}^{n} y_{sj}^b \lambda_j - \theta y_{so}^b + s_s^b = 0, \qquad s = k+1, \ldots, p, \\
&\qquad \lambda_j \geq 0, \qquad j = 1, 2, \ldots, n, \\
&\qquad s_i^- \geq 0, \qquad i = 1, 2, \ldots, m, \\
&\qquad s_r^g \geq 0, \qquad r = 1, 2, \ldots, k, \quad r \in O_D^g \cup O_F^g, \\
&\qquad s_s^b \geq 0, \qquad s = k+1, \ldots, p \\
&\qquad \varepsilon > 0 \text{ (non-Archimedean).}
\end{aligned} \tag{6}
$$

Notice that the efficiency scores from this model are obtained through eliminating the the $\text{DMU}_o$ from the reference set. Thus, the efficient DMUs have super-efficiency score greater than or equal to 1. Since the exclusion of inefficient DMUs cannot affect the efficiency frontier, their super-efficiency score would be the same as their simple efficiency score. In the next section, a numerical example is presented.

## 4 Numerical example

For illustrative purposes, the problem of supplier selection is introduced. The dataset for this example is partially taken from Liu et al. (2000). Tables 2 and 3 depict the definition of the criteria and the dataset for 18 suppliers where price has been used as an input for selecting suppliers. And the outputs been utilised in this study are supply variety, delivery performance and PPM which are non-discretionary desirable output, discretionary desirable output and undesirable output, respectively.

**Table 2** The criteria for evaluation of suppliers performance

| |
|---|
| $x_1$: ***Price***; |
| $y_1^g$ : ***Supply variety***; the number of parts that a supplier supplies is considered as an output and is known as a non-discretionary output variable. |
| $y_2^g$ : ***Delivery performance***; the delivery performance is represented by the percentage of purchase orders delivered within the delivery window according to the purchase orders. |
| $y_1^b$ : ***PPM***; defective parts per million (PPM) detected by the buyer. |

**Table 3** Dataset of input and outputs for 18 suppliers

| *Supplier* | $x_1$ | $y_1^g$ | $y_2^g$ | $y_1^b$ |
|---|---|---|---|---|
| 1 | 100 | 2 | 90 | 25 |
| 2 | 100 | 13 | 80 | 30 |
| 3 | 100 | 3 | 90 | 21.3 |
| 4 | 100 | 3 | 90 | 30 |
| 5 | 100 | 24 | 90 | 13.8 |
| 6 | 100 | 28 | 90 | 18.6 |
| 7 | 100 | 1 | 85 | 30 |
| 8 | 100 | 24 | 97 | 26.4 |
| 9 | 100 | 11 | 90 | 25.8 |
| 10 | 100 | 53 | 100 | 25.8 |
| 11 | 100 | 10 | 95 | 21.9 |
| 12 | 100 | 7 | 98 | 14.7 |
| 13 | 100 | 19 | 90 | 0 |
| 14 | 100 | 12 | 90 | 6.3 |
| 15 | 80 | 33 | 95 | 0 |
| 16 | 100 | 2 | 95 | 15.9 |
| 17 | 80 | 34 | 95 | 0 |
| 18 | 100 | 9 | 85 | 30 |

**Table 4** Results of evaluation by Model (4)

| *Supplier* | *Efficiency scores* | *Reference set* | $s_1^-$ | $s_1^g$ | $s_2^g$ | $s_1^b$ |
|---|---|---|---|---|---|---|
| 1 | 0.7389 | $\lambda_{15} = 0.947$ | 0 | 29.26 | 0 | 18.95 |
| 2 | 0.6535 | $\lambda_{15} = 0.842$ | 0 | 14.79 | 0 | 20.21 |
| 3 | 0.7418 | $\lambda_{15} = 0.947$ | 0 | 28.26 | 0 | 16.14 |
| 4 | 0.7352 | $\lambda_{15} = 0.947$ | 0 | 28.26 | 0 | 22.74 |
| 5 | 0.7474 | $\lambda_{15} = 0.947$ | 0 | 7.26 | 0 | 10.46 |
| 6 | 0.7438 | $\lambda_{15} = 0.947$ | 0 | 3.26 | 0 | 14.09 |
| 7 | 0.6943 | $\lambda_{15} = 0.895$ | 0 | 28.53 | 0 | 21.47 |
| 8 | 0.7953 | $\lambda_{15}= 1.021$ | 0 | 9.69 | 0 | 21.56 |
| 9 | 0.7383 | $\lambda_{15} = 0.947$ | 0 | 20.26 | 0 | 19.55 |
| 10 | 1 | $\lambda_{10} = 1$ | 0 | 0 | 0 | 0 |
| 11 | 0.7824 | $\lambda_{15} = 1$ | 0 | 23 | 0 | 17.52 |
| 12 | 0.8131 | $\lambda_{15} = 1.032$ | 0 | 27.04 | 0 | 12.13 |
| 13 | 0.7579 | $\lambda_{15} = 0.947$ | 0 | 12.26 | 0 | 0 |
| 14 | 0.7531 | $\lambda_{15} = 0.947$ | 0 | 19.26 | 0 | 4.77 |
| 15 | 1 | $\lambda_{15} = 1$ | 0 | 0 | 0 | 0 |
| 16 | 0.7873 | $\lambda_{15} = 1$ | 0 | 31 | 0 | 12.72 |
| 17 | 1 | $\lambda_{17} = 1$ | 0 | 0 | 0 | 0 |
| 18 | 0.6943 | $\lambda_{15} = 0.895$ | 0 | 20.53 | 0 | 21.47 |

Table 4 shows the results of evaluation using Model (4). Outcome of Model (4) is efficiency score of one for the efficient DMUs and less than one for the inefficient DMUs. Therefore, suppliers 10, 15, and 17 are efficient and other suppliers are inefficient. Inefficient suppliers can use these results from a marketing perspective. If a particular supplier is poorly performing, then the supplier can use the analysis results for benchmarking purposes. This result may be interpreted so that the supplier should reduce the input as well as undesirable output and also provide better performance on desirable outputs. For instance, supplier 16 is an inefficient supplier; thus, supplier 15 is chosen as the benchmark supplier for supplier 16 ($\lambda_{15}$ = 1). Since $s_1^g = 31$, supplier 16 must increase its own supply variety to 33 in long-term. And $s_1^b = 12.72$ means that supplier 16 should reduce PPM to 3.18.

It is obvious that for the inefficient suppliers a complete ranking is given; however, efficient suppliers are not ranked. Consequently, the next step is to select the best supplier among those three efficient suppliers applying the developed super-efficiency model [Model (6)].

Table 5 displays the super-efficiency and ranking results obtained by using Model (6). The suppliers have been ranked based on their objective values in descending order.

As Table 5 implies, supplier 10, by objective value of 1.2149, received the highest value and suppliers 17 and 15 were introduced as second and third candidates for selection.

**Table 5** Results of evaluation by Model (6)

| *Supplier rank* | *Supplier no. (DMU)* | *Objective value* |
|---|---|---|
| 1 | 10 | 1.2149 |
| 2 | 17 | 1.0303 |
| 3 | 15 | 1 |

## 5 Concluding remarks

Considering the recent widely spread economic crisis, for companies to survive, it is vital to apply various tools and methods to reduce costs. Based on the fact that in manufacturing industries, the raw materials and component parts comprise up to 70% of total product cost, selecting efficient suppliers is one of the most important roles of decision-makers (Ghodsypour and O'Brien, 1998). Consequently, it is essential to select the suppliers possess a lower price index, lower PPM rate, more supply variety, and better delivery performance. Among the aforementioned criteria, delivery performance is considered as desirable output and price is incorporated as input. Moreover, PPM and supply variety are considered as undesirable output and non-discretionary output, respectively.

This paper proposed an innovative method facilitating the supplier selection problem by super-efficiency technique that takes into account both undesirable and non-discretionary outputs. Furthermore, in order to improve the performance of poorly performing suppliers, improvement targets for inefficient suppliers are determined. Using a numerical example, we demonstrated that decision-makers should use super-efficiency model if they are interested in a complete ranking of suppliers.

Further researches can be done based on the results of this paper. For instance, the developed model can be extended to consider dual-role factors. The behaviour of these factors as inputs or outputs is not known and can be determined after running the DEA model (Farzipoor Saen, 2011). In addition, DEA is suitable for supplier performance analysis over time. Malmqusit (1953) index can be used to measure the growth in the efficiency of suppliers which have cooperation with the company. The results of this paper might be extended to a DEA-based Malmquist index to measure the efficiency growth over time. Noteworthy as well, using this tool, company can recognise the poor performing suppliers to cut collaboration with them.

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