Trends in

Applied Sciences Research

ISSN 1819-3579

Academic
Journals Inc.

www.academicjournals.com

Trends in Applied Sciences Research 7 (4): 314-323, 2012
ISSN 1819-3579 / DOI: 10.3923/tasr.2012.314.323

Using DEA Cross-efficiency Evaluation for Suppliers Ranking in the Presence of Dual-role Factors

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ABSTRACT

For selecting suppliers, Data Envelopment Analysis (DEA), as a multiple criteria decision making tool, has been applied for several times. However, sometimes in supplier selection problem, there may exist some criteria which may be classified either an input or an output. These factors are known as dual-role factors. However, in traditional treatment of dual-role factors in DEA, free reign is given when deciding for each Decision Making Unit (DMU) which outputs and inputs to emphasize, many different avenues are present by which a DMU can appear efficient. Therefore, it is common to have many DMUs that are relatively efficient. In addition, since each DMU has its own set of weights, all of its weight might be put on a single output and input. Therefore, to overcome these drawbacks, this paper proposes a cross-efficiency model which is able to consider dual-role factors. A numerical example demonstrates the application of the proposed model in supplier selection context.

Key words: Data envelopment analysis, supplier ranking, cross-efficiency, dual-role factors

INTRODUCTION

Effective supplier evaluation and selection strategies play a key role for improving organizational productivity and profitability. Nowadays, considering recent economic crisis which is widely spread around the world, for the survival of companies, it is essential to apply methods and tools to reduce costs. Therefore, one of the most important factors to succeed in competitive environment is to select appropriate suppliers which directly affect supply chain performance. Selecting suitable suppliers reduces purchasing costs and help organizations to achieve their purpose by eliminating waste and improving quality of products.

Some approaches have been used for supplier selection in the past. To determine the best set of suppliers and their corresponding order quantities, Xia and Wu (2007) presented an integrated approach of Analytic Hierarchy Process (AHP) improved by rough sets theory and multi-objective mixed integer programming.

Amin *et al*. (2011) proposed a decisional model for selecting suppliers which consists two phases. In the first phase, quantified SWOT analysis (Strengths, Weaknesses, Opportunities and Threats) are applied for evaluating suppliers. The linguistic variables and triangular fuzzy numbers are used to quantify variables. In the second phase, a fuzzy linear programming model is applied to determine the order quantity. To select preferred suppliers during the new product development process, Choy *et al.* (2004) discussed a company's Customer Relationship Management (CRM) system, supplier rating system and product coding system by the Case-based Reasoning (CBR) technique.

Mendoza and Ventura (2010) proposed a mixed integer nonlinear programming model to determine an optimal inventory policy that coordinates the transfer of items between different stages of a serial supply chain, while properly allocating orders to selected suppliers.

Wadhwa and Ravindran (2007) modeled the supplier selection problem as a Multi-objective Programming (MOP) problem, in which there are three objective functions (i.e., minimization of price, lead time and rejects). Three solution approaches, including weighted objective method, Goal Programming (GP) method and compromise programming, were used to compare the solutions.

Azadi and Saen (2012a) developed a new Russell Data Envelopment Analysis (DEA) model in the presence of undesirable outputs and stochastic data for supplier selection.

In current study, DEA which is a nonparametric and multiple criteria decision making tool, is used for ranking suppliers. DEA was first introduced by Charnes *et al.* (1978) (CCR) in 1978 and it is a linear-programming-based methodology that uses multiple inputs and multiple outputs to calculate efficiency scores. The efficiency score for each Decision Making Unit (DMU) is defined as a weighted sum of outputs divided by a weighted sum of inputs, where all efficiencies are restricted to a range from 0 to 1. 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). DEA is a robust, standardized and transparent methodology and a number of extensions and applications have been reported (Niknafs and Parsa, 2011; Koc *et al.*, 2011; Keramidou *et al.*, 2011; Zandieh *et al.*, 2009; Ergulen and Torun, 2009; Rayeni *et al.*, 2010; Mirhedayatian *et al.*, 2011; Asharafi and Jaafar, 2011; Taher and Malek, 2009).

However, sometimes in suppliers' evaluation problem, there may exist some criteria that should be considered as dual-role factors. In some situations 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 does not have the above mentioned limitations. Supplier selection context, the research and development cost can be considered as both an input and an output. Remembering that the simple definition of efficiency is the ratio of output to input, an output can be defined as anything whose increase will cause an increase in efficiency. Similarly, an input can be defined as anything whose decrease will cause an increase in efficiency. If the research and development cost is considered as an output, then the increase in the research and development cost will increase the efficiency of the supplier. Likewise, if the research and development cost is considered as an input, then any decrease in the research and development cost without a proportional decrease in the outputs will increase efficiency. Therefore, depending on how one looks at it, either increasing or decreasing the research and development cost can increase efficiency (Saen, 2010a). Saen (2010b) proposed a model which can consider multiple dual-role factors for selecting third-party reverse logistics providers. As well, Saen (2010a) proposed a method for selecting suppliers in the presence of a dual-role factor and weight restrictions.

In this study the research and development cost is considered as both an input and an output. Recently, Mahdiloo *et al.* (2011) addressed the problem of a factor in supplier selection analysis which may be classified either an input or an output. They demonstrated the validity of the proposed approach via comparing the results with conventional models.

The approaches presented in the works of Beasley (1990, 1995), Cook *et al.* (2006), Saen (2010a, b) and Mahdiloo *et al.* (2011) had perfect contribution for considering dual-role factors through the DEA concept. However, their treatment of dual-role factors in DEA models suffer from some limitations. Since, in traditional DEA, free reign is given when deciding for each DMU which outputs and inputs to emphasize, many different avenues are present by which a DMU can appear efficient. Therefore, it is common to have many DMUs that are relatively efficient. In addition, since each DMU has its own set of weights, all of its weight might be put on a single output and input. While this is permissible, it may not be realistic. To overcome these problems, we propose to incorporate dual-role factors in the cross-efficiency method introduced by Sexton *et al.* (1986) and developed by Doyle and Green (1994). The main idea of cross-efficiency is to use DEA in a peer evaluation instead of a self evaluation mode.

The above discussions make it more reasonable to model the cross-efficiency formulation of considering dual-role factors in DEA models.

PROPOSED MODEL

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 w_k and serves as both an input and output factor. The used nomenclatures in this paper are summarized in Table 1.

Table 1: The nomenclatures

DMU_o: The decision making unit under investigation
k = 1, ..., K collection of DMUs (suppliers)
r = 1, ..., R the set of outputs
i = 1,...,I the set of inputs
f = 1, ..., F the set of dual-role factors
x_{io}: The ith input of the DMU_o
y_{ro}: The rth output of DMU_o
w_o: Level of dual-role factor of DMU_o
u_r: The weight for rth output
x_{ik}: The ith input of DMU_k
y_{rk}: The rth output of DMU_k
w_{fk}: The fth dual-role factor of DMU_k
γ_f: The weight for dual-role factor when it is treated on the output side
β_f: The weight for dual-role factor when it is treated on the input side
E_{ok}: Shows the relative efficiency of DMU_k with optimal weights for inputs and outputs of DMU_o
E_{oo}: Is the efficiency score of DMU_o by the its own optimal weights

Equation 1 is proposed by Cook *et al.* (2006) for considering single dual-role factor:

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

To demonstrate how to consider multiple dual-role factors in DEA equations, Saen (2010b) proposed Eq. 2. Assume that some factors are held by each DMU in the amount w_{fk} (f = 1, ..., F) and serve as both an input and output factors. The proposed equation for considering multiple dual-role factors is as follows:

$$
\begin{aligned}
&\text{Max} \sum_{r=1}^{R} u_r y_{ro} + \gamma w_{fo} - \sum_{f=1}^{F} \beta_f w_{fo}, \\
&\text{s.t.} \sum_{i=1}^{I} v_i x_{io} = 1, \\
&\sum_{r=1}^{R} u_r y_{rk} + \sum_{f=1}^{F} y_f w_{fo} - \sum_{f=1}^{F} \beta_f w_{fk} - \sum_{i=1}^{I} v_i x_{ik} \le 0,\ k = 1,\ldots,K, \\
&\quad u_r \ge 0, \quad r = 1,\ldots,R, \\
&\quad v_i \ge 0, \quad i = 1,\ldots,I, \\
&\quad \gamma_f \ge 0, \quad f = 1,\ldots,F, \\
&\quad \beta_r \ge 0, \quad f = 1,\ldots,F
\end{aligned}
\tag{2}
$$

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 Eq. 2; $\hat{\gamma}-\hat{\beta}$ >0, = 0 or <0:

- Case 1: If $\hat{\gamma}-\hat{\beta}<0$, then the dual-role factor is "behaving like input"
- Case 2: If $\hat{\gamma}-\hat{\beta}>0$, then the dual-role factor is "behaving like output"
- Case 3: If $\hat{\gamma}-\hat{\beta}=0$, then dual-role factor is at equilibrium level

At this juncture to create a unique ordering among the efficient DMUs and to eliminate unrealistic weighting schemes in Eq. 2, we develop the cross-efficiency form of this equation. For each DMU_o (o = 1, ..., K), in Eq. 2, we can obtain a set of optimal weights (multipliers) (u_r^*, v_i^*, γ_f^*, $\boldsymbol{\beta}_f^*$) Using these set of weights, the cross-efficiency for any DMU_k (k = 1,... ,K), is then calculated as:

$$
E_{ok} = \frac{\sum_{r=1}^{R} u_{ro}^* y_{rk} + \sum_{f=1}^{F} \gamma_{fo}^* w_{fk}}{\sum_{i=1}^{I} v_{io}^* x_{ik} + \sum_{f=1}^{F} \beta_{fo}^* w_{fk}}
\tag{3}
$$

where, E_{ok} shows the relative efficiency of DMU_k with optimal weights for inputs and outputs of DMU_o. One can compute the average of the efficiencies in each column to get a measure of how the

DMUs associated with the column are rated by the rest of the DMUs. Good operating practices more likely to be exhibited by relatively efficient DMUs offering high average efficiencies in their associated columns in the cross-efficiency matrix. Since Eq. 2 will be run n times for n DMUs, respectively, each DMU will get n efficiency scores which construct a n×n matrix, called cross-efficiency matrix. For DMU_k (k = 1,... ,K), the average of all E_{ok} (o = 1,..., K), can be used as an efficiency measure for DMU_k and will be referred to as the cross-efficiency score for DMU_k. The formula for averaging is as below:

$$\bar{E}_k = \frac{1}{n}\sum_{o=1}^{K} E_{ok} \tag{4}$$

The non-uniqueness of the DEA optimal weights possibly reduces the usefulness of the cross-efficiency. To overcome this problem, Doyle and Green (1994) suggested the use of aggressive and benevolent cross evaluation. A cross evaluation is aggressive/benevolent in the sense that it selects a set of weights which not only maximize the efficiency of a particular DMU under evaluation but also minimize/ maximize the efficiencies of all other DMUs in some sense. We develop the benevolent formulation of Eq. 2 and show it as Eq. 5.

$$\begin{aligned}
&\max\ h_c = u_r \sum_{k\neq 0} y_{rk} + \gamma_f \sum_{k\neq 0} w_{fk} - \beta_f \sum_{k\neq 0} w_{fk}\\
&\text{s.t.}\quad v_i \sum_{k\neq 0} x_{ik} = 1\\
&\sum_{r=1}^{R} u_r y_{rk} + \sum_{f=1}^{F} \gamma_f w_{fk} - \sum_{f=1}^{F} \beta_f w_{fk} - \sum_{i=1}^{I} v_i x_{ik} \leq 0,\ k \neq 0,\\
&\left(\sum_{r=1}^{R} u_r y_{rk} + \sum_{f=1}^{F} y_f w_{fo}\right) - E_{oo}\left(\sum_{i=1}^{I} v_i x_{io} + \sum_{f=1}^{F} \beta_f w_{fo}\right) = 0,\ k = 1,\ldots,K,\\
&\quad u_r \geq 0,\quad r = 1,\ldots,R,\\
&\quad v_i \geq 0,\quad i = 1,\ldots,I,\\
&\quad \gamma_f \geq 0,\quad f = 1,\ldots,F,\\
&\quad \beta_f \geq 0,\quad f = 1,\ldots,F
\end{aligned} \tag{5}$$

where, E_{oo} is the efficiency of DMU_o obtained from Eq. 2.

NUMERICAL EXAMPLE

In order to demonstrate the application of the proposed equation in supplier selection context, the data set is taken from Saen (2010a). The inputs for selecting suppliers include Total Cost of shipments (TC), Number of Shipments per month (NS) and Research and Development cost (R and 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 and D. R and D plays the role of both input and output. Table 2 illustrates the data set for 18 suppliers.

Table 3 shows the efficiency scores of suppliers, using Eq. 2 and their ranking results. Also, the behavior of dual-role factor for 18 suppliers is depicted in this table. In order to interpret the behavior of dual-role factor, consider for instance suppliers 1 and 2. For supplier 1, with a negative $\hat{\gamma}_1 - \hat{\beta}_1$, R and D is behaving like an input and lower value of such factor would increase the efficiency of the supplier. For supplier 2, with a positive $\hat{\gamma}_1 - \hat{\beta}_1$, R and D is behaving like an output and higher level of such factor would improve the efficiency of the supplier. In this equation, each

Table 2: Data set for 18 suppliers

	Inputs			Outputs	
Supplier (DMU)	TC(1000$) x_{1k}	NS x_{2k}	Dual-role factor R and D (1000$) w_{1k}	NOT y_{1k}	NB y_{2k}
1	253	197	20	187	90
2	268	198	32	194	130
3	259	229	15	220	200
4	180	169	10	160	100
5	257	212	16	204	173
6	248	197	28	192	170
7	272	209	12	194	60
8	330	203	36	195	145
9	327	208	30	200	150
10	330	203	28	171	90
11	321	207	19	174	100
12	329	234	25	209	200
13	281	173	18	165	163
14	309	203	27	199	170
15	291	193	22	188	185
16	334	177	31	168	85
17	249	185	50	177	130
18	216	176	15	167	160

Table 3: Efficiency scores, rankings and output/input behavior using Eq. 2

Supplier (DMU)	Efficiency scores	Rank	$\hat{\gamma}_1$	$\hat{\beta}_1$	$\hat{\gamma}_1 - \hat{\beta}_1$
1	0.979	14	0	0.000731726	-0.000731726
2	1	1	0.000950003	0	0.000950003
3	1	1	0.005283902	0	0.005283902
4	1	1	0.007116105	0	0.007116105
5	0.999	11	0	0.001454203	-0.001454203
6	1	1	0.006706481	0	0.006706481
7	1	1	0	0.1564593	-0.1564593
8	0.986	12	0.000954646	0	0.000954646
9	0.981	13	0.000085092	0	0.000085092
10	0.860	18	0.000087188	0	0.000087188
11	0.864	17	0	0.001489329	-0.001489329
12	0.921	16	0.000970597	0	0.000970597
13	1	1	0	0.01253691	-0.01253691
14	1	1	0.001182036	0	0.001182036
15	1	1	0.004673992	0	0.004673992
16	0.973	15	0.001181457	0	0.001181457
17	1	1	0.007727446	0	0.007727446
18	1	1	0.005524535	0	0.005524535

supplier seeks to maximize its efficiency score by choosing a set of optimal weights for all inputs and outputs. In this evaluation the best suppliers are suppliers 2, 3, 4, 6, 7, 13, 14, 15, 17 and 18 which their efficiency scores equal to unity.

As you see, Eq. 2 cannot give a complete ranking and there are ties among ten efficient suppliers. Therefore, we use Eq. 5 to derive the suppliers' cross-efficiency scores and their complete ranking. The cross-efficiency matrix is shown in Table 4.

Table 4: Matrix of cross-efficiency

Supplier (DMU)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	0.979	1.000	1.000	0.988	0.998	1.000	0.962	0.971	0.978	0.856	0.862	0.917	0.974	1.000	0.997	0.953	0.962	0.982
2	0.979	1.000	1.000	0.988*	0.998	1.000	0.963	0.971	0.978	0.856	0.862	0.917	0.974	1.000	0.997	0.953	0.962	0.982
3	0.979	1.000	1.000	0.988	0.998	1.000	0.963	0.971	0.978	0.856	0.862	0.917	0.974	1.000	0.997	0.953	0.962	0.982
4	0.961	0.988	1.000	1.000	0.985	1.000	0.927	0.916	0.921	0.800	0.802	0.882	0.896	0.946	0.940	0.857	0.988	0.970
5	0.987	1.000	1.000	0.991	0.999	1.000	0.972	0.985	0.988	0.919	0.909	0.948	0.984	1.000	0.998	0.976	0.985	0.988
6	0.979	1.000	1.000	0.988	0.998	1.000	0.963	0.971	0.978	0.856	0.862	0.917	0.974	1.000	0.997	0.953	0.962	0.982
7	0.681	0.483	0.948	1.000	0.860	0.535	1.000	0.438	0.521	0.474	0.651	0.616	0.672	0.568	0.639	0.437	0.301	0.777
8	0.987	1.000	1.000	0.991	0.999	1.000	0.973	0.986	0.988	0.922	0.911	0.950	0.984	1.000	0.998	0.977	0.985	0.988
9	0.981	1.000	1.000	0.989	0.998	1.000	0.965	0.976	0.981	0.876	0.875	0.926	0.977	1.000	0.997	0.961	0.971	0.984
10	0.979	1.000	1.000	0.988	0.998	1.000	0.963	0.972	0.979	0.860	0.864	0.919	0.975	1.000	0.997	0.955	0.964	0.983
11	0.979	1.000	1.000	0.988	0.998	1.000	0.963	0.972	0.979	0.860	0.864	0.919	0.975	1.000	0.997	0.955	0.964	0.983
12	0.980	1.000	1.000	0.988	0.998	1.000	0.964	0.973	0.979	0.863	0.866	0.921	0.975	1.000	0.997	0.956	0.965	0.983
13	0.518	0.651	1.000	0.706	0.921	0.864	0.376	0.684	0.728	0.467	0.547	0.904	1.000	0.853	1.000	0.479	0.588	1.000
14	0.979	1.000	1.000	0.988	0.998	1.000	0.963	0.971	0.978	0.856	0.862	0.917	0.974	1.000	0.997	0.953	0.962	0.982
15	0.975	0.990	1.000	0.986	0.998	0.992	0.965	0.967	0.977	0.856	0.866	0.919	0.982	1.000	1.000	0.954	0.938	0.982
16	0.985	1.000	1.000	0.991	0.998	1.000	0.970	0.983	0.986	0.908	0.900	0.943	0.982	1.000	0.998	0.973	0.982	0.987
17	0.953	1.000	0.974	0.949	0.974	1.000	0.917	0.984	0.979	0.853	0.844	0.913	0.972	1.000	0.995	0.961	1.000	0.966
18	0.775	0.893	1.000	0.859	0.962	1.000	0.668	0.876	0.880	0.680	0.695	0.921	0.962	0.949	1.000	0.733	0.928	1.000

*0.988 represents the cross-efficiency score of supplier No. 4 in terms of optimal weights of supplier No. 2, **Bolded numbers in the leading diagonal are the simple efficiencies

Table 4 provides two main advantages. First, it usually creates a unique ordering among the suppliers. With cross evaluation, since each supplier is rated not only by its own weighting scheme but also the schemes of the others, this amalgamation of weighting schemes makes it far more difficult to have ties and, in effect, creates a unique ordering in practice. Second, cross evaluation appears to eliminate unrealistic weighting schemes that might be used by the suppliers. Under a cross evaluation, once the supplier has a chosen weighting scheme which has been applied to all suppliers, the efficiency value given to each supplier is set aside forming a cross-efficiency matrix. Once the matrix is filled, each supplier has not only its own self evaluation but also the peer evaluations it has received via the other suppliers in the sample. Consequently, a supplier which has a high cross-efficiency value has passed a more rigorous test since it can not only make itself look good but is considered efficient by the majority of its peers (Anderson *et al*., 2002).

Table 5 displays the final efficiency scores of suppliers and final rankings derived by cross-efficiency approach. As the last column of Table 5 shows, supplier 3 is the most efficient supplier and is the first candidate for selection.

MANAGERIAL IMPLICATIONS

Purchasing is an important area of operational decision making. One major aspect of the purchasing function is supplier selection. Selecting good suppliers is important. Otherwise, selecting inappropriate suppliers leads to failure of coordination between a manufacturer and suppliers. Consequently, the total cost of the entire supply chain will increase. In age of competitive and uncertain environment, evaluation of suppliers enables companies to recognize efficient and inefficient suppliers in comparison to each other. In such situations, the purchasing department can play a strategic role in cost reduction and supplier selection is one of the most important functions of purchasing management (Ustun and Demirtas, 2008). After recognition of efficient and inefficient suppliers, decision maker only needs to make one decision to select the most suitable supplier for purchasing.

Table 5: Results of evaluation via cross-efficiency approach

Supplier (DMU)	Cross-efficiency score	Rank
1	0.924	11
2	0.945	9
3	0.996	1
4	0.965	6
5	0.982	2
6	0.966	5
7	0.913	13
8	0.920	12
9	0.932	10
10	0.812	18
11	0.828	17
12	0.904	15
13	0.956	8
14	0.962	7
15	0.974	3
16	0.886	16
17	0.909	14
18	0.972	4

The supplier selection approach developed in this paper includes a number of attractive features, as follows:

- The proposed equation evaluates suppliers in a multi criteria context
- The proposed equation considers dual-role factors for supplier selection
- To achieve the peer appraisal of suppliers instead of their self appraisal, the cross-efficiency equation which considers dual-role factors is developed
- The proposed equation does not demand weights from the decision-maker

DISCUSSION OF THE NUMERICAL FINDINGS

Supplier selection is used to describe various phenomena in supply chain management. The purpose of supplier selection is to determine the optimal supplier who can offer the best products or services for the customer and become a part of the organization's supply chain (Ebrahim *et al.*, 2009). As Azadi and Saen (2012b) mentioned, one of the key competencies for supply chain success is an effective purchasing function. In most industries, the cost of raw materials and component parts comprises the majority of product cost, in some cases reaching up to 70%. Meanwhile, in high-technology companies, purchased materials and services comprise up to 80% of total product cost. Furthermore, strategic partnership with better performing suppliers should be integrated into the supply chain to improve the performance in different aspects including reducing costs by decreasing wastages, continuously improving quality to achieve zero defects, improving flexibility to meet end-customer needs, reducing lead time at different stages of the supply chain, etc. The problem of supplier selection is a Multi-criteria Decision Making (MCDM) problem in the presence of many criteria and sub-criteria. A decision maker needs to make use one of the MCDM methods (Ayag and Ozdemir, 2009).

In this study, DEA as a multiple criteria decision making tool is used to evaluate suppliers. In applying DEA, we discussed about a particular situation in which some factors play the role of both inputs and outputs. To derive a complete ranking of suppliers and eliminate unrealistic weighting schemes among DMUs, the cross-efficiency formulation of dual-role factors is developed.

CONCLUSION

Supplier selection is the process by which suppliers are reviewed, evaluated and chosen to become part of the company's supply chain (Saen, 2010a). Nowadays, there have been major changes in the supplier selection practices. The competition has risen and the market has become globally operating. In such circumstance, it has become highly difficult for industries and companies to satisfy their own customers who have expectations for high-quality and low-cost products successfully (Weber *et al.*, 1991).

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

- Similar research can be repeated in the presence of imprecise data and fuzzy data
- One of the assumptions of this paper is that the proposed model assumes all criteria are discretionary, that is, controlled by the management of each supplier and varied at its discretion. Similar study can be done in the presence of nondiscretionary factors
- Similar research can be repeated in the presence of stochastic data

ACKNOWLEDGMENTS

The authors would like to thank the anonymous reviewer and the editor for their insightful comments and suggestions.

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