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Ranking Units in DEA by Using the Voting System

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Abstract

One of the main problems in Data Envelopment Analysis (DEA) is ranking Decision Making Units (DMUs). There exist many different DEA models. These models often do not have any theoretical problems dealing with most data. However, because each of these models considers a certain theory for ranking, they may give different ranks. So, often in practice, choosing a ranking model, the results of which the Decision Maker (DM) would be able to trust is an important issue. In this article, ranking is done by proposing a method in which the ranks of different ranking models are used, each of which is important and significant. This method is based on the voting system. In voting systems, one candidate may receive different votes in different ranking places. The total score of each candidate is the weighted sum of the votes that the candidate receives in different places. The candidate that has the highest total score has the best rank. In this paper, we consider the various ranking models as voters which can rank DMUs from the top to the end and DMUs as candidates try to obtain a full rank from their votes.

Keywords : Data envelopment analysis; Ranking; Rank voting systems.

1 Introduction

Data envelopment analysis (DEA) was originated in 1978 by Charnes et al.[5] and the first DEA model was called the CCR (Charnes, Cooper and Rhodes) model. DEA is a linear programming based technique for measuring the relative efficiency of a fairly homogeneous set of decision making units (DMUs) in their use of multiple inputs to produce

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multiple outputs. It identifies a subset of efficient 'best practice' DMUs and for the remaining DMUs, the magnitude of their inefficiency is derived by comparison to a frontier constructed from the 'best practices'. Efficient DMUs are identified by an efficiency score equal to 1, and inefficient DMUs have efficiency scores less than 1. Although efficiency score can be a criterion for ranking inefficient DMUs, this criterion cannot rank efficient DMUs. In the last decade, a variety of models were developed to rank DMUs. Adler et.al [1] divided the ranking methods into some areas. The first area involves the evaluation of a cross-efficiency matrix, in which the units are self- and peer-evaluated. The second area, generally known as the super-efficiency method, ranks through the exclusion of the unit from the production possibility set and analyzing the change in the Pareto frontier. The third grouping is based on benchmarking, in which a unit is highly ranked if it is chosen as a useful target for many other units. The fourth group utilizes multivariate statistical techniques, which are generally applied after the DEA dichotomy classification. The fifth research area ranks inefficient units through proportional measures of inefficiency. The last approach requires the collection of additional, preferential information from relevant decision-makers and combines multiple-criteria decision methodologies with the DEA approach. However, whilst each technique is useful in a specialist area, no one methodology can be prescribed here as the complete solution to the question of ranking. Hence, selecting the best ranking model or the way of combining different ranking models for ranking DMUs is an important point in ranking DMUs in DEA. In this paper, we propose a methodology, based upon the voting system, for ranking DMUs. This method is especially applicable if we cannot prefer any ranking model on the others. In voting systems, one candidate may receive different votes in different ranking places. The total score of each candidate is the weighted sum of the votes that the candidate receives in different places. The one that has the highest total score has the best rank. Although the candidates in ranked voting systems are regarded as DMUs in DEA, and each DMU is considered to have t outputs (ranked votes) and only one input with amount unity, in our approach we consider the ranking models as voters and DMUs as candidates.
This paper has been organized as follows. In section 2 we review some ranking models in the voting system. Section 3 introduces our proposed method. A numerical example is given in section 4, and section 5 contains our conclusions.

2 Ranking models for voting systems

In this section we briefly describe some of the existing ranked voting systems which can be seen in the literature. In ranked voting systems each voter selects and ranks candidates in order of preference. It is assumed that there are no ties in each voter's ranking. The total score of each candidate is the weighted sum of the votes he/she receives in different places. The problem is to determine an ordering of all n candidates by obtaining a total score. Some of the voting systems assign fixed weights to the different ranks and the candidates with the highest score are the winners. But it is clear that the winning candidate can vary according to the weights used. To avoid this problem, Cook and Kress [6] proposed a DEA model to assess each candidate with the most favorable weights. DEA often suggests that more than one unit is equally efficient, i.e., they achieve the maximum score. For this reason, several methods to discriminate among efficient candidates have been proposed. Cook and Kress [6] have proposed to maximize the gap between the weights. Green et al.

[9] have proposed a discrimination method using a cross-evaluation matrix. Noguchi et al. [19] have proposed the following model to select the winner in which a strong ordering constraint condition is imposed on weights:

$$\begin{aligned} \max \quad & Z_i = \sum_{j=1}^{m} v_{ij} w_j \\ s.t. \quad & \sum_{j=1}^{m} v_{ij} w_j \leq 1, \qquad i = 1, ..., n, \\ & w_1 \geq 2w_2 \geq ... \geq m w_m, \\ & w_m \geq \epsilon = \tfrac{2}{Nm(m+1)}. \end{aligned} \tag{2.1}$$

in which it is assumed that each voter selects candidates among candidates and ranks them from top to the place, which is the relative importance weight associated with the place , denotes the number of the th place votes earned by candidate and is the number of voters. In this paper we use this model for ranking. Hashimoto [10] has proposed a super-efficiency model to Cook and Kress's ranked voting model. Obata and Ishii [21] have suggested excluding non-DEA efficient candidates and using normalized weights for discrimination. Wang and Chin [28] have proposed a method that discriminates the DEA efficient candidates by considering their best and least relative total scores. Since the least relative total scores and the best relative total scores are not measured within the same range in [28], Wang et al. [29] have proposed a method for solving such a case.

3 Our proposed method

3.1 Illustration

As was mentioned earlier, there is a great variety of DEA ranking models for ranking DMUs, e.g., cross-efficiency, super-efficiency, benchmarking, statistical techniques and so on. Also, there exist different viewpoints for utilizing the DEA technique; for instance, input-oriented and output-oriented views in some of them such as Andersen and Petersen's model in variable returns to scale technologies. Now, the main problem is the selection of the most suitable model and viewpoint, which is because the rankings of units obtained by various models may not be the same. For example, one ranking model may assign a rank A to a DMU while another one assigns a rank B to the same DMU. Thus, one may not trust the rank obtained by a certain ranking model. If we can prefer a ranking model over others, then there is not any problem. But we cannot usually select the best. Each of the above-mentioned models and viewpoints has some advantages which we would like not to ignore. So, it seems logical to try different models and combine the results of the different models and viewpoints. In this paper, we consider the various ranking models as voters which can rank DMUs from the top to the end and try to obtain a full rank from their votes.

In this section, we describe our proposed method with a simple example, taken from Sexton et al. [23], Adler et al. [1] and Jahanshahloo et al. [14]. There are six DMUs, each using two inputs to produce two outputs. The raw data are presented in Table 1. Adler et al. [1] ranked these six DMUs using some ranking models. We use the following ranking models, which can be seen in the literature, as voters to rank DMUs. We use AP [4], L1 [13], changing the reference set [14], MAJ [18], Modified MAJ1 [16], LJK [24], SBM [20], SA DEA [27], L-Infinity [12] and Distance-based approach [2], all of which can be classified as super-efficiency models, and three Common Set of Weights (CSW) models which we denote by CSW1, CSW2 and CSW3 (CSW1 [11], CSW2 [15], CSW3 [7]), Cross-Efficiency model [23], and three statistical methods: CCA (Canonical correlation analysis [8]) , DDEA (linear discriminant analysis [28]) and DR/DEA (Discriminant analysis of ratios [26]). In this example, we consider constant returns to scale. As can be seen in the last column of Table 1, DMUs A, B, C and D are CCR-efficient and DMUs E and F are inefficient. So, some of the ranking models can rank DMUs E and F by these CCR efficiency scores. In all of such ranking models DMUE obtains rank 5 and DMUF receives rank 6. Since the number of such models is more than others, usually, their ranking for inefficient DMUs can be appeared in the ranking presented by our ranking.

Table 1

Raw data for numerical example.

DMU	Input	Input	Output	Output	CCR efficiency
A	150	0.2	14000	3500	1
B	400	0.7	14000	21000	1
C	320	1.2	42000	10500	1
D	520	2.0	28000	42000	1
E	350	1.2	19000	25000	0.978
F	320	0.7	14000	15000	0.868

Now, consider Table 2, which uses 17 ranking models to rank the six DMUs in Table 1. Table 2 shows the ranks assigned to DMUs by ranking models. The results corresponding to the statistical-based models CCA, DDEA and DR/DEA are taken from [1]. The number of rank j assigned to alternative i is easily calculated (see Table 3). In Table 4, results obtained by model 1 and the proposed rank are given. By using this method we can obtain the rank for each DMU with more certainty, because this method has inherently considered various viewpoints based on which the ranking models used in the method are constructed.

Table 2

Ranking DMUs by 17 Ranking Models.

Ranking Model	A	B	C	D	E	F
AP	1	2	3	4	5	6
L1	4	3	1	2	5	6
Ch-Re-Set	2	1	4	3	5	6
Maj	4	3	1	2	5	6
M-Maj	2	1	3	4	6	5
LJK	4	3	1	2	5	6
SBM	1	3	2	4	5	6
SA DEA	1	2	3	4	5	6
L Infinity	3	2	1	4	5	6
CSW1	2	5	1	3	4	6
CSW2	1	5	2	3	4	6
CSW3	1	4	3	2	5	6
Cross Efficiency	1	3	2	4	5	6
CCA	1	2	3	4	5	6
DDEA	3	1	2	4	5	6
DR/DEA	1	5	2	3	4	6
Distance-based	2	4	3	1	5	6

Table 3
The number of assigning each rank to each DMU.

DMU	Place1	Place2	Place3	Place4	Place5	Place6
A	8	4	2	3	0	0
B	3	4	5	2	3	0
C	5	5	6	0	1	0
D	1	4	4	8	0	0
E	0	0	0	3	13	1
F	0	0	0	0	1	16

Table 4
Proposed rank for DMUs.

	A	B	C	D	E	F
Model 1 results	1	0.680292	0.849635	0.5547445	0.3080292	0.2510949
Proposed Rank	1	3	2	4	5	6

3.2 Some practical points

A few points are worth mentioning with respect to the proposed method:

1. Although we can consider a certain group of ranking models such as super-efficiency models, it is better to consider the other ranking models in the other groups, as well. It is clear that combining the results of different DEA ranking models in different groups provides more realistic ranking results for managers. Almost all of the models have some shortcomings, but using the combination of the results obtained from them may reduce the effects of their shortcomings.

2. As mentioned before, in voting systems it is assumed that there are no ties in each voter's ranking. So we must use only the ranking models which can give different ranking scores to DMUs.

3. Some of the ranking models are dependent on a specific technology, a point which must be considered while using them. For example, cross-efficiency is used only for constant returns to scale technology, and the super-efficiency model based on improved outputs proposed by Khodabakhshi [17] must be used for variable returns to scale technology, because using it for constant returns to scale will give the same results as the LJK model. Another point is about the ranking models which are dependent on the orientation, like AP. When they are used for variable returns to scale, input- and output-oriented ranking models may give different ranks, thus each of them can be a voter.

5. It may happen that we confront the case in which a decision maker prefers some ranking models to the others. Moreover, the voters may not have the same value to the decision maker. In such cases, we can consider various weights for the ranking models as voters and therefore their ranks. For example, decision makers can determine the importance of the ranking models by using the pairwise comparison matrices. The weights can be calculated using eigenvector method.

6. Many of the introduced models may not be able to rank in some cases in which they have rarely happened to fall. This should not cause to ignore such models in other cases. As an example, as we know, AP model has some problems and, therefore, after the introduction of the model by Andersen and Petersen, many of the researchers introduced models to overcome these problems. However, in spite of the problems, the model is still in use for reasons like simplicity in the implementation or its theoretical basis.

7. Another point is that we do not only consider ranking efficient units. In some models, like common set of weights model, the number of efficient units is less than some other DEA models and, therefore, some of the units that are efficient in some models may be inefficient in some other models. Moreover, those models that can rank only efficient units can be considered as models that rank all units, because the efficiency score of inefficient units may be considered as their ranking score. In addition, because in most ranking models, it can be seen that inefficient units have a lower rank, therefore, the result of ranking all the units, is inclined to results of ranking only efficient units.

3.3 Steps of the proposed method

Step1 : Determine which of the DMUs must be ranked, all of them or only a subset of them such as the efficient DMUs.
Step2 : Select suitable ranking models and then rank DMUs with them.
Step3 : Consider each of the ranking models as a voter and determine the number of each rank assigned to each DMU.
Step4 : Use model 1 or other ranking voting system models to rank DMUs.

4 Empirical Example

Let us rank 20 Iranian bank branches by our proposed method. The data can be seen in [3] and [14] (see Table 5). As can be seen in the last column of Table 5, DMUs 1,4,7,12,15,17 and 20 are CCR efficient.
Now, consider Table 6, in which 14 ranking models are used to rank these DMUs. Models used in this example can be seen under Table 6. Table 6 shows the ranks assigned to DMUs by ranking models. The number of rank j assigned to DMUi is given in Table 7 and 8 . In Table 9, the results obtained by model 1 and the proposed ranks are presented.

Table 5
DMUs' Data (Empirical Example) and Their CCR Efficiencies.

Branch	Inputs			Outputs			efficiency
	Staff	Computer terminals	Space	Deposits	Loans	Charge	
1	0.950	0.700	0.155	0.190	0.521	0.293	1.000
2	0.796	0.600	1.000	0.227	0.627	0.462	0.833
3	0.798	0.750	0.513	0.228	0.970	0.261	0.991
4	0.865	0.550	0.210	0.193	0.632	1.000	1.000
5	0.815	0.850	0.268	0.233	0.722	0.246	0.899
6	0.842	0.650	0.500	0.207	0.603	0.569	0.748
7	0.719	0.600	0.350	0.182	0.900	0.716	1.000
8	0.785	0.750	0.120	0.125	0.234	0.298	0.798
9	0.476	0.600	0.135	0.080	0.364	0.244	0.789
10	0.678	0.550	0.510	0.082	0.184	0.049	0.289
11	0.711	1.000	0.305	0.212	0.318	0.403	0.604
12	0.811	0.650	0.255	0.123	0.923	0.628	1.000
13	0.659	0.850	0.340	0.176	0.645	0.261	0.817
14	0.976	0.800	0.540	0.144	0.514	0.243	0.470
15	0.685	0.950	0.450	1.000	0.262	0.098	1.000
16	0.613	0.900	0.525	0.115	0.402	0.464	0.639
17	1.000	0.600	0.205	0.090	1.000	0.161	1.000
18	0.634	0.650	0.235	0.059	0.349	0.068	0.473
19	0.372	0.700	0.238	0.039	0.190	0.111	0.408
20	0.583	0.550	0.500	0.110	0.615	0.764	1.000

Table 6
Ranking DMUs by 14 Ranking Models
D DMU, M1 AP [4], M2 L1 [13], M3 changing the reference set [14], M4 MAJ [4], M5 Modified Maj2 [22], M6 LJK [24], M7 SBM [20], M8 SA DEA [27], M9 L Infinity [12], M10 CSW1 [11], M11 CSW2 [15], M12 CSW3 [7], M13 Cross Efficiency [23], M14 Distance-based [2].

DMU	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14
D1	7	7	7	7	7	7	7	7	7	13	13	7	6	7
D2	10	10	10	13	13	10	10	14	12	11	12	10	9	10
D3	8	8	8	8	8	8	8	8	8	6	5	8	7	8
D4	2	2	2	2	2	2	2	2	2	1	1	1	2	2
D5	9	9	9	11	11	9	9	9	11	8	9	9	8	9
D6	14	14	14	16	14	14	14	12	14	7	6	14	13	14
D7	5	3	3	3	5	3	4	3	5	1	2	2	4	3
D8	12	12	12	9	9	12	12	13	9	16	16	12	11	12
D9	13	13	13	10	10	13	13	10	10	12	11	13	12	13
D10	20	20	20	20	19	20	20	20	19	20	20	20	20	20
D11	16	16	16	15	17	16	16	16	17	14	15	16	16	16
D12	6	6	5	6	6	6	6	5	6	4	3	4	5	6
D13	11	11	11	12	12	11	11	11	13	10	10	11	10	11
D14	18	18	18	19	20	18	18	18	20	18	17	18	18	18
D15	1	1	1	1	1	1	1	1	1	3	8	3	1	1
D16	15	15	15	18	15	15	15	15	15	15	14	15	15	15
D17	3	4	6	5	3	4	3	4	3	9	7	6	14	4
D18	17	17	17	14	16	17	17	17	16	18	18	17	17	17
D19	19	19	19	17	18	19	19	19	18	19	19	19	19	19
D20	4	5	4	4	4	5	5	6	4	5	4	5	3	5

Table 7
The number of each rank assigned to each DMU.

DMU	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
D1	0	0	0	0	0	1	11	0	0	0
D2	0	0	0	0	0	0	0	0	1	7
D3	0	0	0	0	1	1	1	11	0	0
D4	3	11	0	0	0	0	0	0	0	0
D5	0	0	0	0	0	0	0	2	9	0
D6	0	0	0	0	0	1	1	0	0	0
D7	1	2	6	2	3	0	0	0	0	0
D8	0	0	0	0	0	0	0	0	3	0
D9	0	0	0	0	0	0	0	0	0	4
D10	0	0	0	0	0	0	0	0	0	0
D11	0	0	0	0	0	0	0	0	0	0
D12	0	0	1	2	2	8	0	0	0	0
D13	0	0	0	0	0	0	0	0	0	3
D14	0	0	0	0	0	0	0	0	0	0
D15	11	0	2	0	0	0	0	1	0	0
D16	0	0	0	0	0	0	0	0	0	0
D17	0	0	4	4	1	2	1	0	1	0
D18	0	0	0	0	0	0	0	0	0	0
D19	0	0	0	0	0	0	0	0	0	0
D20	0	0	1	6	6	1	0	0	0	0

Table 8
The number of each rank assigned to each DMU.

DMU	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20
D1	0	0	2	0	0	0	0	0	0	0
D2	1	2	2	1	0	0	0	0	0	0
D3	0	0	0	0	0	0	0	0	0	0
D4	0	0	0	0	0	0	0	0	0	0
D5	3	0	0	0	0	0	0	0	0	0
D6	0	1	1	9	0	1	0	0	0	0
D7	0	0	0	0	0	0	0	0	0	0
D8	1	7	1	0	0	2	0	0	0	0
D9	1	2	7	0	0	0	0	0	0	0
D10	0	0	0	0	0	0	0	0	2	12
D11	0	0	0	1	2	9	2	0	0	0
D12	0	0	0	0	0	0	0	0	0	0
D13	8	2	1	0	0	0	0	0	0	0
D14	0	0	0	0	0	0	1	10	1	2
D15	0	0	0	0	0	0	0	0	0	0
D16	0	0	0	1	12	0	0	1	0	0
D17	0	0	0	1	0	0	0	0	0	0
D18	0	0	0	1	0	2	9	2		0
D19	0	0	0	0	0	0	1	2	11	0
D20	0	0	0	0	0	0	0	0	0	0

Table 9
Proposed rank for DMUs.

DMU	Results of model 1	Proposed model
D1	0.16044733	7
D2	0.10973526	10
D3	0.15981827	8
D4	0.77260492	2
D5	0.12913588	9
D6	0.09965829	14
D7	0.43713193	3
D8	0.10257234	12
D9	0.10143072	13
D10	0.0598103	20
D11	0.07504528	16
D12	0.2199945	6
D13	0.10777632	11
D14	0.06504684	18
D15	1	1
D16	0.07861349	15
D17	0.27070503	5
D18	0.07097821	17
D19	0.06350943	19
D20	0.27427886	4

As can be seen in Table 9, first position is assigned to D15. It can be seen in Table 8 that this unit gets rank 1 by 11 models, rank 3 by 2 models and rank 8 by only one model. Because it has been assigned rank one by 11 votes, out of a total of 14 votes, therefore choosing this unit as the highest-ranking unit is logical. A similar point holds for units 4 and 7, which get positions 2 and 3. But it may seem that this method will assign the highest rank to the unit which has received the most votes. This means that if voters give the most votes for the t'th position to the l'th unit, then the proposed method does so, as well. Also, it may be suspected that the selection is based on lexicographic maximum. But this is not the case, because according to lexicographic maximum criteria unit 17 must be ranked higher than unit 20, while the proposed model assigns position 4 to unit 20 and position 5 to unit 17.

5 Conclusion

It happens often that in real problems in Data Envelopment Analysis, we would like to rank the Decision Making Units. There exist many different DEA models. Hence, selecting the best model for ranking DMUs is a main question in DEA. These models do not often have any theoretical problems dealing with most data. Because each of these models considers a certain theory for ranking, they may give different ranks. So, often in practice, choosing a ranking model the results of which the Decision Maker (DM) would be able to trust is an important issue. In this article a method has been proposed by which ranking will be done by using the ranks of different ranking models, each of which is important and significant. This method is based on the voting system. In voting systems, one candidate may receive different votes in different ranking places. The total score of each candidate is the weighted sum of the votes that the candidate receives in different places. The candidate that has the biggest total score has the highest rank. In this paper we have considered various ranking models as voters which can rank DMUs from the top to the end and DMUs as candidates, and tried to obtain a full rank from their votes. One of the most important points about the proposed method is that it removes the concern of the DM in choosing a particular model for ranking. Because each model decides the ranking score only based upon one viewpoint, so it can be said that each of the ranking models shows only some percent of the reality and, therefore, using only one model, in the case that we would be able to choose it, should be untrustworthy. Therefore, the proposed method provides the possibility of using the results of all existing ranking models. So, its results will be more reliable for the DM.

Another strong point of the proposed method is that, as mentioned before, each of the ranking models is constructed based on a certain theory or viewpoint, but it may happen that the DM is inclined to ranking base upon viewpoints that have not defined any ranking models for them. The proposed model has the flexibility to deal with such cases. In this article, the proposed method has been used for ranking 20 Iranian bank branches to demonstrate its validity.

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