A novel Data Envelopment Analysis model for solving supplier selection problems with undesirable outputs and lack of inputs

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Abstract: Supplier evaluation and selection problems are inherently multi-criteria decision problems. Numerous analytical techniques ranging from simple weighted scoring to complex mathematical programming approaches have been proposed to solve these problems. Data Envelopment Analysis (DEA) has been used to evaluate suppliers' performance when there are multiple inputs and outputs in the supplier selection problem. The DEA determines the relative efficiencies of multiple suppliers. These relative efficiencies are then used to provide benchmarking data for reducing the number of suppliers. The DEA models used for supplier selection require numerical data for all the inputs and outputs for all the suppliers. However, this information may not be readily available in real-world problems. In this paper, we propose a novel DEA model that addresses this gap in the supplier evaluation literature. The proposed model can measure suppliers' efficiency in problems exhibiting: the presence of undesirable outputs; the lack of input variables and the presence of zero or negative values in the data set. We also present a case study at Saipa, Iran's second-largest car maker, to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms.

Keywords: supplier selection; DEA; data envelopment analysis; undesirable outputs; lack of inputs; translation invariance.

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1 Introduction

The constant pressure for competitive advantage and customer satisfaction has forced organisations to search for effective supplier selection strategies (Chou et al., 2008). The purpose of supplier selection is to pick and choose those suppliers who can offer the best products or services for the customer. Supplier selection decisions affect various functional areas from procurement of raw materials and components to production and delivery of the finished goods. Srinivas et al. (2006) have shown that effective supplier selection strategies can directly impact supply chain performance resulting in organisational productivity and profitability. Kumar et al. (2004) have argued that selecting the right suppliers considerably reduces purchasing costs, improves competitiveness and enhances customer satisfaction. They also showed that organisations can achieve these objectives by eliminating waste, improving quality and flexibility to meet the customer requirements and reducing lead-time at different stages of the network.

Numerous analytical techniques ranging from simple weighted scoring to complex mathematical programming approaches have been proposed to solve these problems (Burke et al., 2007; He et al., 2006; Lee et al., 2001; Maltz and Ellram, 1997; Mishra and Tadikamalla, 2006; Parker, 2000). Ghodsypour and O'Brien (1998) used the Analytic Hierarchy Process (AHP) and linear programming to select suppliers. Akarte et al. (2001) developed an AHP model for evaluating casting quality suppliers. Kahraman et al. (2003) used fuzzy AHP to select the best supplier satisfying a series of predetermined criteria. Özgen et al. (2008) combined AHP with multi-objective possibilistic linear programming to evaluate and select suppliers and to define the optimum order quantities assigned to each. Wang et al. (2004) used an integrated AHP and pre-emptive goal programming method for supplier selection. Bhutta and Huq (2002) used a total cost of ownership model in conjunction with AHP to formulate and solve a supplier selection problem. They concluded that their model is well-suited to solve supplier selection problems when cost is of high priority and detailed cost data are available to make comparisons. Liao and Kao (2010) proposed an integrated method of the Taguchi loss function, AHP and multi-choice goal programming model to solve the supplier selection problem. Their method allowed the decision makers to set multiple aspiration levels for the decision criteria. Hajidimitriou and Georgiou (2002) presented a quantitative model where a goal programming technique was used to evaluate potential candidates and select optimal suppliers. Karpak et al. (2001) presented a user-friendly multiple criteria decision-support system with visual interactive goal programming to facilitate the supplier evaluation and selection process.

Fuzzy sets and systems have also been utilised in supplier selection decisions. Lin and Chen (2004) presented a fuzzy decision making framework for selecting the most favourable strategic supply chain alliance under limited evaluation resources. Chang et al. (2006) proposed a fuzzy multiple attribute decision-making method based on the fuzzy linguistic quantifier. Amin et al. (2011) presented a decision model for supplier selection that consisted of two phases. In the first phase, quantified SWOT analysis (Strengths, Weaknesses, Opportunities and Threats) were applied for evaluating suppliers. Linguistic variables and triangular fuzzy numbers were used to quantify variables. In the second phase, a fuzzy linear programming model was applied to determine the order quantity. Vinodh et al. (2011) used fuzzy analytic network process for the supplier selection process in an Indian electronics manufacturing company.

Ip et al. (2004) formulated the sub-contractor selection problem as a 0–1 integer programming with a non-analytical objective function. Mendoza and Ventura (2010) introduced a mixed integer nonlinear programming model to determine an optimal inventory policy that coordinated the transfer of items between different stages of a serial supply chain, while properly allocating orders to selected suppliers. Jayaraman et al. (1999) proposed a mixed integer linear programming model to solve the supplier selection and order quantity allocation problem. Lasch and Janker (2005) designed a supplier rating system and used multivariate analysis for supplier evaluations and selection. Ndubisi et al. (2005) used a multiple regression model for supplier selection and found that the selection of suppliers based on technology is important for the manufacturer whose focus is on product and launch flexibility.

Supplier evaluation and selection problems are inherently multi-criteria decision problems. Numerous analytical techniques ranging from simple weighted scoring to complex mathematical programming approaches have been proposed to solve these problems. Data Envelopment Analysis (DEA) has been used to evaluate suppliers' performance when there are multiple inputs and outputs in the supplier selection problem. The DEA determines the relative efficiencies of multiple suppliers. These relative efficiencies are then used to provide benchmarking data for reducing the number of suppliers. The DEA models used for supplier selection require numerical data for all the inputs and outputs for all suppliers. However, this information may not be readily available in real-world problems. In this paper, we propose a novel DEA model that measures suppliers' efficiency in problems exhibiting

- presence of undesirable outputs
- lack of input variables
- presence of zero or negative values in the data set.

This paper is organised into five sections. The next section presents the literature review. In Section 3, we illustrate the details of the proposed model. In Section 4, we present a case study to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms. In Section 5, we conclude with our conclusions and future research directions.

2 Literature review

DEA is a powerful mathematical method that utilises linear programming to determine the relative efficiencies of a set of functionally similar Decision-Making Units (DMUs). A DMU is considered efficient when no other DMUs can produce more outputs using an equal or lesser amount of inputs. The DEA generalises the usual efficiency measurement from a single-input single-output ratio to a multiple-input multiple-output ratio by using a ratio of the weighted sum of outputs to the weighted sum of inputs. A score of one is assigned to the frontier (efficient) units. The frontier units in DEA are those with maximum output levels for given input levels or with minimum input levels for given output levels. Charnes et al. (1978) originally proposed the first DEA model known as the Charnes, Cooper and Rhoades (CCR) model.

When a supplier selection decision needs to be made, the buyer establishes a set of evaluation criteria that can be used to compare the potential suppliers. These evaluation factors are classified into input and output factors and DEA is used to measure suppliers' efficiency. Weber (1996) used DEA to evaluate the performance of suppliers for an individual product. In his study, the criteria for the evaluation of suppliers were significant reductions in costs, late deliveries and rejected materials. Braglia and Petroni (2000) proposed a multiple attribute utility theory based on the use of DEA, aimed at helping purchasing managers formulate viable sourcing strategies in the changing market place. Wu (2009) used DEA, decision trees and neural networks in a model to assess suppliers' performance. This model consisted of two modules: Module 1, which applied DEA and classifies suppliers into efficient and inefficient clusters based on the resulting efficiency scores, and Module 2, which used firm performance data in an integrated decision tree and neural network model. Mohammady Garfamy (2006) applied DEA to compare suppliers' performance based on the total cost of ownership concept. Farzipoor Saen (2007) proposed an innovative method for selecting slightly non-homogeneous suppliers and demonstrated that accounting for non-homogeneity in selecting suppliers is important. Talluri et al. (2006) presented a chance-constrained DEA approach in the presence of multiple performance measures that are uncertain. They demonstrated the first application of chance-constrained DEA in the area of purchasing to a previously reported dataset from a pharmaceutical company. Ross and Droge (2002) used DEA to measure the productivity of distribution centres in a large scale setting and detected performance trends with four years data. Wu et al. (2007) developed a so-called augmented imprecise DEA for supplier selection. The proposed model was able to handle imprecise data and derive a complete ranking of suppliers. Narasimhan et al. (2001) proposed a methodology where the efficiencies derived from their DEA model were utilised in identifying supplier clusters categorised into several categories such as efficient, high performers, inefficient, etc. Other researchers have also studied the application of DEA in supplier selection and negotiating with inefficient suppliers (Weber and Desai, 1996; Weber et al., 1998).

2.1 Undesirable outputs

DEA usually assumes that producing more outputs relative to less input resources is a criterion of efficiency. However, in the presence of undesirable outputs, DMUs with more good (desirable) outputs and less bad (undesirable) outputs relative to less input resources should be recognised as efficient (Cooper et al., 2007). In our performance evaluation of the suppliers' problem in which some outputs are undesirable, classical DEA models cannot be used because of the requirement that inputs have to be minimised and outputs have to be maximised.

In the case of undesirable outputs, pioneering works in different areas can be found in Pittman (1983), Färe et al. (1989, 1996) and Yaisawarng and Klein (1994). Jahanshahloo et al. (2005) have proposed four strategies for dealing with undesirable factors in DEA models. The first strategy is to simply ignore the undesirable factors. The second strategy is to treat the undesirable outputs as inputs and the undesirable inputs as outputs. The third strategy is to treat the undesirable outputs in the non-linear DEA model. The fourth strategy is to apply a monotone decreasing transformation to the undesirable outputs and to use the adapted variable as outputs. Seiford and Zhu (2002) proposed a DEA model, in the presence of undesirable outputs, to improve the performance via increasing the desirable outputs and decreasing the undesirable outputs. Amirteimoori et al. (2006) extended the standard CCR (Charnes et al., 1978) model to a DEA like model that determined the relative efficiency via increasing undesirable inputs and decreasing undesirable outputs. Korhonen and Luptacik (2004) used DEA to measure the eco-efficiency of 24 coal-fired power plants in a European country. They treated production emissions directly as inputs in the sense that they wanted to increase desirable outputs and decrease pollutants and inputs. Jahanshahloo et al. (2005) presented an approach to treat both undesirable inputs and outputs simultaneously in non-radial DEA models. Recently, Farzipoor Saen (2010) proposed a model for supplier selection in the presence of both undesirable outputs and imprecise data. In his paper, defective Parts Per Million (PPM) was used as an undesirable output.

2.2 DEA models without inputs

There are two published strategies for dealing with the evaluation of the DMUs when there are no inputs. The first strategy is to use a model with a single constant input; and the second strategy is to face a pure output model without any input. To find the best location of a superconducting supercollider in Texas, Thompson et al. (1986) used an input-oriented CCR model. In their study, three kinds of costs (facility cost, user cost and environmental damage) were used as inputs and the output of each site was set equal to unity. Adolphson et al. (1991) solved the same problem of Thompson et al. (1986) as a pure input model (with no outputs). However, they used an input-oriented Banker, Charnes, and Cooper (BCC) (Banker et al., 1984) model instead of using an input-oriented CCR model and reached the same results as Thompson et al. (1986). Nevertheless, they were unable to fully explain the reasons for the similarity of results.

Lovell and Pastor (1997) proposed a pure output model and evaluated the performance of bank branches with regard to their target setting procedure. However, as Lovell and Pastor (1999) state, from a production perspective it could be argued that each branch office was by itself 'the input' and, therefore, a single constant input was at hand. To consider radial DEA models without inputs (or without outputs), and radial DEA models with a single constant input (or with a single constant output), Lovell and Pastor (1999) demonstrated that

- since a CCR model without inputs (or without outputs) rates all the DMUs as infinitely inefficient it is meaningless to use a CCR model without inputs
- a CCR model with a single constant input (or with a single constant output) is similar to the corresponding BCC model
- a BCC model with a single constant input (or a single constant output) is similar to a BCC model without inputs (or without outputs).

Regardless, since Lovell and Pastor (1999) modelled the problem of lack of inputs or outputs in radial DEA models, they could not fully measure the inefficiency of the DMUs. In DEA, non-zero input and output slacks are very likely to reveal themselves after the radial efficiency score improvement. Often, the non-zero slack values reveal a considerable amount of inefficiency. Therefore, to fully measure the inefficiency in DMUs performance, it is crucial to consider the inefficiency represented by the non-zero slack variables. As a result, we develop the additive model (Charnes et al., 1985) without inputs in this paper.

2.3 Zero values in data set

In some real-world problems, it is possible for the data set to contain negative numbers and/or zero values. DEA models are not capable of completing an analysis with negative numbers since all numbers must be non-negative and preferably strictly positive (no zero values). This condition has been defined as the 'positivity' requirement in DEA. One of the more common strategies for eliminating the problems of non-positive values in DEA has been through the addition of a sufficiently large positive constant to the values of the input or output that has the non-positive number (Pastor and Ruiz, 2005).

The data set used for the case study presented in Section 4 includes several zeros. We eliminate all zero values by adding a unit to each zero so that we can satisfy the strictly positive requirement in the DEA model. Therefore, in order to solve the problem with the new (adjusted) data, a type of translation invariant DEA model should be used (because using a model that is not translation invariant my result in the change in the efficiency results). According to Lovell and Pastor (1995), the envelopment form of the additive model is translation invariant in any variable. As Zhu and Cook (2007) discussed, the translation invariance property allows the envelopment form of many DEA models to translate inputs or outputs data without any difference between the results of translated data and the original data. The envelopment form of the input (output)-oriented BCC model is translation invariant with respect only to outputs (inputs). In other words, we can deal with any output variable in the input-oriented BCC model, even if all its data are translated. It should also be noted that both the BCC and the additive models are Variable Returns to Scale (VRS) models, in contrast to the CCR model, which exhibits Constant Returns to Scale (CRS). In fact, being a VRS model is the key for satisfying translation invariance or, in other words, the convexity constraint (the sum of the intensity variables equals 1, i.e., $\left(\sum_{j=1}^{n} \lambda_j = 1\right)$ is critical (see Appendix 1 for a more elaborate explanation of the translation invariance concept).

3 Proposed model

In recent years, DEA has been used to measure the efficiency of DMUs in many different settings, such as efficiency and effectiveness in operations management (Parkan, 2006; Goncharuk, 2007), supply chain management (Wong et al., 2008; Parkan and Wang, 2007), the farming industry (Mulwa et al., 2009), the stock market (Emrouznejad and Thanassoulis, 2010), the hotel industry (Cheng et al., 2010), financial statement analysis (Ho, 2007), healthcare (Dharmapala, 2009) and the banking industry (Azadeh et al., 2010a; Cooper et al., 2008).

To the best of our knowledge, there is no reference to the evaluation of the suppliers' performance in the presence of undesirable outputs, zero values and lack of inputs in the literature. The multiplier form of the additive model developed by Charnes et al. (1985) is shown as Model (1). The nomenclatures used in this paper are presented in Appendix 2.

$$\text{Min } \sum_{i=1}^{m} v_i \, x_{i_o} - \sum_{r=1}^{s} u_r \, y_{r_o} + w_o$$

s.t.

$$\sum_{i=1}^{m} v_i \, x_{i_o} - \sum_{r=1}^{s} u_r \, y_{r_o} + w_o \geq 0 \quad j = 1, \ldots n, \tag{1}$$

$$v_i \geq 1, \quad i = 1, \ldots, m,$$

$$u_r \geq 1, \quad r = 1, \ldots, s,$$

w_o free.

The dual form of the Model (1) is written as Model (2), which is known as the envelopment additive model.

$$\begin{aligned}
&\text{Max } \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \\
&\text{s.t.} \\
&\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{i_o}, \quad i = 1, ..., m, \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{r_o}, \quad r = 1, ..., s, \\
&\sum_{j=1}^{n} \lambda_j = 1, \quad j = 1, \ldots, n, \\
&\lambda_j \ge 0, \quad j = 1, ..., n, \\
&s_i^- \ge 0, \quad i = 1, ..., m, \\
&s_r^+ \ge 0, \quad r = 1, ..., s.
\end{aligned} \tag{2}$$

Models (1) and (2) are based on the VRS assumption. Similar to Korhonen and Luptacik (2004) and Yang and Pollitt (2009), undesirable outputs are incorporated into the Model (1) like inputs. This idea leads to a type of multiplier VRS additive model that can deal with undesirable outputs (Model 3). Suppose that the output variables could be partitioned into subsets of desirable (y_{rj}^D) and undesirable (y_{rj}^U) outputs. Thus, $O = \{1,2, \ldots, s\} = O_D \cup O_U$. In addition, there is a set of n DMUs (suppliers), DMU_j: $j = \{1,2, \ldots, n\}$, which use multiple inputs x_{ij} ($i = 1,2, \ldots, m$) to produce multiple undesirable outputs y_{rj}^U ($r \in O_U$) and desirable outputs y_{rj}^D ($r \in O_D$). The model is as follows:

$$\begin{aligned}
&\text{Min } \sum_{i=1}^{m} v_i \, x_{i_o} + \sum_{r \in O_U} u_r^U y_{r_o}^U - \sum_{r \in O_D} u_r^D y_{r_o}^D + w_o \\
&\text{s.t.} \\
&\sum_{i=1}^{m} v_i x_{ij} + \sum_{r \in O_U} u_r^U y_{r_j}^U - \sum_{r \in O_D} u_r^D y_{r_j}^D + w_o \ge 0, \quad j = 1, ..., n, \\
&v_i \ge 1, \quad i = 1, \ldots, m, \\
&u_r^U \ge 1, \quad r \in O_U, \\
&u_r^D \ge 1, \quad r \in O_D, \\
&w_o \text{ free.}
\end{aligned} \tag{3}$$

Therefore, Model (3) is a VRS additive model with undesirable outputs. The dual of Model (3) is as follows:

$$\text{Max} \sum_{i=1}^{m} s_i^- + \sum_{r \in O_U} s_r^{+U} + \sum_{r \in O_D} s_r^{+D}.$$

s.t.

$$\begin{aligned}
&\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i_o}, \quad i = 1, \ldots, m, \\
&\sum_{j=1}^{n} \lambda_j y_{rj}^U + s_r^{+U} = y_{r_o}^U, \quad r \in O_U, \\
&\sum_{j=1}^{n} \lambda_j y_{rj}^D - s_r^{+D} = y_{r_o}^D, \quad r \in O_D, \\
&\sum_{j=1}^{n} \lambda_j = 1, \quad j = 1, \ldots, n, \\
&\lambda_j \geq 0, \quad j = 1, \ldots, n, \\
&s_i^- \geq 0, \quad i = 1, \ldots, m, \\
&s_r^{+U} \geq 0, \quad r \in U, \\
&s_r^{+D} \geq 0, \quad r \in D.
\end{aligned} \tag{4}$$

Since there is no input factor in our supplier selection problem, the following is discussed. The first strategy for dealing with this issue is to use a single constant input for all the DMUs.

Theorem 1: *The additive model with a single constant input is equivalent to an additive model without inputs.*

Proof: Suppose that the single constant input is considered 1 for all DMUs. Since $x_{ij} = x_{i_o} = 1$ and $\sum_{j=1}^{n} \lambda_j = 1$, the amount of s_i^- in the constraint $\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i_o}$ of Model (4) becomes zero. With regard to

$$\begin{cases} x_{ij}, x_{i_o} = 1, \\ s_i^- = 0, \end{cases}$$

the constraint $\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i_o}$ in Model (4) is converted to $\sum_{j=1}^{n} \lambda_j = 1$. Therefore, the presence of the convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$ causes the restriction associated with a single constant input $\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i_o}$ to be a redundant restriction, so it can be deleted. Therefore, using a pure output additive model is recommended. □

Now, to consider undesirable outputs in an additive model without inputs, Model (5) is proposed. This model has the translation invariance property and the restriction associated with the constant input is deleted from this model.

$$\text{Max} \sum_{r \in O_U} s_r^{+U} + \sum_{r \in O_D} s_r^{+D}$$

s.t.

$$\begin{aligned}
&\sum_{j=1}^{n} \lambda_j y_{rj}^U + s_r^{+U} = y_{r_o}^U, \quad r \in O_U, \\
&\sum_{j=1}^{n} \lambda_j y_{rj}^D + s_r^{+D} = y_{r_o, I}^D \in O_D, \\
&\sum_{j=1}^{n} \lambda_j = 1, \quad j = 1, ..., n, \\
&\lambda_j \geq 0, \quad j = 1, ..., n \\
&s_r^{+U} \geq 0, \quad I \in U, \\
&s_r^{+D} \geq 0, \quad r \in D,
\end{aligned} \tag{5}$$

where ë is the intensity vector, determining the 'best practice' for the DMU_o. Subscript 'o' refers to the DMU under evaluation. The variable s_r^{+D} expresses shortages in desirable outputs and s_r^{+U} corresponds to excesses in undesirable outputs. In the presence of undesirable outputs and lack of inputs, DMU_o is the additive efficient, if and only if

$$\sum_{r \in O_U} s_r^{+U} + \sum_{r \in O_D} s_r^{+D} = 0.$$

4 Case study

In this section, we present a case study at SAIPA (Societe Annonyme Iranienne de Production Automobile), Iran's second-largest car maker, to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms. Saipa was established in 1966 to assemble Citroëns under license for the Iranian market. Over the past four decades, SAIPA has implemented a joint venture with CITROEN and RENAULT of France, NISSAN of Japan and KIA of Korea. A 2008 data set is used in this study. Suppliers of engine cylinder heads are evaluated based on seven criteria presented in Table 1.

Table 2 presents the original data set for 36 suppliers. To meet the strictly positivity requirement of the data set, zero values are eliminated by adding a unity. The translation invariance property of the developed model guarantees that the efficiency scores of the suppliers using the original and translated data are the same. Table 3 presents the translated data set for the 36 suppliers under evaluation.

Table 1 The suppliers' evaluation criteria

Criteria	*Description*
y_1^D	*Standardisation certificate:* • suppliers with no standardisation certificates (receiving a score of 0) • suppliers with 'in progress' standardisation certificates (receiving a score of 16) • suppliers with standardisation certificates (receiving a score of 40)
y_2^D	*Process and the product audit:* the process and product audit score with a 70–30% split for process and product audit, respectively
y_3^D	*Price gap:* the ratio of the target price to the price proposed by the supplier
y_4^D	*Order fulfilment:* the ratio of the delivered items by suppliers to the ordered items
y_5^D	*On time delivery*: the percentage of the delivered parts that have met the predetermined delivery schedule
y_6^D	*Oversupply*: the ratio of the delivered parts in out-of- the program orders to the number of parts which are ordered out-of- the program[1]
y_1^U	*Defective parts*: the number of defective Parts Per Million (PPM) detected in the quality control department

[1]Since some of the variables of our empirical illustration are ratio variables (see, comments and considerations should be added in relation to the developed model. Hollingsworth and Smith (2003) argue that it is often necessary to use ratios rather than absolute numbers as inputs and outputs in DEA. This may be necessary in order to reflect accurately the underlying production function, or because of the nature of the data available. They prove that in the presence of ratio variables, use of the standard CCR model with the CRS assumption is technically incorrect, and should be rejected in favour of the BCC model. They argue that this advantage of DEA is due to its VRS assumption. Therefore, while our proposed model is a VRS model, it does not suffer from the problem discussed in Hollingsworth and Smith (2003).

Table 2 The original data set for the 36 suppliers

Suppliers	y_1^D	y_2^D	y_3^D	y_4^D	y_5^D	y_6^D	y_1^U
1	40	51.6	80	47	49.29	20.4	0
2	40	51.6	71.43	47	45.58	22.08	0
3	40	51.6	67.3	47	53	0	0
4	40	51.6	67.38	47	53	24	30
5	40	51.6	67.38	47	53	24	30
6	40	36	80	47	53	3.12	30
7	40	36	80	47	53	3.12	30
8	0	18	80	46	48.23	24	13.8
9	40	0	80	47	53	0	0
10	40	51.6	70.56	47	53	0	30
11	0	18	80	47	47.7	24	26.4
12	16	18	80	47	53	3.6	25.8

Table 2 The original data set for the 36 suppliers (continued)

Suppliers	y_1^D	y_2^D	y_3^D	y_4^D	y_5^D	y_6^D	y_1^U
13	16	18	80	47	53	3.6	25.8
14	40	25.2	80	33	53	4.32	21.9
15	40	43.2	0	45	53	0	0
16	40	51.6	67.57	47	0	0	0
17	16	43.2	33.72	47	53	5.52	6.3
18	40	51.6	70.82	47	43.99	9.36	28.8
19	40	0	42.14	40	22.79	0	0
20	16	43.2	80	39	11	0	0
21	40	36	65.94	10	42.4	6.24	30
22	40	14.4	57.95	33	25.97	2.16	0
23	16	18	80	47	32	0	30
24	40	0	42.14	17	19.61	0	0
25	16	14.4	80	39	11.66	0.72	18.6
26	40	18	57.95	38	15.9	0.48	30
27	0	18	76.68	47	18	0	14.7
28	16	39.6	31.67	47	53	5.76	15.9
29	16	36	0	47	23.85	7.92	30
30	16	18	0	47	13.78	0	0
31	0	18	80	25	0	0	0
32	0	10.8	80	5	20.67	2.4	0
33	16	36	0	33	23.85	7.92	30
34	16	14.4	76.49	0	18.02	0	18.3
35	16	0	80	0	0	4.56	23.4
36	16	10.8	80	26	29.68	5.28	23.7

Table 3 The translated data set for the 36 suppliers

Suppliers	y_1^D	y_2^D	y_3^D	y_4^D	y_5^D	y_6^D	y_1^U
1	41	51.6	80	47	49.29	20.4	0
2	41	51.6	71.43	47	45.58	22.08	0
3	41	51.6	67.3	47	53	0	0
4	41	51.6	67.38	47	53	24	30
5	41	51.6	67.38	47	53	24	30
6	41	36	80	47	53	3.12	30
7	41	36	80	47	53	3.12	30
8	1	18	80	46	48.23	24	13.8
9	41	0	80	47	53	0	0
10	41	51.6	70.56	47	53	0	30

Table 3 The translated data set for the 36 suppliers (continued)

Suppliers	y_1^D	y_2^D	y_3^D	y_4^D	y_5^D	y_6^D	y_1^U
11	1	18	80	47	47.7	24	26.4
12	17	18	80	47	53	3.6	25.8
13	17	18	80	47	53	3.6	25.8
14	41	25.2	80	33	53	4.32	21.9
15	41	43.2	0	45	53	0	0
16	41	51.6	67.57	47	0	0	0
17	17	43.2	33.72	47	53	5.52	6.3
18	41	51.6	70.82	47	43.99	9.36	28.8
19	41	0	42.14	40	22.79	0	0
20	17	43.2	80	39	11	0	0
21	41	36	65.94	10	42.4	6.24	30
22	41	14.4	57.95	33	25.97	2.16	0
23	17	18	80	47	32	0	30
24	41	0	42.14	17	19.61	0	0
25	17	14.4	80	39	11.66	0.72	18.6
26	41	18	57.95	38	15.9	0.48	30
27	0	18	76.68	47	18	0	14.7
28	16	39.6	31.67	47	53	5.76	15.9
29	16	36	0	47	23.85	7.92	30
30	16	18	0	47	13.78	0	0
31	0	18	80	25	0	0	0
32	0	10.8	80	5	20.67	2.4	0
33	16	36	0	33	23.85	7.92	30
34	16	14.4	76.49	0	18.02	0	18.3
35	16	0	80	0	0	4.56	23.4
36	16	10.8	80	26	29.68	5.28	23.7

Next, we use Model (5) to consider undesirable outputs in an additive model without inputs. The results are presented in Table 4. While $\sum_{r\in O_U} s_r^{+U} + \sum_{r\in O_D} s_r^{+D}$ for suppliers 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 and 17 is equal to zero, they are additive efficient. Inefficient suppliers can use these results from a marketing perspective. If a particular supplier is poorly performing, then the supplier can use the analysis for benchmarking purposes. This result implies that the supplier should reduce the undesirable outputs and provide better performance on desirable outputs. For example, consider supplier 18 which is an inefficient supplier. Table 4 indicates that $\lambda_1 = 1$, implying that supplier 1 is the benchmark for supplier 18. Furthermore, $s_3^{+D} = 9.2$, $s_5^{+D} = 5.3$, $s_6^{+D} = 11$, and $s_1^{+U} = 28.8$, implying that supplier 18 must increase y_3^D, y_5^D and y_6^D to 81, 50.3, and 21.36, respectively, and reduce y_1^U to 1 to become efficient.

Table 4 The evaluation results from Model (5)

Suppliers	*Supplier score*	*Reference set*	s_1^{+D}	s_2^{+D}	s_3^{+D}	s_4^{+D}	s_5^{+D}	s_6^{+D}	s_1^{+U}
1	0	$\lambda_1 = 1$	0	0	0	0	0	0	0
2	0	$\lambda_2 = 1$	0	0	0	0	0	0	0
3	0	$\lambda_3 = 1$	0	0	0	0	0	0	0
4	0	$\lambda_5 = 1$	0	0	0	0	0	0	0
5	0	$\lambda_5 = 1$	0	0	0	0	0	0	0
6	0	$\lambda_6 = 1$	0	0	0	0	0	0	0
7	0	$\lambda_6 = 1$	0	0	0	0	0	0	0
8	0	$\lambda_8 = 1$	0	0	0	0	0	0	0
9	0	$\lambda_9 = 1$	0	0	0	0	0	0	0
10	0	$\lambda_{10} = 1$	0	0	0	0	0	0	0
11	0	$\lambda_{11} = 1$	0	0	0	0	0	0	0
12	0	$\lambda_{13} = 1$	0	0	0	0	0	0	0
13	0	$\lambda_{13} = 1$	0	0	0	0	0	0	0
14	0	$\lambda_{14} = 1$	0	0	0	0	0	0	0
15	77.7	$\lambda_3 = 1$	0	8.4	67.3	2	0	0	0
16	82.1	$\lambda_1 = 1$	0	0	12.4	0	49.2	0	0
17	0	$\lambda_{17} = 1$	0	0	0	0	0	0	0
18	54.3	$\lambda_1 = 1$	0	0	9.2	0	5.3	11	28.8
19	143.3	$\lambda_1 = 1$	0	51.6	37.8	7	26.5	20.4	0
20	99.1	$\lambda_1 = 1$	24	8.4	0	8	38.2	20.4	0
21	117.7	$\lambda_1 = 1$	0	15.6	14	37	6.8	14.1	30
22	114.7	$\lambda_1 = 1$	0	37.2	22	14	23.2	18.2	0
23	125.2	$\lambda_1 = 1$	24	33.6	0	0	17.2	20.4	30
24	169.5	$\lambda_1 = 1$	0	51.6	37.8	30	29.6	20.4	0
25	145.1	$\lambda_1 = 1$	24	37.2	0	8	37.6	19.7	18.6
26	147.9	$\lambda_1 = 1$	0	33.6	22	9	33.3	19.9	30
27	143.3	$\lambda_1 = 1$	40	33.6	3.3	9	31.2	20.4	14.7
28	80.3	$\lambda_3 = 0.76$, $\lambda_5 = 0.24$	24	12	35.6	0	0	0	8.7
29	187.5	$\lambda_1 = 1$	24	15.6	80	0	25.4	12.5	30
30	193.5	$\lambda_1 = 1$	24	33.6	80	0	35.5	20.4	0
31	165.2	$\lambda_1 = 1$	40	33.6	0	22	49.2	20.4	0
32	169.4	$\lambda_1 = 1$	40	40.8	0	42	28.6	18	0
33	201.5	$\lambda_1 = 1$	24	15.6	80	14	25.4	12.5	30
34	181.7	$\lambda_1 = 1$	24	37.2	3.5	47	31.2	20.4	18.3
35	211.1	$\lambda_1 = 1$	24	51.6	0	47	49.2	15.8	23.4
36	144.2	$\lambda_1 = 1$	24	40.8	0	21	19.6	15.1	23.7

Developing a robust and easy-to-deploy method for evaluating suppliers is a critical competency in supply chain management. The results show that the proposed methodology is sound and the approach is practical.

5 Conclusions and future research directions

The selection and maintenance of an effective supply base is one of the most important objectives in supply chain management. Talluri and Narasimhan (2004) argue that the need to gain a global competitive edge on the supply side has increased substantially and an effective identification, selection and management of suppliers for a long-term partnership is the key ingredient for the success of a supply chain. Especially for those companies who spend a high percentage of their sales revenue on parts and material supplies, or those companies whose material costs represent a larger portion of their total costs, a systematic and transparent approach to purchasing decision making is of particular importance (Farzipoor Saen, 2007).

In this paper, we proposed a model to evaluate the suppliers' performance in the presence of undesirable outputs, zero values and lack of inputs. The proposed model is based on the VRS additive model. The presence of the convexity constraint

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

in the proposed model allows us to:

- solve the suppliers' evaluation problem without input and get similar results to using a single constant
- translate the zero values in the data set while the efficiency score of the suppliers remains unchanged before and after the translation
- use the ratio numbers.

In summary, the contributions of this paper are fourfold:

- undesirable outputs are considered to evaluate suppliers' performance
- an additive model is developed to consider undesirable outputs
- an additive model is developed to evaluate the efficiency of DMUs without inputs
- due to the translation invariance property of the proposed model, any zero or negative value can be translated without changing the efficiency of the DMUs before and after the translation.

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

- In many real-world situations, there may be some criteria that are beyond the control of the management. These factors are known as nondiscretionary or exogenously fixed factors. Similar research can be repeated for supplier selection in the presence of nondiscretionary factors, undesirable outputs, zero values and lack of inputs.

- Similar research can be repeated for supplier selection in the presence of dual-role factors. Dual-role factors refer to those factors that could serve as either inputs or outputs.

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Nomenclature

Parameter	*Definition*
$j = 1, \ldots, n$	The collection of suppliers (DMUs)
n	The set of suppliers (DMUs)
$r = 1, \ldots, s$	The set of outputs
$i = 1, \ldots, m$	The set of inputs
DMU_o	The DMU under investigation
x_{i_o}	The *i*th input of the DMU_o
y_{r_o}	The *r*th output of the DMU_o
v_I	The weight for the *i*th input
u_r	The weight for the *r*th output
x_{ij}	The *i*th input of the *j*th DMU
y_{rj}	The *r*th output of the *j*th DMU
$y_{r_o}^D$	The *r*th desirable output of the DMU_o
$y_{r_o}^U$	The *r*th undesirable output of the DMU_o
u_r^D	The weight for *r*th desirable output
u_r^U	The weight for *r*th undesirable output
$y_{r_j}^D$	The *r*th desirable output of *j*th DMU
$y_{r_j}^U$	The *r*th undesirable output of *j*th DMU
w_o	The variable which determines the 'return to scale' of the DMU_o
s_i^-	The excesses in the *i*th input
s_r^{+U}	The excesses in the *r*th undesirable output
s_r^+	The shortages in the *r*th output
s_r^{+D}	The shortages in the *r*th desirable output
ë = $[\lambda_j]$	The vector of the DMU loadings, determining the 'best practice' for DMU_o
U	The set of undesirable outputs
D	The set of desirable outputs

Appendix 1: The translation invariance concept

Figure 1 depicts the lack of the translation invariance property of the input oriented BCC model with respect to inputs. In the input-oriented BCC efficiency of, which is the distance of DMU_D from the efficiency frontier constructed by efficient units A and B. This ratio is not values by deducting unity from them. Now, the efficiency frontier oriented BCC efficiency of $DMU_{D'}$, DMU_D after translation becomes, which is the distance of from the efficiency frontier constructed by efficient units A' and B'. Since OR/OD# OR'/OD', the input-oriented BCC model is not translation invariant with respect to the inputs.

Figure 1 Translation in the BCC model