A supplier evaluation approach for designing an optimal supply chain network: A novel mathematical DEA model

Javad Mohammad Ghasemi[1]– Seyyed Esmaeil Najafi [2*]– Mohammad Fallah[1]– Mohammad Reza Nabatchian[1]

[1] Department of industrial engineering, Central tehran Branch, Islamic Azad University, Tehran, Iran
[2] Department of industrial engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

Abstract

The supplier evaluation process is a systematic approach used by organizations to determine and choose the best vendors to construct an optimal supply chain network. In other words, in supply chain management, identifying the suitable suppliers can play a key role in the success of the supply chain networks. To this end, different researchers have developed various approaches to evaluate and select the best suppliers. The current study provides a novel mathematical data envelopment analysis (DEA) approach to evaluate the suppliers and select the best efficient supplier among the set of efficient suppliers. The proposed approach solves only one mixed integer DEA model to determine the best efficient supplier. The approach not only determines the best efficient supplier, but also finds and ranks all efficient suppliers. Moreover, the presented model considers the decision maker preferences about the relative importance of supplier evaluation factors. We provide a real-life numerical example to illustrate and show the applicability and efficacy of the new approach.

Keywords: Supplier evaluation, optimal supply chain, best efficient supplier, data envelopment analysis (DEA), mathematical model.

1- Introduction

Supplier evaluation and selection is a vital aspect of supply chain management which supports companies to identify and select the best efficient suppliers to meet their requirements. The major goals of the supplier evaluation and selection procedure are reducing the costs, supply risk, and increase the overall value, and making a proper relationship between suppliers and organizations. Therefore, the success of a supply chain network is very related to the finding the best efficient suppliers. To this end, different researchers have developed various methods to evaluate and find the best suppliers in the supply chain management. The main approaches are: mathematical models, analytic hierarchy process (AHP) (Sharma et al. 2024), linear, mixed integer, and non-linear models (Ware, 2024), multi-criteria decision-making approaches (Kaur et al. 2024), neural networks, fuzzy theory (Kumar Kar, 2015), and data envelopment analysis (DEA) (Guneri et al., 2009).

Among the mentioned methods, DEA has been widely used in the supplier selection problem. Saen (2008) developed a DEA model to the supplier selection problem in the presence of interval data, ordinal data and weight restrictions. Their model classifies the suppliers into two group: efficient and inefficient suppliers. Indeed, their model is unable to find the best efficient supplier. Toloo and Nalchigar (2011) presented a mixed binary DEA model to determine the best supplier in the presence of imprecise inputs and outputs factors. Their model randomly selects an efficient supplier as the best efficient supplier. Ebrahimi and Khalili (2018) presented a mixed integer DEA model to identify the best efficient suppliers in the presence of different types of imprecise data, including weak ordinal data, interval data, ratio data, and strong ordinal data. Dobos & Vörösmarty (2019) developed a DEA method to the supplier selection problem by considering the green factors as the output variables, and the management variables as the input factors. Rashidi and Cullinane (2019) compared the methods of fuzzy DEA and fuzzy TOPSIS in the supplier selection problem and demonstrated that both approaches yield a valuable pooled shortlist of potential suppliers. Ebrahimi and Toloo (2020) have presented a pair of DEA models to estimate the lower and upper bound efficiency scores of suppliers in the space industries under uncertainty. Ebrahimi et al. (2021) developed a robust DEA model to evaluate the suppliers in the Iranian space research center institute in the presence of ordinal dual-role factors. Nazari-Shirkouhi et al. (2023) presented an integrated method to the supplier selection problem using DEA and artificial neural network (ANN).

It should be emphasized that in traditional DEA models the weights of inputs and outputs factors are free which can lead to overestimating or ignoring some inputs and outputs in the supplier evaluation process. Moreover, the decision maker preferences cannot be considered about the importance of evaluating factors. To overcome these problems, several types of weight restrictions have been developed in DEA. The most popular types are assurance regions type 1 (ARI), type 2 (ARII), and absolute weight constraints. By using the absolute weight constraints and ARII some problems such as infeasibility and underestimating the efficiency scores may be occurs (Ebrahimi et al. 2020). The problems do not exist in ARI applications. Therefore, in this paper we will apply ARI to consider the decision maker preferences in our developed model.

The current study has several contributions, which can be summarized as follows:

- The approach developed in this paper uses the weight restrictions to incorporate the decision-makers' preferences regarding the importance of inputs and outputs factors in the process of the supplier selection problem.
- The presented method solves only one mathematical DEA model to determine the best efficient supplier.
- Our presented method does not only identify the best efficient supplier, but is also able to determine and rank the set of efficient suppliers.

It should be noted that there are two main differences between the new approach and the basic DEA model. First, our proposed model is able to find the best efficient DMU just by solving a mixed binary model. However, the basic DEA model solve at least one model to each DMU to determine the best unit. Second, in contrast to the basic DEA model our developed method is able to consider the decision maker preferences regarding the importance of evaluating criteria.

The reminder of the paper is organized as follows: Section 2, briefly reviews the major existing DEA approaches which have been developed for the supplier selection problem in the supply chain network. In section 3, a novel mathematical DEA model is presented to evaluate and identify the best efficient suppliers. Moreover, a new algorithm is proposed to find a rank the set of all efficient suppliers. The developed approach is able to consider the decision-making preferences regarding the importance of evaluation factors. Section 4 presented a supplier selection application to illustrate the proposed methodology in this paper. Section 5 concludes the paper.

2- A literature review of the supplier evaluation DEA models

In the literature of supplier evaluation and selection problem there are a lot of DEA-based papers that have been proposed different approaches to select the most suitable suppliers. In this section, we briefly review some this DEA models. It should be noted that DEA is a powerful measurement tool to efficiency measure of several decision-making units (DMUs), that use multiple inputs to produce multiple outputs. The linear DEA model to evaluate DMU_p is as follows (Charnes, Cooper, and Rhodes, 1978):

$$
\begin{aligned}
& max \sum_{r=1}^{m} u_r y_{rp} \\
& s.t. \\
& \quad \sum_{i=1}^{n} v_i x_{ip} = 1 \\
& \quad \sum_{r=1}^{m} u_r y_{rj} - \sum_{i=1}^{n} v_i x_{ij} \leq 0, j = 1, \ldots, k \\
& \quad u_r, v_i \geq 0
\end{aligned}
\tag{1}
$$

Where x_{ij} is the amount of i^{th} input consumed by DMU_j, y_{rj} is the amount of r^{th} output produced by DMU_j, u_r is the weight of r^{th} output and v_i is the weight of i^{th} input ($j = 1,2,\ldots,k; r = 1,2,\ldots,m \;\&\; i = 1,2,\ldots,n$). In model (1), it is supposed that the inputs and outputs data are precise. Amin and Toloo (2007) modified model (1) and developed model (2) to select a single efficient unit.

$$M^* = Min \quad M \tag{2}$$

$$\sum_{r=1}^{m} u_r y_{rj} - \sum_{i=1}^{n} v_i x_{ij} + d_j - \beta_j = 0\,; j = 1,\ldots,k$$
$$\sum_{j=1}^{k} d_j = k - 1$$
$$0 \le \beta_j \le 1, \quad d_j \in \{0,1\}; \quad j = 1,\ldots,k$$
$$u_r, v_i \ge \varepsilon^*; \quad \forall r, i$$

Where d_j is a integer variable denotes the deviation variable of DMU$_j$ from the efficiency. β_j is a non-negative real variable, and *M* is the maximum inefficiency score which should be minimized. ε^* is a very small strictly positive number. Toloo & Nalchigar (2011) enhanced model (2) to consider interval and ordinal data. They applied the improved model to find the best supplier among the 18 suppliers. It should be noted that Saen (2008) presented a DEA model to the supplier selection problem in the presence of weight constraints and imprecise data. Indeed, he considered interval and ordinal data in basic DEA model and employed it to the supplier evaluation problem. Lam (2015) improved the proposed approaches by Toloo & Nalchigar (2011) and developed a new mixed integer DEA model to determine a single efficient unit with the efficiency score of strictly greater than one. Ebrahimi (2020) developed the mixed-binary DEA model (3) to find the most efficient unit in the presence of dual-role factors. He applied the model for evaluating of suppliers to determine the best supplier.

$$\begin{aligned}
& max\, t \\
& s.t. \\
& \quad \sum_{r=1}^{s} u_r y_{rj} + \sum_{k=1}^{K} \alpha_k w_{kj} - \sum_{k=1}^{K} \beta_k w_{kj} - \sum_{i=1}^{m} v_i x_{ij} \le M d_j, j = 1,\ldots,n \\
& \quad \sum_{r=1}^{s} u_r y_{rj} + \sum_{k=1}^{K} \alpha_k w_{kj} - \sum_{k=1}^{K} \beta_k w_{kj} - \sum_{i=1}^{m} v_i x_{ij} \ge t + M(d_j - 1), j = 1,\ldots,n \\
& \quad \sum_{j=1}^{n} d_j = 1 \\
& \quad d_j \in \{0,1\}, j = 1,\ldots,n \\
& \quad u_r, v_i \ge \varepsilon^*, \forall i, r \\
& \quad t, \alpha_k, \beta_k \ge 0, \forall k
\end{aligned} \tag{3}$$

Ebrahimi and Toloo (2019) presented a new linear DEA model to the supplier selection problem in the Iranian Space Agency (ISA) industry in the presence of ordinal and interval data. Ebrahimi and Khalili (2020) developed a comprehensive DEA model to the supplier selection problem in the presence of both weight constraints and imprecise data. Ebrahimi et al. (2021) developed a pair of linear DEA models to estimate the lower and upper bound efficiency scores of the supplier in space industry in the presence of interval and ordinal dual-role factors. They classified the suppliers into three groups: inefficient suppliers, potential efficient suppliers and strong efficient suppliers. Toloo et al. (2021) developed the following mixed-integer linear DEA model (4) to the supplier selection problem in the Iranian space research center institute in the presence of flexible measures. The model considers a small positive number for the epsilon to prevent the evaluating factors from being zero.

$$
\begin{array}{ll}
\max \sum_{r=1}^{s} u_r y_{rk} + \sum_{l=1}^{L} \delta_l z_{lk} & \\
\text{s.t.} & \\
\sum_{i=1}^{m} v_i x_{ik} + \sum_{l=1}^{L} \gamma_l z_{lk} = 1 & \\
\sum_{r=1}^{s} u_r y_{rj} + \sum_{l=1}^{L} \delta_l z_{lj} - \sum_{i=1}^{m} v_i x_{ij} - \sum_{l=1}^{L} \gamma_l z_{lj} \leq 0 & j = 1, \dots, n \\
\delta_l - M d_l \leq 0 & l = 1, \dots, L \\
\gamma_l - M(1 - d_l) \leq 0 & l = 1, \dots, L \\
d_l \in \{0,1\} & l = 1, \dots, L \\
\delta_l + \gamma_l \geq \varepsilon & l = 1, \dots, L \\
v_i \geq \varepsilon & i = 1, \dots, m \\
u_r \geq \varepsilon & r = 1, \dots, s
\end{array}
\qquad (4)
$$

Ebrahimi et al. (2022) proposed a cross-inefficiency method based on the deviation variables framework to rank the efficient DMUs which can be used in the supplier selection problem to determine the best efficient supplier among the set of efficient suppliers. Sarkar et al. (2024) presented a Slacks-Based DEA approach for supplier performance evaluation in the presence of imprecise data. Lin et al. (2024) integrated a machine learning approach with the invers DEA model to assess the performance of suppliers in the apple supply chain.

The explained models are unable to find the best efficient supplier by considering the decision maker preferences. To this end, in the next section we have developed a novel mathematical DEA model to determine the best efficient supplier.

3- A novel mathematical DEA-based supplier evaluation approach

In traditional DEA methods, the decision-making units are free to select the most favorable weights to obtain their maximum possible efficiency scores. In other words, in these approaches, there is no constraint on the weights of the input and output factors. In other word, the obtained weights may be inconsistent with the viewpoint of the decision maker (DM). To tackle this problem, several types of weight constraints have been presented in the literature on DEA which can be categorized into three groups (Ebrahimi et al. 2021):

Absolute weight restrictions**:** In this type of weight constraint, the DM determines a lower and an upper bound for each input and output weight. In fact, the numbers $a_i, b_i, h_r, t_r, \forall i, r$ are specified to attain the constraint $a_i \leq v_i \leq b_i$ & $h_r \leq u_r \leq t_r, \forall i, r$.

Assurance region type 1 **(*ARI*):** This category of weight restriction determines limits on the ratios between the weights of output or input factors. In other words, the DM determines the numbers

$a_i, b_i, h_r, t_r, \forall i, r$ to get the constraints $a_i \leq \frac{v_i}{v_{i-1}} \leq b_i \& \, h_r \leq \frac{u_r}{u_{r-1}} \leq t_r, i = 2,3, \ldots m; r = 2,3, \ldots, s$.

***Assurance region type 2* (*ARII*):** This category of weight restriction enforces constraints on the ratio between the output and input weights. Indeed, the DM determines the numbers $b_{ir}, \forall i, r$ to get the constraints $v_i \leq b_{ir} u_r, \forall i, r$.

The explained weight restrictions are used in DEA approaches to combine the DM' preferences and also to avoid getting unusual weights in the supplier selection process. It should be noted imposing the absolute WRs and ARII in DEA models may lead to several problems, e.g., infeasibility and unbounded production problems. Nonetheless, by using ARI in DEA methods we could estimate the correct efficiency scores. Therefore, we will apply ARI in our presented novel mathematical DEA model to find the best efficient supplier. It should be mentioned that ARI has been effectively used in the numerous real-life performance measurement problems such as bank branches, hospitals, and so on (Ebrahimi et al. 2017).

As illustrated, utilizing weight restrictions in DEA is an appropriate way to prevent the DMUs to overestimate or ignore some evaluation factors in the supplier selection process. As mentioned, in this paper we use the ARI in our developed approach. The presented novel mathematical DEA model to find the best efficient supplier in presence of weight restrictions is formulated as follows:

$$
\begin{aligned}
& Min \quad d \\
& s.t. \\
& \quad \sum_{r=1}^{m} u_r y_{rj} - \sum_{i=1}^{n} v_i x_{ij} + d_j = 0\,; j = 1, \ldots, k \\
& \quad \sum_{j=1}^{k} d_j - d \leq 0 \\
& \quad \sum_{j=1}^{k} \theta_j - k + 1 = 0 \\
& \quad d_j - M\theta_j \leq 0;\ j = 1, \ldots, k \\
& \quad \theta_j - N d_j \leq 0;\ j = 1, \ldots, k \\
& \quad \theta_j \in \{0,1\}; j = 1, \ldots, k \\
& \quad \alpha_i^- \leq \frac{v_i}{v_{i-1}} \leq \alpha_i^+, i = 2,3, \ldots, n \\
& \quad \beta_r^- \leq \frac{u_r}{u_{r-1}} \leq \beta_r^+, r = 2,3, \ldots, m \\
& \quad u_r, v_i, d \geq \varepsilon; \quad r = 1,2, \ldots, m; i = 1,2, \ldots, n \\
& \qquad\qquad d_j \geq 0; \quad j = 1,2, \ldots, k
\end{aligned}
\tag{5}
$$

where, x_{ij} is the amount of i[th] input consumed by supplier$_j$, y_{rj} is the amount of r[th] output produced by supplier$_j$ ($j = 1,2,\ldots,k; r = 1,2,\ldots,m$ & $i = 1,2,\ldots,n$), d_j represents the deviation variable of supplier$_j$ from the efficiency. u_r is the weight of r[th] output, and v_i is the weight of i[th] input, and θ_j is a binary variable. M and N are large positive numbers. α_i^-, α_i^+, β_r^-, β_r^+ are real positive numbers. ε is a small positive number.

It should be emphasized that the proposed model (5) is able to find the best efficient supplier in the constant return to scale (CRS) situations. However, it can be extended to the variable return to scale (VRS) situations by adding the free in sign variable *w* to the first type constraints of the model. This model minimizes the sum of deviation variables. We will show that solving model (5) determines the most efficient supplier. It should be emphasized that selecting a suitable value for ε is very important in the supplier selection process. In other words, a big value for the epsilon may make model (5) infeasible, and a very small value for it could lead to ignore some evaluating factors. To this end, we present the following model to find a suitable value for ε.

$$\begin{aligned}
& Max\ \varepsilon \\
& s.t. \\
& \qquad \sum_{r=1}^{m} u_r y_{rj} - \sum_{i=1}^{n} v_i x_{ij} \le 0\,; j = 1,\ldots,k \\
& \qquad \alpha_i^- \le \frac{v_i}{v_{i-1}} \le \alpha_i^+, i = 2,3,\ldots,n \\
& \qquad \beta_r^- \le \frac{u_r}{u_{r-1}} \le \beta_r^+, r = 2,3,\ldots,m \\
& \qquad u_r, v_i \ge \varepsilon; \quad r = 1,2,\ldots,m, i = 1,2,\ldots,n
\end{aligned} \tag{6}$$

In the following, we prove that solving model (5) determines the best efficient supplier.

Theorem 1: solving model (5) gives the best efficient supplier.

Proof: According to the efficiency definition in the literature of DEA, DMU$_p$ is efficient if and only if there exists at least a common set of optimal weights $u^* > 0, v^* > 0$, such that $\sum_{r=1}^{m} u_r^* y_{rp} - \sum_{i=1}^{n} v_i^* x_{ip} \ge 0$ and $\sum_{r=1}^{m} u_r^* y_{rj} - \sum_{i=1}^{n} v_i^* x_{ij} \le 0, \forall j \ne p$.

Obviously, in the optimal solution of model (5) for only one $p \in \{1,2,\ldots,k\}$ we have $d_p^* = 0$, and $d_j^* \ne 0, \forall j \ne p$. In the other words, this model finds a common set of positive optimal weights $u^* = (u_1^*, u_2^*, \ldots, u_m^*)$ & $v^* = (v_1^*, v_2^*, \ldots, v_n^*)$ such that the efficiency score of DMU$_p$ is equal to one and the efficiency scores of other DMUs are less than one. Thus, solving model (5), gives a single most efficient DMU as the best efficient supplier. ☐

3-1- Identifying and ranking other efficient suppliers

The developed model (5) is able to determine the best efficient supplier in the presence of weight restrictions. For the case that the decision maker needs to specify and rank all efficient suppliers, we present the following algorithm.

a. Solve Model (6) and find a suitable value for epsilon to use in model (5).

b. Solve Model (5) and let us suppose that Supplier$_k$ is determined as the best efficient supplier. Indeed, assume $\theta_k = 0$, and let $ES = \{k\}$.

c. Solve Model (5) with the extra constraint $\theta_k = 1, \forall k \in ES$. If the new model is feasible, then assume $\theta_p = 0$ and go to the next step. Otherwise, stop, *ES* is the set of efficient suppliers.

d. Let $ES = ES \cup \{p\}$, and go to step c.

In the first iteration of the above algorithm, the best efficient supplier is determined. In the second iteration the second efficient supplier is determined, if it exists. We could identify and rank all efficient suppliers by continuing the algorithm. Indeed, the efficient supplier is determined in the first iteration has the rank one, i.e., best efficient supplier, and the supplier is identified in the last iteration of the algorithm has the last rank among the set of efficient suppliers. The steps of the algorithm are depicted in Figure 1.

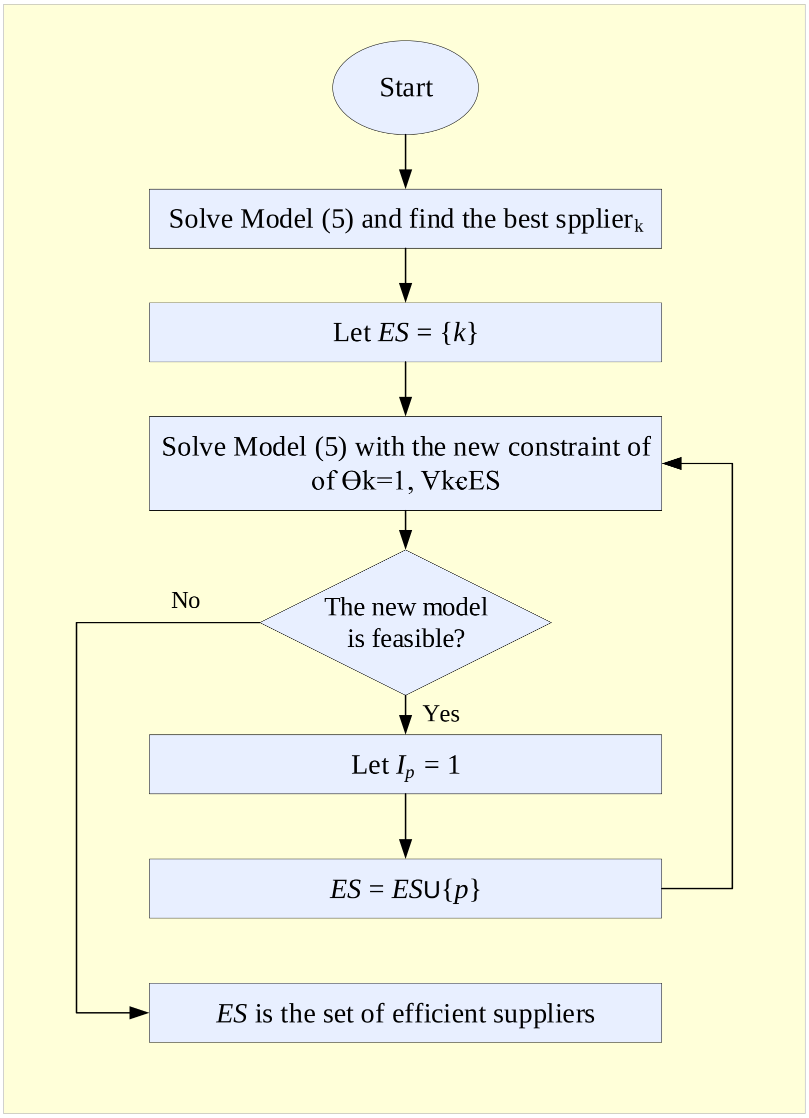

Figure 1: Flowchart of the presented algorithm

The developed approach in this paper has several advantages over the existing methods which can be summarized as follows:

a. The presented model uses the ARI to consider the decision maker preferences about the importance of input and output factors. As a result, in contrast to the existing approaches, the obtained weights will be consistent with the decision maker preferences.

b. The approach not only is able to find the set of efficient DMUs, but also, is able to rank the efficient DMUs and determines the best efficient unit.

4- Numerical illustration

In this section a real data set of 18 suppliers are used to illustrate the capability and usefulness of the proposed approach in this paper. The data set for this example is partially taken from Talluri and Baker (2002) and contains specifications on 18 suppliers. The supplier inputs considered are Total Cost of shipments (TC) and Number of Shipments per month (NS). The outputs utilized in the study are Number of shipments to arrive On Time (NOT) and Number of Bills received from the supplier without errors (NB). Assume that the decision maker preferences about the weights of inputs and outputs criteria are as follows:

$$1 \leq \frac{v_1}{v_2} \leq 2 \; \& \; 2 \leq \frac{u_1}{u_2} \leq 3$$

The above equations show that the input factor TC is at least one times as important as the input factor NS and at most 2 time as important as the input factor NS. Moreover, the output factor NOT is at least 2 times as important as the output factor NB and at most 3 time as important as the output factor NB.

To find the best supplier, first we have applied the traditional DEA model and solved 18 models to calculate the efficiency scores of 18 suppliers. The result is given in the last column of Table 1. As the result shows, suppliers 3, 12 and 15 are efficient with the efficiency core of one. The efficiency score of other suppliers are strictly less than one, which mean these suppliers are inefficient. Therefore, by using the traditional DEA model the decision maker is unable to find the best supplier. To fill this gap, we employ our presented novel mathematical DEA model in section 3. First, we solve model (6) to find a suitable value for epsilon to use in model (5). The optimal solution of model (6) implies that $\varepsilon^* = 0.0027$.

Now, solving model (5) by considering $N = 10000$, $M = 10000$ and $\varepsilon = 0.0027$ gives the following results:

$$d_3^* = 0, d_j^* > 0, \forall j \neq 3 \& \; d^* = \sum_{j=1}^{k} d_j{}^* = 3.022$$

As illustrated in Theorem 1, this solution implies that supplier 3 is best efficient suppliers among the 18 suppliers. It should be emphasized that our proposed approach solves only one model to determine the best efficient supplier. However, the traditional DEA model solve 18 model and is unable to identify the best supplier. Consequently, the presented model in this paper is more computationally efficient and could decrease the burden of computation.

Table 1: Inputs, outputs and the efficiency score of 18 suppliers

Supplier NO. (DMU)	Outputs		Inputs		Efficiency score
	NB y_{1j}	NOT y_{2j}	NS X_{1j}	TC (1000$) X_{2j}	
1	90	187	197	253	0.823
2	130	194	198	268	0.851

3	200	220	229	259	1
4	100	160	169	180	0.875
5	173	204	212	257	0.942
6	170	192	197	248	0.936
7	60	194	209	272	0.758
8	145	195	203	330	0.735
9	150	200	208	327	0.756
10	90	171	203	330	0.607
11	100	174	207	321	0.638
12	200	209	234	329	1
13	163	165	173	281	0.778
14	170	199	203	309	0.812
15	185	188	193	291	1
16	85	168	177	334	0.607
17	130	177	185	249	0.849
18	160	167	176	216	0.944

Now, we apply the presented algorithm in section 3 to identify and rank the set of efficient suppliers. To determine the second efficient supplier, we add the restriction $\theta_3 = 1$, to Model (5) and solve it, which gives $d_{12}^* = 0$. Therefore, supplier 12 is the second-best efficient unit. Solving Model (5) with the additional constraint $\theta_3 + \theta_{12} = 2$ gives $d_{15}^* = 0$, that shows supplier 15 is the third best efficient unit. Model (5) with the additional constraint $\theta_3 + \theta_{12} + \theta_{15} = 3$ is infeasible which means there are no other efficient suppliers.

We have used the presented approach in this study to the supplier selection problem in the supply chain management to find the best efficient suppliers. The approach can be used in other applications such as: evaluating the bank branches, ranking the universities, etc.

5- Conclusion

Supplier evaluation and selection problem is the procedure of determining the best suppliers for supply the goods and facilities that an organization need. It is evident that selecting the best suppliers could play a significant role in a success of supply chain network. Indeed, finding and choosing the best efficient suppliers could have a substantial effect on the organization's quality, costs, and overall performance. To this end, the current paper developed a novel mathematical data envelopment analysis model to identify the best supplier by considering the decision maker preferences regarding the importance of the evaluating factors. It is mathematically demonstrated that the proposed approach identifies the best efficient supplier by solving only one model. Moreover, a new algorithm is presented to identify and rank the set of all efficient suppliers for the situation that the decision maker needs to select more than one efficient supplier. The capability and usefulness of the presented approach is indicated by determining the best efficient supplier among 18 suppliers. It was shown that our proposed approach solves just one model to identify the best efficient supplier, while the traditional DEA model solves 18 model and determine 3 efficient suppliers. In other words, in contrast to our novel model, the basic DEA models are unable to identify the best efficient supplier. The developed approach in this paper can be extended to contain the different types of imprecise data such as weak ordinal and interval data.

References

Amin G.R., Toloo, M. (2007). Finding the most efficient DMUs in DEA: An improved integrated model. Computers and Industrial Engineering, 52 (2), 71–77.

Dobos I., Vörösmarty, G. (2019). Inventory-related costs in green supplier selection problems with Data Envelopment Analysis (DEA). International Journal of Production Economics, 209, 374-380.

Ebrahimi B. (2020). Efficiency measurement to identify the best efficient unit in the presence of dual-role factors. International Journal of Applied Decision Sciences, 13, 93 - 108.

Ebrahimi B., Dellnitz A., Kleine A., Tavana M. (2021). A novel method for solving data envelopment analysis problems with weak ordinal data using robust measures. Expert Systems with Applications, 164, 113835.

Ebrahimi B., Khalili M. (2018). A new integrated AR-IDEA model to find the best DMU in the presence of both weight restrictions and imprecise data. Computers & Industrial Engineering, 125, 357-363.

Ebrahimi B., Dhamotharan L., Ghasemi M.R., Charles V. (2022). A cross-inefficiency approach based on the deviation variables framework. Omega, 111, 102668.

Ebrahimi B., Rahmani M., Ghodsypour S.H. (2017). A new simulation-based genetic algorithm to efficiency measure in IDEA with weight restrictions. Measurement, 108, 26-33.

Ebrahimi B., Toloo M. (2020). Efficiency bounds and efficiency classifications in imprecise DEA: An extension. Journal of the Operational Research Society, 71 (3), 491-504.

Ebrahimi B., Tavana M., Toloo M., Charles V. (2020). A novel mixed binary linear DEA model for ranking decision-making units with preference information. Computers & Industrial Engineering, 149, 106720.

Ebrahimi B., Tavana M., Kleine A., Dellnitz A. (2021). An Epsilon-based Data Envelopment Analysis Approach for Solving Performance Measurement Problems with Interval and Ordinal Dual-Role Factors. OR Spectrum, 43, 1103–1124.

E Momeni, FH Lotfi, RF Saen, E Najafi. (2019). Centralized DEA-based reallocation of emission permits under cap and trade regulationJournal of cleaner production 234, 306-314.

Charnes A., Cooper W.W., Rhodes E. (1978). Measuring the efficiency of decision-making units. European Journal of Operational Research, 2 (6), 428–444.

Guneri A.F., Yucel A., Ayyildiz G. (2009). An integrated fuzzy-lp approach for a supplier selection problem in supply chain management. Expert Systems with Applications, 36, 9223–9228.

Farzipoor Saen R. (2008). Supplier selection by the new AR-IDEA model. International Journal of Advanced Manufacturing Technology, 39, 1061–1070.

Kaur H., Gupta M., Singh S.P. (2024). Integrated model to optimize supplier selection and investments for cyber resilience in digital supply chains. International Journal of Production Economics, 275, 109338.

Kumar Kar A. (2015). A hybrid group decision support system for supplier selection using analytic hierarchy process, fuzzy set theory and neural network. Journal of Computational Science. 6, 23-33.

Lam K. F. (2015). In the determination of the most efficient decision-making unit in data envelopment analysis. Computers & Industrial Engineering, 79, 76–84.

Lin S.W., Lu M.V. (2024). Using inverse DEA and machine learning algorithms to evaluate and predict suppliers' performance in the apple supply chain. International Journal of Production Economics. 271, 109203.

Mojtaba Akbarian, Esmaeil Najafi, Reza Tavakkoli-Moghaddam, Farhad Hosseinzadeh-Lotfi(2015). A Network-Based Data Envelope Analysis Model in a Dynamic Balanced Score Card. Mathematical problems in engineering (1), 914108 .

Nazari-Shirkouhi,S., Tavakoli M., Govindan K., Mousakhani S. (2023). A hybrid approach using Z-number DEA model and Artificial Neural Network for Resilient supplier Selection. Expert Systems with Applications, 222, 119746.

Rashidi K., Cullinane K. (2019). A comparison of fuzzy DEA and fuzzy TOPSIS in sustainable supplier selection: Implications for sourcing strategy. Expert Systems with Applications, 121, 266-281.

Sarkar S., Paramanik R.A., Mahanty B. (2024). A-Number Slacks-Based Measure DEA model-based framework for sustainable supplier selection with imprecise information. Journal of Cleaner Production. 436, 140563.

SH Kassani, PH Kassani, SE Najafi (2018). .Introducing a hybrid model of DEA and data mining in evaluating efficiency. Case study: Bank Branches. arXiv preprint arXiv:1810.05524

Sharma R., Kannan D., Darbari J.D., Jha P.C. (2024). Group decision making model for selection of performance indicators for sustainable supplier evaluation in agro-food supply chain. International Journal of Production Economics, 277, 109353.

Talluri S., Baker R.C. (2002). A multi-phase mathematical programming approach for effective supply chain design. European Journal of Operational Research, 141 (3), 544–558.

Toloo M., Nalchigar S. (2011). A new DEA method for supplier selection in presence of both cardinal and ordinal data. Expert Systems with Applications, 38, 14726–14731.

Toloo M., Ebrahimi B., Amin G.R. (2021). New data envelopment analysis models for classifying flexible measures: the role of non-Archimedean epsilon. European Journal of Operational Research, 292, 1037-1050.

Ware N.R., Singh S.P., Banwet D.K. (2024). A mixed-integer non-linear program to model dynamic supplier selection problem.. Expert Systems with Applications, 41, 671-678.