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Efficiency ranking method using DEA and TOPSIS (ERM-DT): case of an Indian bank

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Abstract

Purpose – The purpose of this paper is to present a tie-breaking procedure for computing performance efficiencies to improve benchmarking and performance evaluation process in a business situation.

Design/methodology/approach – The authors propose a unified approach based on data envelopment analysis (DEA) and technique for order of preference by similarity to ideal solution (TOPSIS), to overcome the difficulty of unique ranking in the prevalent benchmarking and performance evaluation processes such as DEA, Super efficiency DEA model, etc., under constant return to scale (CRS) assumption. This model is called as efficiency ranking method using DEA and TOPSIS (ERM-DT). In order to check the consistency of the approach, various input-output combinations (to calculate the efficiencies) have been illustrated. Further, the authors present a case of an Indian Bank to illustrate an application of the proposed approach.

Findings – The proposed approach, ERM-DT enables assign a unique rank to decision making units and provides a tie breaking procedure. Results obtained using the proposed approach are statistically compared with those obtained from the CRS DEA approach and super efficiency DEA approach using Friedman's test.

Practical implications – The proposed model provides an efficiency ranking method based on a score obtained by considering the minimum distance from the best value and maximum distance from the worst value. The proposed methodology is capable of handling negative data and undesirable output variables. This approach is unit invariant and makes the calculations simple. The authors present an application to compute the efficiency of various branches of an Indian bank. The authors hope the proposed method can enhance the decision-making ability of the management in complex situations.

Originality/value – The authors propose an integrated DEA and TOPSIS framework for better benchmarking and performance evaluation. This approach provides a tie-breaking procedure for the efficiencies computed using CRS DEA approach. Ranks are assigned based on score obtained by considering the distance from the worst and the best solution. The proposed approach can be used with non-positive data points and undesirable output variables.

Keywords Indian Bank, Keywords data envelopment analysis (DEA), MCDM tools, Technique for order of preference by similarity to ideal solution (TOPSIS)

Paper type Research paper

1. Introduction

A decision maker evaluates several business alternatives, using multiple criteria before making the final decision. In such a scenario, multi-criteria decision making (MCDM) tools play an important role in making the evaluation transparent and simple.

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These MCDM tools use numeric techniques to help decision makers choose from a discrete set of decision alternatives. Various decision alternatives are evaluated on the basis of pre-defined criteria and are ranked accordingly. Data envelopment analysis (DEA) (Charnes *et al.*, 1978) is one such decision-making tool that enables a practicing manager make proper evaluation and assessment of the complex business situation. DEA is being used widely for its advantages. Few of them being:

- Its ability to indicate the potential improvement in the performance of an inefficient decision making unit (DMU) (Duffy *et al.*, 2006; Sherman, 1984).
- No need to specify a priori weights on the input-output criteria (factors). The DEA approach, allows each DMU to choose a set of weights (also called as multipliers) for the input-output criteria that enables it to appear in the best light (George and Rangaraj, 2008; Sufian, 2007; Avkiran, 1999; Al-Faraj *et al.*, 1993; Banker, 1984).
- DEA uses the data to derive an efficiency frontier. This frontier sets the benchmark for less performing units. It is with the reference to this frontier that each DMU is evaluated (Soteriou and Stavrinides, 2002; Ramanathan, 2005; Koster *et al.*, 2009).

DEA, though popular, has a few limitations. Some of them are as follows:

- The discrimination ability of DEA reduces, if sufficiently large numbers of DMUs are identified as efficient units. This may happen because the sum of the number of inputs and outputs is large as compared to the total number of DMUs in the sample. Or at times, a DMU gets highest efficiency due to very low value of single input or very high value of output, even though that input or output is seen as relatively unimportant (Andersen and Petersen, 1993; Saen, 2008; Zhu, 2001; Seiford and Zhu, 1999).
- Although it can differentiate between efficient and inefficient DMUs, at times, it is seen that getting a unique rank is not possible (Doyle and Green, 1994; Zhu, 2001; Ramanathan, 2003; Saen, 2008; Wang and Chin, 2010; Goncharuk, 2011; Wu *et al.*, 2011).
- The efficiency of a DMU is computed by considering its efficiency (or distance) only from the best efficiency frontier. The notion of its distance from the worst scenario is not considered. Ideally, an efficient DMU should have minimum distance from the best frontier and maximum distance from the worst frontier.
- The BCC, Charnes, Cooper and Rhodes (CCR) and super efficiency models in DEA, assume variables (input and output) to be positive (Fare *et al.*, 1994). On the other hand, one can find numerous applications, where, the decision maker has to deal with negative data. Few examples being, financial statements, ratings of mutual funds, growth rates, etc.
- Conventional DEA approaches (such as BCC, CCR and super efficiency) are silent on the treatment of undesirable output variables. Few of undesirable output examples being, pollution, accidents, carbon dioxide emissions, etc.
- It is difficult to estimate the value of the maximum score obtained using the super efficiency approach; and hence, setting an appropriate benchmark for effective performance of a DMU is not easy.

Some attempts have been made in the past by researchers to solve few of the stated problems. For instance: the notion of cross-efficiency initially presented by Sexton *et al.* (1986) and later modified by Doyle and Green (1995). The cross-efficiency procedure developed by Sexton *et al.* is as follows: in the initial phase, for each DMU, a set of weights are identified. This results in *n* set of weights for *n* DMUs. In the next phase, each of the DMUs is evaluated considering *n* weights identified in the earlier phase. This results in *n* efficiency values to each DMU. Finally, an average efficiency score is assigned to each DMU. It is perceived that this cross-efficiency evaluation approach will lead to unique ranking scheme (Doyle and Green, 1995). Thus, the cross-efficiency approach is advantageous in: providing the unique ordering scheme, and in eliminating unrealistic weight restrictions (Lu and Lo, 2007; Saen, 2008; Nigam *et al.*, 2012). An overview of evolvement of cross-efficiency DEA model is presented by Saen (2010). But, this approach was further challenged by Wang and Chin (2010) where they showed that these formulations may result in two distinct efficiency rankings, which may force the decision maker to make subjective choice between the two formulations. In order to overcome this subjectivity, they suggested a neutral method of cross-efficiency DEA model where a common set of weights is obtained to evaluate all DMUs.

Jahanshahloo and Shahmirzadi (2013), proposed two new approaches for enhancing the discrimination power of conventional DEA model. These approaches are based on the model suggested by Bal *et al.* (2008), which considers minimization of the coefficient of variation for input and output weights in the framework of DEA. In the first approach, the authors replaced the mean of optimal weight of inputs (and/or outputs) by price or relative importance of input (the cost of product) or relative importance of corresponding output. The other approach is based on "Norm 1" and "means of inputs outputs weights." Here, sum of weights of mean for the input and output are considered along with efficiency disparity index to compute the efficiency scores. This approach is called as Disparity Index DEA or SWDIDEA.

There have been few studies to handle non-positive data, for instance, Ali and Seiford, 1990, used DEA by transforming negative data by adding a number to make data positive. Few other models consider directional distance function and evaluate efficiency considering the best frontier. Pastor and Ruiz (2007) provide a brief about extensions of DEA to handle negative data. However, such extensions ignore the distance from the worst frontier.

Models developed to incorporate undesirable output variables are classified as direct and indirect approaches. Indirect approaches transform output data by a decreasing function (Ali and Seiford, 1990). Direct approaches do not alter values but modify the DEA analysis (Fare *et al.*, 2004). In this case also it is important to note that the concept of distance from the worst and the best frontier is not considered, while handling undesirable output variables.

In this paper, we propose a unified approach of DEA and technique for order of preference by similarity to ideal solutions (TOPSIS) (Hwang and Yoon, 1981). Few researchers have presented an integrated DEA and TOPSIS approach. For instance, Wang and Lu (2009) discuss the issue of rank reversal among various multi-criteria decision-making tools, namely, SAW, AHP, DEA and TOPSIS. The authors conclude that "rank reversal" is a common phenomenon among various MCDM tools and is not limited to AHP. Hosseinzadeh *et al.* (2011) computed scores based on the efficiencies of the DMUs by applying various DEA approaches and the distance approach realized in TOPSIS framework. Few authors presented an approach by applying the cross-efficiency approach of DEA and later updating efficiency to a score based on TOPSIS

(Jahanshahloo *et al.*, 2011) and SAW (Jahanshahloo and Fallahnejad, 2012; Wu *et al.*, 2011). Wu *et al.* (2013) presented an approach to enable manage imprecise data expressed as interval or ordinal data. Bian and Xu (2013) presented an approach as an extension to the weighted TOPSIS method. DEA analysis is used to obtain weights. Wang and Lu (2006) computed efficiencies by considering two viewpoints. Here, DEA approach computes best possible relative efficiency and a modified DEA approach computes worst possible efficiency. These efficiencies enable calculate a relative index using and approach similar to TOPSIS.

The proposed framework, called as efficiency ranking method using DEA and TOPSIS (ERM-DT) enables obtain:

- a unique ranking scheme for each of the DMU;
- improve discrimination power of DEA analysis;
- handle negative data (input and output variables) and undesirable outputs; and
- assign efficiency (or distance) based on the best and the worst efficiency frontier.

In this paper, we also look at the suitability of the proposed approach, by comparing results obtained with the super efficiency approach (henceforth called as Super CCR approach). We use Friedman's test for this purpose.

This paper is organized as follows: in Section 2, we explain the theme of DEA and TOPSIS models. Section 3, presents the proposed integrated framework with an illustration using hypothetical data. This analysis is further verified with various input and output combinations. Case of an Indian bank is then presented in Section 4. Finally, in Section 5 conclusions are discussed.

2. Preliminaries

In this section, the three multi-criteria decision-making tools, namely, DEA, Super CCR and TOPSIS are briefly discussed.

2.1 DEA

DEA is a non-parametric benchmarking tool, based on linear programming technique. It was originally developed by Farrell (1957) and further extended by Charnes *et al.* (1978). CCR model measures the relative efficiency of a set of firms that use a variety of inputs to produce a range of outputs under the assumption of constant return to scale (CRS).

An individual unit in this set (of firms) is referred to as DMU. A DMU, for instance, can include hospitals, power plants, universities, schools, banks, bank branches, etc. Performance of a DMU is measured using the concept of efficiency or productivity, which is defined as the ratio of total weighted outputs to total weighted inputs. While measuring the performance, this model captures not only the productivity efficiency of a firm at its actual scale size, but also the inefficiency (Banker, 1984). The best performing unit in the set of DMUs is assigned a score of 100 percent or 1, and the remaining DMUs get a score ranging between 0 and 100 percent, or equivalently between 0 and 1, relative to the score of best performing DMU. DEA forms a linear efficiency frontier that passes through the best performing units within the group whereas all the remaining less efficient units lie off the frontier. The term efficiency used in DEA is the relative efficiency and not the absolute efficiency.

Here, we illustrate the CRS DEA model and the Super CCR model using hypothetical data. The results from these two approaches are compared and discussed in Section 3.

Let there be N DMUs each with K inputs and M outputs. For the pth DMU under evaluation, the technical efficiency is measured using the CRS DEA model the model given by:

Maximize:

$$E_p = Z = \sum_{i=1}^{K} (u_{ip} x_{ip})$$

Subject to:

$$\sum_{j=1}^{m} \left(v_{jp} y_{jp}\right) = 1$$

$$\sum_{j=1}^{M} \left(v_{jp} y_{jn}\right) - \sum_{i=1}^{K} \left(u_{ip} x_{in}\right) \leqslant 0; \quad n = 1, 2, \ldots, N$$

with v_{jm}, $u_{im} \geqslant \varepsilon$; $i = 1, \ldots, K$, $j = 1, \ldots, M$. Where E_P is the efficiency of the pth DMU; x_{ip} the value for input criteria i for pth DMU; u_{ip} the weight of input i; y_{jp} the value for output criteria j for pth DMU; v_{jp} the weight of output j; x_{in} the value for input criteria i for nth DMU; y_{jn} the value for output criteria j for nth DMU; ε an infinitesimal or non-Archimedean constant usually in the order of 10^{-5} or 10^{-6}, where $n = 1, 2, \ldots, N$ and here note that n includes p.

Usually, DEA is carried out using two methods: namely, CRS DEA and VRS DEA model. The discrimination power of the CRS DEA model is better than the VRS DEA model. In the present work we conduct the study by considering the CRS DEA as base model.

2.2 Super efficiency DEA

The difference between CRS DEA model and super efficiency DEA model lies in the treatment of efficient units (Saen, 2008). The basic idea, in super efficiency DEA model is to compare the DMU with a linear combination of all other DMUs under consideration. This is done by excluding the DMU under consideration. Here, an efficient DMU may increase its input vector (or weight) proportionally. In such situations, the DMU under consideration obtains the efficiency score of more than one. This score indicates the radial distance from the DMU under evaluation to the efficiency frontier recomputed by excluding the DMU under consideration. This exclusion of the DMU from the group may result into a one-sided relative efficiency (Wang and Lu, 2006).

The super efficiency DEA model formulated by Andersen and Petersen (1993) with CRS assumption can be explained as follows:

Maximize:

$$E_p = Z = \sum_{i=1}^{k} \left(u_{ip} x_{ip}\right)$$

Subject to:

$$\sum_{j=1}^{m} \left(v_{jp} y_{jp}\right) = 1$$

$$\sum_{j=1}^{m} \left(v_{jp} y_{jn}\right) - \sum_{\substack{i=1 \\ i \neq p}}^{k} \left(u_{ip} x_{in}\right) \leqslant 0; \quad n = 1, 2, \ldots, N$$

with $v_{jm}, u_{im} \geqslant \varepsilon; i = 1, \ldots, k, j = 1, \ldots, m$. Where E_P is the efficiency of the pth DMU; x_{ip} the value for input criteria i for pth DMU; u_{ip} the weight of input i; y_{jp} the value for output criteria j for pth DMU; v_{jp} the weight of output j; x_{in} the value for input criteria i for nth DMU; ε an infinitesimal or non-Archimedean constant usually in the order of 10^{-5} or 10^{-6} where $n = 1, 2, \ldots, N$ and here note that n includes p.

The problem with super efficiency DEA is that under some specific conditions, it may result into infeasible solution. These conditions are described by Seiford and Zhu (1999). Specifically, they discussed the link between infeasibility and return to scale. However, this study on infeasibility in super efficiency DEA models, proposed that ranking of whole set may be impossible and therefore suggested that the use of the super efficiency DEA models should be restricted under alternate return to scale assumptions.

We now present an illustration of two different DEA models, namely, CRS DEA model and the Super efficiency DEA model. We consider a data set of ten DMUs with two outputs (O1 and O2) and two inputs (I1 and I2) as shown in Table I.

The basic efficiency measure used in DEA (as proposed by Farrell, 1957) is given by:

$$\text{Efficiency of DMU} = \frac{\text{Output}}{\text{Input}} \tag{1}$$

Next, we analyze the data using the CRS DEA model in its form as stated in Expression (1) and Super efficiency model (as proposed by Andersen and Petersen, 1993). The data set and the efficiency calculations are shown in Table I.

The efficiency of DMUs A, B, C, F and H are equal to 1 as they have high value in at least one of the ratios computed (as indicated by italic text in the Table I). Here the weight assigned to the input and output values for these DMUs can uniformly be equal to one. Further, it can also be noted that the efficiency score for DMUs D, G and O are also

DMU	O1	O2	I1	I2	O1/I1	O1/I2	O2/I1	O2/I2	CRS DEA efficiency	CRS DEA rank	Super CCR efficiency	Super CCR rank
A	15	22	4	4	3.75	*3.75*	5.5	*5.5*	1	1	1.1	6
B	30	30	1	14	*30*	2.14	30	2.14	1	1	1.12	3
C	30	20	1	16	*30*	1.88	20	1.25	1	1	1	8
D	23	40	3	8	7.67	2.88	13.33	5	1	1	1.11	4
E	8	28	4	11	2	0.72	7	2.54	0.517	14	0.516	14
F	23	34	1	12	23	1.91	*34*	2.83	1	1	1.214	2
G	15	22	1	6	15	2.5	22	3.66	1	1	1.103	5
H	30	40	4	8	7.5	*3.75*	10	5	1	1	1.23	1
I	23	15	1	18	23	1.27	15	0.83	0.767	9	0.767	9
J	13	17	5	20	2.6	0.65	3.4	0.85	0.23	15	0.229	15
K	20	24	2	10	10	2	12	2.4	0.753	10	0.753	10
L	24	28	3	15	8	1.6	9.333	1.86	0.602	13	0.60	13
M	25	20	4	13	6.25	1.92	5	1.53	0.630	12	0.62	12
N	25	30	3	12	8.33	2.083	10	2.5	0.733	11	0.733	11
O	23	24	1	10	23	2.3	24	2.4	1	1	1.022	7

Table I. Efficiency scores and ranks equal to 1. This is by the virtue of the weights assigned to the input and output values of these DMUs. It can be observed here that the DEA approach allows in obtaining the maximum efficiency of a DMU, by virtue of the weights assigned to its input and output values. Note that DMU "*H*" emerges as the most efficient DMU using Super CCR model.

However, some of the limitations of this approach have been highlighted in the literature. Few of them are: it is likely that a specific set of DMUs are ranked too high (Balf *et al.*, 2012). This model is not unit invariant, that is to say that the super efficiency model proposed by Andersen and Petersen (1993) is deficient in its treatment of the non-zero slacks as its treatment of the slack does not yield a measure that is "unit invariant" (Cooper *et al.*, 2007). In some cases, DMUs rated efficient (efficiency score equal to one) using conventional DEA model do not have feasible solution in super efficiency DEA model (Lovell and Rouse, 2003).

2.3 TOPSIS

TOPSIS is based on a principle that it selects an alternative (here DMU) as the best, which is close to the positive ideal solution and, as away from the negative ideal solution as possible. The ideal solution is a set of the best performance values for each attribute (here criterion) exhibited (in the decision matrix). These values can be obtained by any alternative (here DMUs). Similarly, the negative ideal solution is a set of the worst performance values for each attribute (here criterion) exhibited (in the decision matrix). Proximity to each of these performance poles is measured in the Euclidean sense with or without weights to each of the attribute (criterion) (Opricovic and Tzeng, 2004). The mathematical procedure for TOPSIS is as follows:

- Step 0:

  Let x_{ij} be the value for alternative i with respect to attribute j.

  Let $X = (x_{ij})$ be the $(m \times n)$ matrix.

- Step 1:

  Construct a normalized decision matrix to facilitate the comparisons across criteria.

  Normalize scores or data are as given by:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum x_{ij}^2}} \quad \text{for } i = 1, \ldots, m; j = 1, \ldots, n$$

- Step 2:

  Construct a weighted normalized decision matrix. Assume a set of weights for each criterion w_j for $j = 1, \ldots, n$. Multiply each column of the normalized decision matrix by its associated weight to get v_{ij} given by $v_{ij} = w_j \times r_{ij}$.

  In the present problem under consideration, we consider uniform weights to all the criteria. Therefore, this step may be ignored here.

  Next, identify the maximum and minimum values of each criterion.

- Step 3:

  Determine the ideal solution A^* (set of maximum values v_j^* with respect to each criterion) and negative ideal solution A^- (set of minimum values v_j^- with respect to each criterion) given by:

$$A^* = \{v_1^*, v_2^*, v_3^*, \ldots, v_m^*\}$$

$$A^- = \{v_1^-, v_2^-, v_3^-, \ldots, v_m^-\}$$

where:

$$\begin{aligned} v_j^* &= \{\max(v_{ij})\} \text{ if } j \text{ is benefit criterion} \\ &= \{\min(v_{ij})\} \text{ if } j \text{ is cost criterion} \\ v_j^- &= \{\max(v_{ij})\} \text{ if } j \text{ is cost criterion} \\ &= \{\min(v_{ij})\} \text{ if } j \text{ is benefit criterion} \end{aligned}$$

- Step 4:

  Calculate the separation measures S_i^* and S_i^- for each alternative (DMU) where S_i^* represents separation measure from the ideal solution and S_i^- represents the separation measure from the negative ideal solution.

  where:

$$S_i^* = \sqrt{\sum_{j=1}^{m} \left(v_j^* - v_{ij}\right)^2} \quad \forall\, i = 1, 2, \ldots, n$$

$$S_i^- = \sqrt{\sum_{j=1}^{m} \left(v_j^- - v_{ij}\right)^2} \quad \forall\, i = 1, 2, \ldots, n$$

- Step 5:

  Calculate the relative closeness to the ideal solution C_i^*, where:

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*} \quad \text{where, } 0 < C_i^* < 1$$

- Step 6:

  Rank the alternatives or DMUs in the descending order of C_i^*, the alternative with maximum value of C_i^* is the best performing alternative.

3. Proposed framework

In this section, we explain the proposed framework. This approach is based on the following theme. Initially, we compute the efficiency of a DMU using Expression (1) based on Farrell (1957) approach. The various input and output combinations, will lead to a range of efficiency scores. Then, given an input-output combination, we identify the best and worst efficiency values, across all DMUs. Later, for each DMU, known efficiency values, for all the input-output combinations, we compute the Euclidean distance from the best value and the worst value. Based on the Euclidean distances, a score (closeness value) is obtained. This score is used for ranking the DMUs. The proposed framework is explained elaborately, in the next sub-section.

3.1 ERM-DT

We now present the proposed ERM-DT, stepwise. In the first stage, efficiency of DMUs or different decision alternatives are measured using CRS DEA model (Charnes *et al.*, 1978), based on Farrell (1957) and in the second stage, TOPSIS model (proposed by Hwang and Yoon, 1981) is applied to find the best alternative by ranking these alternatives. The procedure is outlined as follows:

- Step 0: initialization:

  Identify "n" DMUs to be evaluated with "k" inputs and "l" outputs.

- Step 1:

  Identify "m" ratios of output to input for evaluating each DMU. In this case, some criteria could be benefit (more the better) and some could be cost (less the better) alternatives.

- Step 2:

  Consider these ratios as the criterion value for each alternative. This forms the decision matrix. Where, individual member of this decision matrix is denoted by v_{ij} where $i = 1, \ldots, n$ (DMUs) and $j = 1, \ldots, m$ (Criterion).

  Normalize scores using the following expression:

$$\frac{x_{ij}}{x_{ij}^*} \quad \text{where } x_{ij}^* = \max\{x_{ij}\}; \quad i = 1, \ldots, n$$

  The weights in the proposed approach are considered to be equal for all the criteria.

  Next, identify the maximum and minimum values of each criterion.

- Step 3:

  Determine the ideal solution A^* as a set of maximum values v_1^* with respect to each criterion j and negative ideal solution A^- as a set of minimum values v_1^- with respect to each criterion j these values are given by:

$$A^* = \{v_1^*, v_2^*, v_3^*, \ldots, v_m^*\}$$

$$A^- = \{v_1^-, v_2^-, v_3^-, \ldots, v_m^-\}$$

  where:

$$\begin{aligned} v_j^* &= \{\max(v_{ij})\} \text{ if } j \text{ is benefit criterion (for desirable output)} \\ &= \{\min(v_{ij})\} \text{ if } j \text{ is cost criterion (for undesirable output)} \\ v_j^- &= \{\max(v_{ij})\} \text{ if } j \text{ is cost criterion (for undesirable output)} \\ &= \{\min(v_{ij})\} \text{ if } j \text{ is benefit criterion (for desirable output)} \end{aligned}$$

- Step 4:

  Calculate the separation measures S_i^* and S_i^- for each alternative (DMU) where represents separation measure from the ideal solution and S_i^- represents the separation measure from the negative ideal solution.

where:

$$S_i^* = \sqrt{\sum_{j=1}^{m} \left(v_j^* - v_{ij}\right)^2} \quad \forall i = 1,\ 2,\ \ldots,\ n \tag{2}$$

$$S_i^- = \sqrt{\sum_{j=1}^{m} \left(v_j^- - v_{ij}\right)^2} \quad \forall i = 1, 2,\ \ldots,\ n \tag{3}$$

- Step 5:

  Calculate the relative closeness to the ideal solution C_i^*, where:

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*} \quad \text{where,} \ \ 0 < C_i^* < 1 \tag{4}$$

- Step 6:

  Rank the DMUs in the descending order of C_i^*.

Note: it can be seen that the negative input and/or output values, do not impact the computations in the proposed approach and hence can be easily incorporated. However, in order to consider undesirable output/s, proper selection of v_j^* and v_j^- as indicated in Step 3 is essential.

3.2 *Illustration*

In this section, we illustrate the application of the proposed model by considering the data discussed in Section 2. Table II provides the ranking of these DMUs using the proposed method along with the calculations. The values of S^* and S^-obtained are after normalizing the ratios. For comparison purpose, we reproduce ranks of these DMUs in Table II using CRS DEA and Super efficiency CCR models calculated earlier in Table I. Assumptions made while computing the rank, using the proposed ERM-DT approach are that all the criteria are benefit criteria and the weights for all criteria are equal.

Table II. ERM-DT, CRS DEA and Super CCR ranks for two output and two input data

DMU	O1/I1	O1/I2	O2/I1	O2/I2	S^*	S^-	C^*	ERM-DT rank	CRS DEA rank	Super CCR rank
A	0.125	**1**	0.162	**1**	1.212	1.188	0.495	8	1	6
B	**1**	0.571	0.882	0.39	0.755	1.303	0.633	1	1	3
C	**1**	0.5	0.588	0.227	1.008	1.105	0.523	6	1	8
D	0.256	0.767	0.392	0.909	0.993	1.023	0.507	7	1	4
E	*0.067*	0.194	0.206	0.463	1.562	0.329	0.174	14	14	14
F	0.767	0.511	**1**	0.515	0.727	1.244	0.631	2	1	2
G	0.5	0.667	0.647	0.667	0.773	0.998	0.564	4	1	5
H	0.25	**1**	0.294	0.909	1.034	1.153	0.527	5	1	1
I	0.767	0.341	0.441	*0.152*	1.233	0.797	0.392	9	9	9
J	0.087	*0.173*	*0.1*	0.155	1.744	0.02	0.011	15	15	15
K	0.333	0.533	0.353	0.436	1.183	0.588	0.332	10	10	10
L	0.267	0.427	0.275	0.339	1.352	0.412	0.234	12	13	13
M	0.208	0.513	0.147	0.28	1.453	0.392	0.213	13	12	12
N	0.278	0.556	0.294	0.455	1.231	0.566	0.315	11	11	11
O	0.767	0.613	0.706	0.436	0.78	1.064	0.577	3	1	7

Note: The maximum values are marked with bold and minimum values are marked as italics

Refer to the Table II. Comparing ranks obtained by the ERM-DT approach with those obtained by CRS DEA and Super CCR method, we can observe that eight DMUs are tied at rank 1 in CRS DEA approach. However, this issue is resolved in the Super CCR approach and ERM-DT approach. There is only one DMU, i.e., DMU "*B*" at the first rank using the proposed approach and DMU "*H*" using Super CCR model. This indicates a better discrimination power of the proposed approach.

One may observe that the proposed approach (ERM-DT) is unit invariant (Step 1 considered ratios of output to input). Further, we note that the efficient DMU using the proposed approach has been selected by measuring its distance from the best and the worst alternative.

In order to verify the similarity of the results obtained by using the three approaches, we conduct a Friedman's test of hypothesis. This test compares ranks of each of DMUs by three different methods. The null and the alternative hypotheses to be tested using Friedman's test are stated below:

H0. There is no significant difference between ranks of individual DMUs obtained by three methods, namely: CRS DEA, Super CCR and ERM-DT.

H1. There is significant difference between ranks of individual DMUs obtained by three methods, namely: CRS DEA, Super CCR and ERM-DT.

We test the hypothesis at 5 percent level of significance. The results obtained are shown in Table III.

The results indicate that there is a significant difference in ranks obtained by three methods, and hence we reject the null hypothesis and accept the alternate.

In order to identify the method that results in such a difference, we run this hypothesis again, now pair-wise. Initially, we consider ranks obtained by ERM-DT and Super CCR methods.

Following hypothesis is formulated for the purpose:

H0. There is no significant difference between ranks of individual DMUs obtained by the methods, namely: Super CCR and ERM-DT.

H1. There is significant difference between ranks of individual DMUs obtained by the methods, namely: Super CCR and ERM-DT.

We test the hypothesis at 5 percent level of significance. Following results are computed (Table IV).

This test indicates that we accept the null hypothesis, and conclude that there is no difference between ranks obtained by these two methods, namely, the ERM-DT and Super CCR. In the Friedman's test, the estimated medians associated with treatments (here methods) are the grand median plus estimated treatment effects. The sum of ranks value is the sum of the treatment (here methods) ranks, when ranked within each block (here DMUs).

Method	*N*	Estimated median	Sum of rank
CRS DEA	15	5.667	23.0
ERM-DT	15	6.333	33.0
Super CCR	15	6.000	34.0
Grand median = 6.00			

Notes: Test statistic $S = 8.46$; df = 2; $p = 0.015$ (adjusted for ties)

Table III. Friedman's test results for two input and two output data (for all three methods)

Referring to Tables III and IV, we conclude that, there is a significant difference from ranks obtained by CRS DEA and other two (ERM-DT and Super CCR) methods. We also conclude that, there is no significant difference between ranks obtained from ERM-DT and Super CCR method.

In order to check the consistency of the proposed approach, we conduct tests with two more cases, three inputs, three outputs with a set of 20 DMUs, and four inputs, four outputs with a set of 25 DMUs. Data (for three inputs and three outputs) together with the ranking of DMUs using CRS DEA, Super CCR and ERM-DT method are presented in Table V and the results obtained from Friedman's test are shown in Table VI.

Similarly, the Table VII shows the data and ranks obtained for four inputs and four outputs with a set of 25 DMUs. Table VIII summarizes the results from Friedman's test.

For various input-output combinations analyzed, we generalize that there exists significant difference between ranks obtained by the CRS approach of DEA and that of the proposed ERM-DT approach. It can also be inferred that there is no significant difference in ranks obtained by the super efficiency approach and the proposed ERM-DT approach.

Table IV.
Friedman's test results for two input and two output data (for two methods)

Method	N	Estimated median	Sum of rank
ERM-DT	15	7.00	22.0
Super CCR	15	7.00	23.0
Grand median = 6.00			

Notes: Test statistic $S = 0.11$; df = 1; $p = 0.739$ (adjusted for ties)

Table V.
ERM-DT, CRS DEA and Super CCR ranks for three output and three input data

DMU	O1	O2	O3	I1	I2	I3	S^*	S^-	C^*	ERM-DT rank	CRS DEA rank	Super CCR rank
A	14	30	2.5	9	2	3	1.4	1.19	0.45	7	1	1
B	16	27	2	5	3	4	1.58	1.2	0.43	8	1	9
C	28.5	36	3	10	3.5	4	1.35	1.16	0.46	5	1	8
D	12	27	3	10	2	5	1.71	0.96	0.36	13	14	14
E	21	36	3	15	4	3	1.64	1.01	0.38	12	11	11
F	30	20	3	20	5	2	1.76	1.24	0.41	9	1	6
G	15	12	3	8	4	3	1.92	0.64	0.25	17	17	17
H	17	20	4	5	2.5	4.5	1.34	1.46	0.52	3	1	1
I	28	40	4	7	5	3.5	1.14	1.65	0.59	2	1	2
J	20	38	3	18	3	6	1.84	0.78	0.3	16	16	16
K	17	14	5	11	3	3	1.66	1.13	0.4	11	1	5
L	23	22	2	20	4	2	1.85	0.99	0.35	14	13	13
M	22	24	3	12	4.5	4	1.85	0.59	0.24	18	18	18
N	30	28	4	13	4	3	1.37	1.16	0.46	6	12	12
O	23	25	3	11	2	2	1.11	1.62	0.6	1	1	3
P	21	33	2	10	3	3	1.53	1.08	0.41	10	10	10
Q	20	34	4	12	2	4.5	1.35	1.43	0.51	4	1	4
R	15	36	5	23	4	4	1.81	0.9	0.33	15	15	15
S	18	15	2	16	3	5	2.2	0.28	0.11	20	20	20
T	24	16	4	20	4	4	1.96	0.58	0.23	19	19	19

Table VI. Friedman's test results for three input and three output data

Method	N	Estimated median	Sum of rank
For all three methods[a]			
CRS DEA	20	10.417	32.0
ERM-DT	20	10.750	44.0
Super CCR	20	10.583	44.0
Grand median = 10.583			
For ERM-DT and Super CCR method[b]			
ERM-DT	20	9.50	32.0
Super CCR	20	9.50	32.0
Grand median = 10.583			

Notes: [a]Test statistic $S = 8.93$; df = 2; $p = 0.012$ (adjusted for ties); [b]test statistic $S = 0.0$; df = 1; $p = 1$ (adjusted for ties)

4. An application of the proposed approach

In this section, we illustrate the application of the proposed framework for various branches of a nationalized bank operating in India. This premier Indian Bank has the largest network of branches in any public sector bank in the state of Maharashtra. The bank has 1,728 branches, with nearly 14,000 dedicated work force managing the total business of INR 1,707.34 billion (as on March 31, 2013). All the branches provide "anywhere any time banking" facilities.

Table VII. ERM-DT, CRS DEA and Super CCR ranks for three output and three input data

DMU	O1	O2	O3	O4	I1	I2	I3	I4	$S*$	S^-	$C*$	DEA TOPSIS rank	CRS DEA rank	Super CCR rank
A	10	20	3	14	8	40	1	13	2.7	1.7	0.38	1	1	5
B	19	30	2	17	1	17	4	15	2.1	2.4	0.54	2	1	3
C	27	8	1	6	6	27	8	25	3.5	0.5	0.12	24	24	24
D	25	14	1	5	6	40	6	30	3.5	0.3	0.08	25	25	25
E	17	29	2	9	5	25	3	23	3	0.9	0.23	21	17	17
F	15	7	3	9	7	14	3	17	3	1	0.24	20	20	20
G	26	16	4	17	6	20	1	25	2.3	2.1	0.47	3	1	1
H	18	28	1	11	6	39	3	23	3.2	0.7	0.18	23	22	22
I	23	23	3	20	7	34	5	15	2.9	1.1	0.28	17	21	21
J	12	9	4	17	4	28	4	15	2.9	1	0.26	18	1	15
K	25	6	4	15	5	28	7	12	2.9	1.2	0.3	12	1	12
L	25	17	2	19	7	12	6	20	2.8	1.7	0.37	6	1	10
M	26	5	3	8	2	32	5	28	3.1	1.1	0.25	19	23	23
N	13	20	4	20	8	34	2	21	2.8	1.2	0.29	14	19	19
O	16	10	1	15	6	23	5	8	3.1	1.2	0.29	15	1	13
P	18	17	2	17	1	11	2	10	1.7	2.6	0.61	1	1	4
Q	11	16	4	7	5	28	7	7	2.9	1.4	0.32	10	1	2
R	23	5	1	5	8	24	3	10	3.3	0.9	0.21	22	1	11
S	28	12	1	14	9	40	1	16	2.9	1.5	0.34	8	1	9
T	12	26	2	10	7	38	7	7	3	1.4	0.31	11	1	6
U	27	15	1	13	4	15	4	18	2.9	1.2	0.3	13	1	16
V	29	23	4	14	2	30	2	27	2.3	1.7	0.43	4	1	8
W	29	13	1	15	8	28	1	24	2.9	1.6	0.35	7	1	14
X	13	26	5	12	9	16	5	21	2.9	1.5	0.34	9	1	7
Y	22	26	4	13	9	31	7	13	2.9	1.1	0.28	16	18	18

Method	N	Estimated median	Sum of rank
For all three methods[a]			
CRS DEA	25	8.33	36.0
ERM-DT	25	12.00	55.5
Super CCR	25	11.67	58.5
Grand median = 10.667			
For ERM-DT and Super CCR method[b]			
ERM-DT	25	13.0	37.5
Super CCR	25	13.0	37.5
Grand median = 13.0			

Notes: [a]Test statistic $S = 15.31$; df = 2; $p = 0.00$ (adjusted for ties); [b]test statistic $S = 0.00$; df = 1; $p = 1.00$ (adjusted for ties)

Table VIII. Results obtained from Friedman's test for four input and four output data

We consider 15 branches (DMUs) of this bank in the rural area. Here, "total business" and "total income" are outputs and "number of employees" and "operating expenses" are inputs for this model.

Branch data together with analysis has been presented in Table IX. The results from Friedman's test are presented in Table X.

Comparing rankings using the proposed integrated approach with those obtained from CRS DEA model and Super CCR model, we observe that branch "R54" has emerged as the best branch according to all three models. Moreover, CRS DEA model has assigned first rank to branch R42, R47, R50, R54, R86 and R97.

Analyzing the results obtained from the Friedman's test, considering all the three methods, we can conclude that there is a significant difference in ranks obtained. Therefore, we reject the null hypothesis. By considering the proposed approach (ERM-DT) and the Super CCR method, we conclude that there is no significant difference in ranks obtained. This confirms the difference in ranks were because of the CRS DEA approach.

Sr no.	Branch code	Total business	Total income	Operating expenses	No. of employees	$S*$	S^-	$C*$	ERM-DT rank	CRS DEA rank	Super CCR rank
1	R16	1,719.16	98.06	20.70	5	0.94	0.35	0.27	8	8	8
2	R17	1,711.14	108.71	26.94	7	1.13	0.13	0.1	15	15	15
3	R18	1,713.95	109.23	21.67	6	1	0.34	0.25	9	9	9
4	R19	1,754.14	75.33	23.28	4	0.99	0.26	0.21	12	11	11
5	R42	1,817.96	124.60	20.43	3	0.43	0.81	0.65	3	1	2
6	R47	2,014.41	127.85	22.64	5	0.79	0.54	0.4	4	1	5
7	R50	3,156.70	210.54	37.46	4	0.2	0.99	0.83	2	1	4
8	R54	1,808.24	115.08	21.10	2	0.15	1.12	0.88	1	1	1
9	R68	1,750.56	103.35	24.79	5	0.97	0.22	0.19	14	14	14
10	R81	1,819.17	128.20	25.60	6	0.96	0.32	0.25	11	13	13
11	R85	1,802.15	96.69	24.01	5	0.98	0.23	0.19	13	12	12
12	R86	1,828.60	130.57	20.55	6	0.91	0.58	0.39	5	1	3
13	R86	1,828.60	130.57	21.18	6	0.91	0.54	0.37	7	7	7
14	R94	1,890.07	107.03	24.28	5	0.92	0.3	0.25	10	10	10
15	R97	1,754.29	98.49	19.72	4	0.8	0.48	0.37	6	1	6

Table IX. Branch data and results

Method	N	Estimated median	Sum of rank
For all three methods[a]			
CRS DEA	15	8.00	32.0
ERM-DT	15	8.00	24.5
Super CCR	15	8.00	33.5
Grand median = 8.00			
For ERM-DT and Super CCR method[b]			
ERM-DT	15	13.0	37.5
Super CCR	15	13.0	37.5
Grand median = 13.0			

Notes: [a]Test statistic $S = 6.64$; df = 2; $p = 0.036$ (adjusted for ties); [b]test statistic $S = 0.14$; df = 1; $p = 0.705$ (adjusted for ties)

Table X. Friedman's test results for the case

5. Conclusions

The conventional DEA (CRS DEA) model has seen its applicability in the past. However, few researchers have pointed out some limitations. Various improved versions of DEA such as super efficiency DEA model, cross-efficiency DEA model, etc., have been suggested to overcome some of these limitations.

In this study, we address the issue of assigning a unique rank to the DMUs and provide a tie-breaking procedure. The theme of the approach is based on the fact that the efficiency of a DMU is obtained in conventional DEA (CRS) by considering its distance only from the best DMU (here frontier) and not from the worst DMU.

In the conventional DEA (CRS) approach, possible biases in ranks obtained because of skewed data across the input and output values, is resolved by assigning appropriate weights to the input and output values of a DMU. This method provides an opportunity for every DMU to select the weights to maximize its efficiency. In the proposed approach, we eliminate the bias of the data, by adopting the normalization procedure. Here, the output input ratios are normalized and are later used to compute the distance from the best and the worst value. For each DMU, there is scope to assign weights to the ratios obtained, however, in order to simplify the approach, we have considered uniform weights. This distance is used to rank the DMUs. We can therefore call the proposed approach (CRM-DT) as unit invariant while the super efficiency DEA as a unit variant approach.

It can also be noted that it is difficult to estimate the value of the maximum score obtained using the super efficiency approach; and hence, setting an appropriate benchmark for effective performance of a DMU is not easy. In the proposed approach, the range of the scores obtained is from zero to maximum one. This approach, therefore, can be used to provide suitable guidelines to set a benchmark for non-efficient DMUs. One can also note that the proposed approach is capable of handling non-positive values (in inputs and outputs) and also incorporate the undesirable output variables. The proposed ERM-DT approach therefore can be used as a substitute to super efficiency approach under these conditions. Further, calculation efforts for the proposed approach are comparatively less and yet provide the desired results. The proposed approach does not need development of any advanced software to evaluate the efficiencies, a Microsoft Excel or spreadsheet template is sufficient to provide required computations. For large scale data, however, a macro program in Microsoft Excel may be essential.

We have carried out the analysis for various combinations of input and output data points, for instance, two inputs and two outputs; three inputs and three outputs; and four inputs and four outputs. We have also shown that there is no significant difference in ranks obtained from Super efficiency method and the proposed ERM-DT method. Here, results obtained are validated by using the Friedman's test of hypothesis.

As an extension to this work, one can validate results for more input and output data. It would be interesting to study the impact of number of DMUs on the proposed procedure.

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