A NEW APPROACH FOR CONSIDERING A DUAL-ROLE FACTOR IN SUPPLIER SELECTION PROBLEM

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ABSTRACT

This paper addresses the problem of a factor in supplier selection analysis which may be classified either an input or an output. The quantity of such a factor may influence the relative efficiency of the Suppliers. Despite the fact that there are several publications addressing dual-role factors, it seems that their idea of classifying a factor as an input or an output within a single model cannot consider the causality relationships between inputs and outputs. A simple approach is proposed to resolve this limitation and to consider dual-role factor as well. A numerical example demonstrates the application of the proposed approach in supplier selection context.

Key words: Supplier selection; Data envelopment analysis; Dual-role factor

1. INTRODUCTION

Today firms are more actively involving suppliers in their integrated development processes and have identified suppliers as a source of competitive advantage. That means that there is room for development and identification of factors that could help sustain or improve the relationship between the buyer and the supplier in outsourced product development (Nellore, 2001). Carr and Pearson (1999) declare that firms with a strategic approach to purchasing are more involved in supplier evaluation than other firms. It was also shown that this strategic approach has a positive impact on buyer-seller relationships and finally, supplier evaluation systems has a positive effect on the buying firm's financial performance and may benefit various departments of the buying company. Hahn et al. (1990) emphasize that an organization's ability to produce a quality product at a reasonable cost and in a timely manner is heavily influenced by its suppliers' capabilities. In the current competitive environment, suppliers are important resources for manufacturers. Suppliers have a large and direct impact on the cost, quality, technology, and time-to-market of new products (Handfield et al., 1999). Talluri and Narasimhan (2004) emphasize that managing the supply base by identifying, selecting and managing suppliers for strategic, long term partnerships is a key ingredient to the success of a supply chain.

Data envelopment analysis (DEA) has been widely applied to address various decision analysis problems due to its usefulness in evaluating multi-criterion systems. DEA is a nonparametric mathematical programming technique that determines an efficient frontier of the most efficient decision making units (DMUs) and calculates the efficiency of each DMU relative to this efficient frontier based on multiple observed inputs and outputs. An efficiency score of a DMU is generally defined as the weighted sum of outputs divided by the weighted sum of inputs, while weights need to be assigned. To avoid the potential difficulty in assigning these weights among various DMUs, a DEA model computes weights that give the highest possible relative efficiency score to a DMU while keeping the efficiency scores of all DMUs less than or equal to one under the same set of weights (Liu et al., 2000). However, there is a strong argument for permitting certain factors to simultaneously play the role of both inputs and outputs. Beasley (1990, 1995), in a study of the efficiency of university departments, treated research funding on both the input and output sides. However, as Cook et al. (2006) addressed, the model proposed by Beasley (1990, 1995) has two limitations. The first limitation is that in the absence of constraints (e.g., assurance region or cone-ratio) on the multipliers, each DMU may be 100% efficient. The second limitation is that the dual-role factor is considered differently on the input than on the output side. Cook et al. (2006) developed a new model that has not the above mentioned limitations. However, the aforementioned references suffer from a big limitation: They classify a factor as an input or an output within a single model and cannot guarantee that the production function and the causality relationships between inputs and outputs are verified. That is, considering a factor simultaneously as an input and an output in a single model means that there is a factor that is used to produce itself.

The objective of this paper is to propose a simple approach for selecting suppliers in the presence of a dual-role factor.

This paper proceeds as follows. In Section 2, literature review is presented. Section 3 introduces the approach. Numerical example and concluding remarks are discussed in Sections 4 and 5, respectively.

2. LITERATURE REVIEW

Some mathematical programming approaches have been used for supplier selection in the past. Nydick and Hill (1992), Barbarosoglu and Yazgac (1997), and Narasimhan (1983) used analytic hierarchy process (AHP) to support supplier selection decisions. Kahraman et al. (2003) suggested fuzzy AHP for selecting the best supplier providing the most satisfaction for the determined criteria. Özgen et al. (2008) developed an integration of the AHP and a multi-objective possibilistic linear programming (MOPLP) to evaluate and select suppliers. Ghodsypour and O'Brien (1998) used AHP and linear programming to select suppliers.

Lin and Chen (2004) presented a fuzzy decision making framework for selecting the most favorable strategic supply chain alliance under limited evaluation resources. Also, Holt (1998) and Li et al. (1997) applied fuzzy sets theory in supplier selection. Chang et al. (2006) proposed a fuzzy multiple attribute decision making method based on the fuzzy linguistic quantifier for supplier selection. Morlacchi (1999) combined AHP with fuzzy set and applied it to evaluate suppliers in the engineering and machine sectors.

Weber (1996) applied DEA in supplier evaluation for an individual product and demonstrated the advantages of applying DEA to such a system. In this study, the criteria for selecting suppliers were significant reductions in costs, late deliveries and rejected materials. Weber et al. (2000) also presented an approach for evaluating suppliers using multi-objective programming (MOP) and DEA. Talluri et al. (2006) developed a chance-constrained DEA model for selecting suppliers. Talluri and Narasimhan (2003) developed a max-min DEA model for supplier selection problem. Mohammady Garfamy (2006) presented the methodology of applying DEA to compare overall supplier performances based on total cost of ownership (TCO) concept and demonstrated this application through a study for a hypothetical firm. Braglia and Petroni (2000) described a multiple attribute utility theory based on the use of DEA, aimed at helping purchasing managers to formulate viable sourcing strategies in the changing market place. Recently Farzipoor Saen (2010a) considered the ratings for service-quality experience and service-quality credence as dual-role factors for selecting third-party reverse logistics providers. From the perspective of decision maker who intends to select the best supplier, such measures may play the role of proxy for "high quality of services", hence can reasonably be classified as outputs. On the other hand, from the perspective of supplier that intends to supply reverse logistics services, they can be considered as inputs that help the supplier in obtaining more customers. As well, Farzipoor Saen (2010b) proposed a method for selecting suppliers in the presence of dual-role factors and weight restrictions. In this paper the research and development cost was considered as both an input and an output. However, Farzipoor Saen (2010a) and Farzipoor Saen (2010b) classified a factor as an input or an output within a single model which does not consider the causality relationships between inputs and outputs.

To the best of knowledge of authors, there is not any reference dealing with a dual-role factor in a simplistic and straightforward way. The approach presented in this paper has some distinctive contributions.

- The proposed approach is very simple and straightforward.
- The proposed approach considers the causality relationships between inputs and outputs.
- The proposed approach can be easily used in each kind of DEA model without any effort to combine concept of dual-role factor with these models.

3. PROPOSED APPROACH

Beasley (1990, 1995) proposed Model (1) which is based on the standard CCR (Charnes et al., 1978) model to evaluate the efficiency of 50 university departments. Consider a situation where members *k* of a set of *K* DMUs are to be evaluated in terms of *R* outputs $Y_k = (y_{rk})_{r=1}^{R}$ and *I* inputs $X_k = (x_{ik})_{i=1}^{I}$. In addition, assume that a particular factor is held by each DMU in the amount of w_k, and serves as both an input and output factor. The used nomenclatures in this paper are summarized in Table 1.

$$\max \frac{(\sum_{r=1}^{R}\mu_r y_{ro}+\gamma w_o)}{(\sum_{i=1}^{I}v_i x_{io}+\beta w_o)}$$

s.t.

$$\sum_{r=1}^{R}\mu_r y_{rk}+\gamma w_k-\sum_{i=1}^{I}v_i x_{ik}-\beta w_k\le 0, \quad k=1,\ldots,K, \tag{1}$$

$$\mu_r, v_i, \gamma, \beta \ge 0$$

Table 1. The nomenclatures

DMU_o: the decision making unit under investigation	
$k=1,\ldots,k$	collection of DMUs (suppliers)
$r=1,\ldots,R$	the set of outputs
$i=1,\ldots,I$	the set of inputs
x_{io}: *i*th input of the DMU_o	
v_i: the weight for *i*th input	
y_{ro}: *r*th output of DMU_o	
μ_r: the weight for *r*th outpu	
w_o: level of dual-role factor of DMU_o	
γ: the weight for dual-role factor when it is treated on the output side	
β: the weight for dual-role factor when it is treated on the input side	
x_{ik}: the *i*th input of DMU_k	
y_{rk}: *r*th output of DMU_k	
w_k: level of dual-role factor of DMU_k	
λ_k : Vector of DMU loadings, determining "best practice" for the DMU_o	
θ_1: Radial efficiency measure for DMU_o when dual-role factor is treated on the input side	
θ_2: Radial efficiency measure for DMU_o when dual-role factor is treated on the output side	
θ^*: max (θ_1, θ_2)	

Cook et al. (2006) argue that Beasley's (1990, 1995) treatment of dual-role factor on both the input and output sides is not entirely appropriate and represents somewhat of a contradiction. The contradiction is that Model (1) treats w_o differently on the input than on the output side.

To correct this apparent flaw, Cook et al. (2006) recommend treating w_o as being nondiscretionary on the input side. Since, on the output side, variables generally remain fixed in the optimization process of an input-oriented model, w_o can be viewed as nondiscretionary as well. From this perspective, Cook et al. (2006) modified Model (1) and showed its linear programming as below:

$$
\begin{aligned}
\text{Max } & \textstyle\sum_{r=1}^{R} \mu_r y_{ro} + \gamma w_o - \beta w_o \\
\text{s.t.} & \\
& \textstyle\sum_{i=1}^{I} v_i x_{io} = 1, \\
& \textstyle\sum_{r=1}^{R} \mu_r y_{rk} + \gamma w_k - \beta w_k - \sum_{i=1}^{I} v_i x_{ik} \le 0, \quad k=1, \ldots, K, \\
& \mu_r, v_i, \gamma, \beta \ge 0,
\end{aligned} \qquad (2)
$$

The inclusion of dual-role factor on the input side of Model (2) as a nondiscretionary input is based on the idea of Banker and Morey (1986). The authors prove that, the way to model such inputs is to move them to the output side, but with the opposite sign. This idea often arises in situations where there are criteria that are beyond the control of the management but influence the efficiency of DMUs. Thus, in evaluating process, these factors are generally expected to remain at their current level.

Now, one of three possibilities exists in regard to the sign of $\hat{\gamma} - \hat{\beta}$, where $\hat{\gamma}$, $\hat{\beta}$ are the optimal values from Model (3); $\hat{\gamma} - \hat{\beta} > 0$, $= 0$, or < 0 (Cook et al., 2006).

Case 1: If $\hat{\gamma} - \hat{\beta} < 0$, then the dual-role factor is "behaving like input". Hence less of this factor is better, and would lead to an increase in efficiency.

Case 2: If $\hat{\gamma} - \hat{\beta} > 0$, then the dual-role factor is "behaving like output". Hence more of this factor is better, and would lead to an increase in efficiency.

Case 3: If $\hat{\gamma} - \hat{\beta} = 0$, then dual-role factor is at equilibrium level.

At this juncture, we discuss about a simple approach to treat with a dual-role factor and find the behavior of this factor as input, output, or equilibrium.

Model (3) treats dual-role factor only on the input side and as a nondiscretionary input.

$$
\begin{aligned}
\text{Min } & \theta_1 \\
\text{s.t.} & \\
& \textstyle\sum_{k=1}^{K} x_{ik} \lambda_k \le \theta_1 x_{io}, \quad i=1, \ldots, I, \\
& \textstyle\sum_{k=1}^{K} w_k \lambda_k \le w_o, \\
& \textstyle\sum_{k=1}^{K} y_{rk} \lambda_k \ge y_{ro}, \quad r=1, \ldots, R, \\
& \lambda_k \ge 0, \\
& \theta_1 \text{ free}
\end{aligned} \qquad (3)
$$

Model (4) treats dual-role factor only on the output side.

$$
\begin{aligned}
\text{min } & \theta_2 \\
\text{s.t.} & \\
& \textstyle\sum_{k=1}^{K} x_{ik} \lambda_k \le \theta_2 x_{io}, \quad i=1, \ldots, I, \\
& \textstyle\sum_{k=1}^{K} y_{rk} \lambda_k \ge y_{ro}, \quad r=1, \ldots, R, \\
& \textstyle\sum_{k=1}^{K} w_k \lambda_k \ge w_o, \\
& \lambda_k \ge 0, \\
& \theta_2 \text{ free}
\end{aligned} \qquad (4)
$$

Table 2 shows the algorithm of this new approach.

Table 2. Algorithm of the proposed approach

Step 1. Start.
Step 2. Treat dual-role factor only on the input side and run Model (3).
Step 3. Treat dual-role factor on the output side and run Model (4).
Step 4. Find max $(\theta_1, \theta_2) = \theta^*$ and consider it as efficiency score of DMU_o.
Step 5. Now, consider θ_1, θ_2 as an indicator of dual-role factor's behavior as well. The θ_1, θ_2 are interpreted as below[1].

Case 1: If $\theta_1 > \theta_2$, then the dual-role factor is "behaving as input".
Case 2: If $\theta_1 < \theta_2$, then the dual-role factor is "behaving as output".
Case 3: If $\theta_1 = \theta_2$, then the dual-role factor is at equilibrium level.

[1] Since DEA computes weights that give the highest possible relative efficiency score to a DMU while keeping the efficiency scores of all DMUs less than or equal to one under the same set of weights, so we select max (θ_1, θ_2) as the indicator of dual role-factor's behavior.

Therefore, by using the above algorithm the limitation of conventional treatment of dual-role factor discussed in Section 1 has been resolved. In the next section, a numerical example is presented. In this example we examine the ability of our proposed approach in determining the efficiency scorers of suppliers and the behavior of dual-role factor.

4. NUMERICAL EXAMPLE

To demonstrate the application of the proposed approach in supplier selection context, we use the data set from Farzipoor Saen (2010b). The inputs for selecting suppliers include Total Cost of shipments (TC), Number of Shipments per month (NS), and Research and Development cost (R&D). The outputs utilized in the study are Number of shipments to arrive On Time (NOT), Number of Bills received from the supplier without errors (NB), and R&D. R&D plays the role of both input and output. Table 3 shows the data set for 18 suppliers.

Table 3. Data set for 18 suppliers

Supplier	*TC*	*NS*	*NOT*	*NB*	*R&D*
1	253	197	187	90	20
2	268	198	194	130	32
3	259	229	220	200	15
4	180	169	160	100	10
5	257	212	204	173	16
6	248	197	192	170	28
7	272	209	194	60	12
8	330	203	195	145	36
9	327	208	200	150	30
10	330	203	171	90	28
11	321	207	174	100	19
12	329	234	209	200	25
13	281	173	165	163	18
14	309	203	199	170	27
15	291	193	188	185	22
16	334	177	168	85	31
17	249	185	177	130	50
18	216	176	167	160	15

Table 4 shows the results of the evaluation using conventional model (Model 2) and our proposed approach (Models 3 and 4), respectively.

Table 4. Efficiency scores and output/input behavior

Supplier (DMU)	Efficiency score derived by Model (2)	θ_1	θ_2	θ^*	Dual-role factor's Behavior
1	0.971024	0.971024	0.965187	0.971024	K_2
2	1	0.999252	1	1	K_1
3	1	1	1	1	K_3
4	1	1	1	1	K_3
5	0.996941	0.997029	0.990751	0.997029	K_2
6	1	1	1	1	K_3
7	1	1	0.938749	1	K_2
8	0.980852	0.977741	0.980852	0.980852	K_1
9	0.977673	0.977442	0.977673	0.977673	K_1
10	0.852475	0.851726	0.852475	0.852475	K_1
11	0.855143	0.855809	0.851216	0.855809	K_2
12	0.9205	0.919077	0.9205	0.9205	K_1
13	0.977534	0.997048	0.980756	0.997048	K_2
14	1	1	0.999626	1	K_2
15	1	1	1	1	K_3
16	0.957823	0.956127	0.960464	0.960464	K_1
17	1	0.977296	1	1	K_1
18	1	1	1	1	K_3

Results of evaluation by using Model (2) show that, suppliers 2, 3, 4, 6, 7, 14, 15, 17, and 18 are efficient with a relative efficiency score of 1 and the remaining 9 suppliers with relative efficiency scores of less than 1 are considered to be inefficient. The θ_1 shows the radial efficiency score of DMU_o derived by Model (3), that the R&D cost is treated on the input side and as a nondiscretionary input. The θ_2 shows the radial efficiency score of DMU_o by using Model (4), that the R&D cost is treated on the output side. The θ^* is the final radial efficiency score of DMU_o derived by max (θ_1, θ_2). Notice that, the θ^* and results of Model (2), found the same efficient suppliers.

Also the results show that K_1=7, K_2=6, and K_3=5. Suppliers in K_1 are those wherein the R&D is behaving like an output, and where more of such factor would improve the efficiencies of the members of that set. For those suppliers in K_2, R&D is behaving like an input, and less of such factor would increase the efficiency of the members. The three suppliers in K_3 are at an equilibrium level.

To highlight the validity of our proposed approach and its difference from the classical model (Model 2), the nonparametric Spearman correlation analysis between their results is shown in Table 5.

Table 5. Correlation coefficient between scores of proposed approach and Model (2)

			Proposed approach	Model (2)
Spearman's rho	Proposed approach	Correlation Coefficient	1.000	0.986
		Sig. (2-tailed)		0.000
	Model (2)	Correlation Coefficient	0.986	1.000
		Sig. (2-tailed)	0.000	

Since correlation coefficient between the results of two approaches, at significant level of 0.01, is 0.986, there is a significant relationship between their results. Therefore, the proposed approach is able to find efficiency scores of DMUs in an easier way than conventional model. It also has the capability to be easily combined with each kind of DEA models.

5. CONCLUDING REMARKS

Supplier selection strategy is the strategy adopted by the manufacturer, to evaluate and select suppliers, which fulfills the requirements of the manufacturer (Lemke et al., 2000). Because of the multi-criteria nature of supplier selection problem, DEA as an appropriate multi-criteria decision making tool, has been applied. To consider dual-role factor for supplier selection problem, a new approach is presented. We demonstrated the validity of the proposed approach via comparing the results with conventional models.

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

- The proposed algorithm can be used in the presence of imprecise data.
- Preferences of decision maker can be incorporated into the proposed algorithm by restricting the feasible region of the inputs and outputs' weights.

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