GU J Sci 30(2): 237-245 (2017)

Gazi University

Journal of Science

http://dergipark.gov.tr/gujs

Ranking the Airports with Data Envelopment Analysis and Canonical Correlation Analysis

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Article Info

Received: 18/07/2016
Accepted: 04/04/2017

Keywords

Canonical Correlation Analysis, Data Envelopment Analysis, Efficiency Evaluation.

Abstract

This paper deals with joint use Canonical correlation analysis (CCA) and Data envelopment analysis (DEA) techniques. CCA is a multivariate statistical technique that can be used to determine the relationship between two multiple variable sets. DEA is a nonparametric approach for measuring the relative efficiency of peer decision making units(DMUs) when multiple inputs and outputs are present. Data envelopment analysis (DEA) model selection is problematic. The estimated efficiency for any DMU depends on the inputs and outputs included in the model. A benefical method for model selection is proposed in this paper. Efficiencies are calculated for all possible DEA model specifications. The results are analysed using Canonical Correlation Analysis. It is shown that model equivalence or dissimilarity can be easily assessed using this approach. The aim of this study is to get an effective result by using the CCA for the correct model choice in DEA. For this purpose, data set of airports in Turkey were used. The correlation calculations are carried out to understand the nature of the relationship between the models of DEA. It is aimed to find the most effective DEA model by using CCA technique.

1. INTRODUCTION

Various model selection methods have been suggested in DEA. Most researchers choose a one model, without considering any alternatives. However, selected variables may affect the efficiency scores. It is possible that a variable included in the model in this way may contribute little or nothing to the calculation of efficiency values. The converse is also true, it is possible that a variable for which data are available, and has not been included in the model on a priori considerations, may be important in the determination of efficiencies. There are many studies in the literature in order to determine this. Multivariate statistical analyzes can be used in model selection of data envelopment analysis.

CCA is a multidimensional exploratory statistical method. A canonical correlation is the correlation of two canonical variables, one representing a set of independent variables, the other a set of dependent variables. Each set may be considered a canonical variable based on measured original variables in its set. The canonical correlation is optimized such that the linear correlation between the two canonical variables is maximized.

DEA is a methodology for measuring the relative efficiencies of a group decision making units(DMUs) that use multiple inputs to produce multiple outputs. Effectiveness and efficiency is an important part of the basic management approach. DEA is used in different areas and can be used, not only for estimating the performance of units, but also for solving other problems of management. DEA has been compared with other methods such as CCA. In addition, DEA can also be improved by using other methods.

Data Envelopment Analysis (DEA) model selection is very important. Efficiency values for decision making units are connected to input and output data. It also depends on the correlation of outputs plus inputs. In this study, two-input, three-output variable was used. We consider Terminal pitch size, Airport size as inputs variables; Aircraft Movements, Passenger traffic and Freight Traffic are the outputs (Örkcü et al. (2016). There are many DEA models and for 21 models efficiency measurement is calculated by DEA

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for data set of airports in Turkey. With canonical correlation analysis aimed to find the most suitable DEA model. Also structure of the DEA model has been examined by the CCA. It is shown that model similarity or differences can be easily obtained.

In this study, various information will be presented for the most appropriate model selection in DEA by using CCA technique and ınput oriented CCR model of DEA will be used.

1.1.Canonical Correlation Analysis

The Canonical Correlation Analysis(CCA) is a technique which developed by Hotelling [1] , to define the relationship between two random variables set. and CCA is one of the main methods of multivariate statistics. CCA is used as a statistical model to examine the correlation between multiple dependent variables with multiple independent variables. Thus, sets of variables can be analyzed whether it is a linear relation.

The general structure of CCA to examine the relationship between the two variables set can be expressed as follows:

$\beta_1 Y_1+ \beta_2 Y_2+\ldots+\beta_p Y_p = a_1X_1+a_2X_2+\ldots+a_qX_q$

There are p (1-p) / 2 correlations between the Y_P variables. And there are q (1-q) / 2 correlations between X_P variables. There is also p × q correlation between these two sets of variables. It is difficult to interpret so many correlation coefficients. CCA aims to reduce the number of these correlation coefficients.

The mathematical representation of CCA can be expressed as follows;

$$\begin{array}{ll} V1=a_{11}y_{11} +\ldots + a_{1p}y_{1p} & U1=b_{11}x_{11}+\ldots+b_{1q}x_{1q} \\ . & . \\ . & . \\ . & . \\ Vi=ai1yi1+\ldots+a_{ip}y_{ip} & Ui=b_{i1}x_{i1}+\ldots+b_{iq}x_{iq} \end{array} \tag{1}$$

Explanations of the abbreviations in the formula are as follows;

$y_{ij;}$ criterion variables $(1 \leq j \leq p)$,

$x_{ik;}$ forecast variables $(1 \leq k \leq q)$,

i; number of variable pairs,

p; number of criterion variables

q; number of forecast variables

V_i; The criterion variables of the i th variable pairs of canonical random variable

$U_{i;}$ The canonical random variable of the i. variable pairs of forecast variables

a_{ij} ; The canonical weight of the j. variable in the i. pair of criteria variable $(1 \leq j \leq p)$,

b_{ik}; The canonical weight of the j. variable in the i. pair of forecast variable $(1 \leq j \leq p)$.

In the canonical correlation analysis, which consists of n units of observation, there are q independent variable (Xq) and p dependent variable (Yp). Variable pairs that may be derived from Xq and Yp variables to called canonical variables and these are indicated by, respectively, U and V.

Canonical correlation coefficient is calculated as follows;

$$KOR(U,V) = \frac{KOV(U,V)}{\sqrt{VAR(V)VAR(U)}} \tag{2}$$

Explanations of the abbreviations in the formula are as follows;

KOR(U,V);Correlation U and V

KOV(U,V); Covariance U and V

VAR(U);Variance U

VAR(V);Variance V

1.2.Data Envelopment Analysis

Effectiveness and efficiency is an important part of the basic management approach. Data envelopment analysis is an important technique used to measure the relative effectiveness. DEA method use in different areas. DEA can be used, not only for estimating the performance of units, but also for solving other problems of management. DEA is one popular optimization method used for measuring the relative efficiency of DMUs.
Data Envelopment Analysis (DEA) model selection is very important. Efficiency values for decision making units are connected to input and output data. It also depends on the correlation of outputs plus inputs. There are many studies in the literature with using DEA method.
Data envelopment analysis (DEA) is a nonparametric method based on linear programming concepts. DEA is an analysis that makes a relative comparison between decision making units.
The DEA method measure that decision-making units which operating in the same market. This constraint in the analysis, all the decision-unit activity should be above or below the limit. Thus, the active units may take the value of 1 and value of inactive units is less than 1.

Data envelopment analysis measuring the relative efficiency of peer decision making units(DMUs) when multiple inputs and outputs are present. This objective method was originated by Charnes et al. (1978) [2]. Basic CCR model is as follows:

CCR Model;

$$\max E = \sum_{r=1}^{s} u_{r0} y_{r0} \tag{3}$$

$$\sum_{r=1}^{s} u_{rk} y_{rk} - \sum_{r=1}^{s} v_{ik} x_{ij} \leq 0 \qquad j = 1, \dots, n \tag{4}$$

$$\sum_{r=1}^{s} v_{i0} x_{ij} = 1 \tag{5}$$

$$u, v \geq 0$$

$$r = 1, \dots, s \quad i = 1, \dots, m$$

This paper is organized as follows. The next section introduces the notation and models table. Modelling is described next with details of the various steps followed. The last section contains the conclusions.

2. EXPERIMENTS

The first step in the study requires the listing of all possible DEA models that can be derived from possible inputs and outputs. Firstly, there are two inputs and three outputs, resulting in 21 possible DEA models, each model containing a combination of one or more inputs with one or more outputs. These are shown in Table 1. There are two inputs and three outputs defined as follows:

Input 1, (X1): Terminal pitch size
Input 2, (X2): Airport size

Output 1, (Y1): Aircraft Movements
Output 2, (Y2): Passenger traffic
Output 3, (Y3): Freight Traffic

For each model DEA efficiency results are shown in Table 2. In this table two models are identified as A and B and the first input, X1, is associated with the letter A in the name; the second input, X2, is associated with the letter B; outputs are associated with numbers in an obvious way. For example,the model A1 contains one input, X1, and one output, Y1. B12 contains one input, X2, and two outputs Y1 and Y2. AB123 contains two inputs X1 and X2,three outputs Y1, Y2 and Y3.

Table 1. *Models and input-output combinations*

DMU	INPUT	OUTPUT
A1	X1	Y1
A12	X1	Y1 Y2
A123	X1	Y1 Y2 Y3
A13	X1	Y1 Y3
A23	X1	Y2 Y3
A2	X1	Y2
A3	X1	Y3
B1	X2	Y1
B12	X2	Y1 Y2
B123	X2	Y1 Y2 Y3
B13	X2	Y1 Y3
B23	X2	Y2 Y3
B2	X2	Y2
B3	X2	Y3
AB1	X1 X2	Y1
AB12	X1 X2	Y1 Y2
AB123	X1 X2	Y1 Y2 Y3
AB13	X1 X2	Y1 Y3
AB23	X1 X2	Y2 Y3
AB2	X1 X2	Y2
AB3	X1 X2	Y3

Table 2. *DEA efficiency scores of each models*

DMU	A1	A2	A3	A12	A13	A23	A123	B1	B2	B3	B12	B13	B23	B123	AB1	AB2	AB3	AB12	AB13	AB23	AB123
İstanbul Atatürk	0,35	0,43	1,00	0,43	1,00	1,00	1,00	0,38	0,47	1,00	0,47	1,00	1,00	1,00	0,38	0,47	1,00	0,47	1,00	1,00	1,00
İstanbul Sabiha Gökçen (*)	0,26	0,32	0,10	0,32	0,29	0,33	0,33	0,27	0,32	0,09	0,32	0,29	0,34	0,34	0,27	0,32	0,10	0,32	0,29	0,34	0,34
Antalya	0,27	0,41	0,02	0,41	0,27	0,41	0,41	0,31	0,47	0,02	0,47	0,31	0,47	0,47	0,31	0,47	0,02	0,47	0,31	0,47	0,47
Ankara Esenboğa	0,14	0,16	0,05	0,16	0,15	0,17	0,17	0,17	0,19	0,05	0,19	0,18	0,20	0,20	0,17	0,19	0,05	0,19	0,18	0,20	0,20
İzmir Adnan Menderes	0,07	0,09	0,04	0,09	0,08	0,10	0,10	0,09	0,11	0,04	0,11	0,10	0,12	0,12	0,09	0,11	0,04	0,11	0,10	0,12	0,12
Adana	1,00	1,00	0,24	1,00	1,00	1,00	1,00	1,00	1,00	0,22	1,00	1,00	1,00	1,00	1,00	1,00	0,24	1,00	1,00	1,00	1,00
Muğla Milas-Bodrum	0,08	0,09	0,00	0,09	0,08	0,09	0,09	0,09	0,10	0,00	0,10	0,09	0,10	0,10	0,09	0,10	0,00	0,10	0,09	0,10	0,10
Muğla Dalaman	0,06	0,08	0,00	0,08	0,06	0,08	0,08	0,08	0,10	0,00	0,10	0,08	0,10	0,10	0,08	0,10	0,00	0,10	0,08	0,10	0,10
Trabzon	0,25	0,30	0,20	0,30	0,35	0,38	0,38	0,26	0,32	0,19	0,32	0,34	0,39	0,39	0,26	0,32	0,20	0,32	0,35	0,39	0,39
Tekirdağ Çorlu	0,80	0,05	0,01	0,80	0,80	0,05	0,80	0,92	0,06	0,01	0,92	0,92	0,06	0,92	0,92	0,06	0,01	0,92	0,92	0,06	0,92
Gaziantep	0,20	0,24	0,04	0,24	0,20	0,24	0,24	0,24	0,29	0,05	0,29	0,24	0,29	0,29	0,24	0,29	0,05	0,29	0,24	0,29	0,29

Eskişehir Anadolu (*)	0,32	0,03	0,00	0,32	0,32	0,03	0,32	0,36	0,03	0,00	0,36	0,36	0,03	0,36	0,36	0,03	0,00	0,36	0,36	0,03	0,36
Sivas Nuri Demirağ	0,05	0,06	0,00	0,06	0,05	0,06	0,06	0,06	0,07	0,00	0,07	0,06	0,07	0,07	0,06	0,07	0,00	0,07	0,06	0,07	0,07
Batman	0,05	0,06	0,01	0,06	0,05	0,06	0,06	0,06	0,07	0,01	0,07	0,06	0,07	0,07	0,06	0,07	0,01	0,07	0,06	0,07	0,07
Mardin	0,03	0,04	0,00	0,04	0,03	0,04	0,04	0,04	0,04	0,00	0,04	0,04	0,04	0,04	0,04	0,04	0,00	0,04	0,04	0,04	0,04
Kars Harakani	0,02	0,03	0,00	0,03	0,02	0,03	0,03	0,03	0,04	0,00	0,04	0,03	0,04	0,04	0,03	0,04	0,00	0,04	0,03	0,04	0,04
Nevşehir Kapadokya	0,23	0,22	0,00	0,23	0,23	0,22	0,23	0,23	0,22	0,00	0,23	0,23	0,22	0,23	0,23	0,22	0,00	0,23	0,23	0,22	0,23
Erzincan	0,03	0,03	0,00	0,03	0,03	0,03	0,03	0,03	0,03	0,00	0,03	0,03	0,03	0,03	0,03	0,03	0,00	0,03	0,03	0,03	0,03
Şırnak Şerafettin Elçi	0,16	0,17	0,00	0,17	0,16	0,17	0,17	0,17	0,18	0,00	0,18	0,17	0,18	0,18	0,17	0,18	0,00	0,18	0,17	0,18	0,18
Muş	0,41	0,55	0,02	0,55	0,41	0,55	0,55	0,41	0,54	0,02	0,54	0,41	0,54	0,54	0,41	0,55	0,02	0,55	0,41	0,55	0,54
Uşak	0,41	0,02	0,00	0,41	0,41	0,02	0,41	0,41	0,02	0,00	0,41	0,41	0,02	0,41	0,41	0,02	0,00	0,41	0,41	0,02	0,41
Kahramanmaraş	0,33	0,32	0,02	0,33	0,33	0,32	0,33	0,38	0,36	0,02	0,38	0,38	0,36	0,38	0,38	0,36	0,02	0,38	0,38	0,36	0,38
Ağrı	0,61	0,70	0,02	0,70	0,61	0,70	0,70	0,58	0,67	0,02	0,67	0,58	0,67	0,67	0,61	0,70	0,02	0,70	0,61	0,70	0,67

In the study, different DEA models for the same decision-making units are discussed. Thus, the input and output that significantly impact the transportation process will be determined. Here, airports which has an efficiency score of 1, are considered to be active airports. According to the calculations, the 21 models show differences and some similarities. When the tables are examined, airports show several similarities and differences for the different models. And A3, B3, AB3 models has very different value all airports. In addition, some airports is seen that the same event values for almost all models.

The influence of the model on efficiency can be clearly observed in Table 2. For example, DMU 1 is 100% efficient in 12 models that include output Y3 in their specification (A123, A13, A23, A3, B123, B13, B23, B3, AB123, AB13, AB23 and AB3). But if Y3 is removed from the specification, the efficiency of DMU 1 drops to very low values ranging from 0.35 to 0.47. DMU 6 is %100 efficient in 18 models. However, if only Y3 is present in the model, the efficiency of DMU 2 falls to very low values ranging from 0.22 to 0.24. DMU 7 and 8 have a same efficiency values for all models. Something similar could be said about DMU 28 and DMU 29. They are inefficient in all models and have the same efficiency values. Are they similar or not? If they are not, where are the differences? The method suggested here makes it possible to answer these questions.

Table 2 in search of clues that may explain which inputs or outputs are responsible for the changes. It is, however, desirable to analyse Table 2 in a multivariate analysis context. Models can be treated as variables and DMUs as observations. The aim is to explore the structure of the data and to visualize their most important features.

It is clear that Table 2 contains much information, but that it also contains redundancy, since some DEA models may be equivalent, and some may contain independent information. Multivariate techniques aimed at data reduction and representation such as CCA may be used in this context. This is discussed in the next section.

2.1. DEA and CCA

This section will be concerned with the analysis of Table 2 within a multivariate statistical context. First, CCA will be used as a data reduction technique. The results obtained by DEA was investigated by CCA. These are shown in Table 3. Correlation scores are represented in a graphical form, highlighting the similarities and differences between the models.

Table 3.*Canonical Correlation Analysis Results for CCR Method*

Models	Canonical Correlation	Significance Level
A1	0,396417	0,016530
A2	0,394661	0,017196
A3	0,958616	0,000000

A12	0,454093	0,011905
A13	0,604197	0,000080
A23	0,617430	0,000045
A123	0,662139	0,000019
B1	0,395301	0,016951
B2	0,415592	0,010568
B3	0,964424	0,000000
B12	0,467286	0,008485
B13	0,590890	0,000141
B23	0,622699	0,000035
B123	0,675403	0,000009
AB1	0,399792	0,040723
AB2	0,411605	0,031835
AB3	0,959600	0,000000
AB12	0,477797	0,016076
AB13	0,597007	0,000362
AB23	0,617332	0,000156
AB123	0,726549	0,000002

Models in Table 3 have been treated as variables and DMUs as observations, and a CCA exercise has been performed. When Table 3 is examined, it is seen that all models are meaningful at the level of 5% significance. A3, B3 and AB3 models have the highest canonical correlation coefficient. This models different from the others. All these models contain a single output in their specification, Y3. It is interesting to note that all of the models containing Y3 have a high canonical correlation coefficient. This models are clearly associated with the ability that DMUs have of generating output Y3. Turning to the other models, A1, A2, A12, B1, B2, B12, AB1, AB2, AB12 have a similar canonical correlation coefficient. All these models contain output Y1, Y2 or both outputs. Using similar reasoning, it can be argued that this model cluster is related to the efficient use of inputs. A13, A23, A123, B13, B23, B123, AB13, AB23, AB123 models have a similar canonical correlation coefficient.

In summary, the clusters give an overall measure of efficiency; the first cluster is related to output Y3; the second cluster is a contrast between input X1 and input X2; and the third cluster is relation to Y1 and Y2.

All these models can be classified by clustering analysis. A complementary way of analysing the data in Table 3 is to use Cluster Analysis. It is good practice to supplement the results obtained from graphical representations of multivariate data with the cluster lines. For each DMU, canonical correlation coefficients have been calculated and plotted in a graph. This graph can be seen in Figure 1.

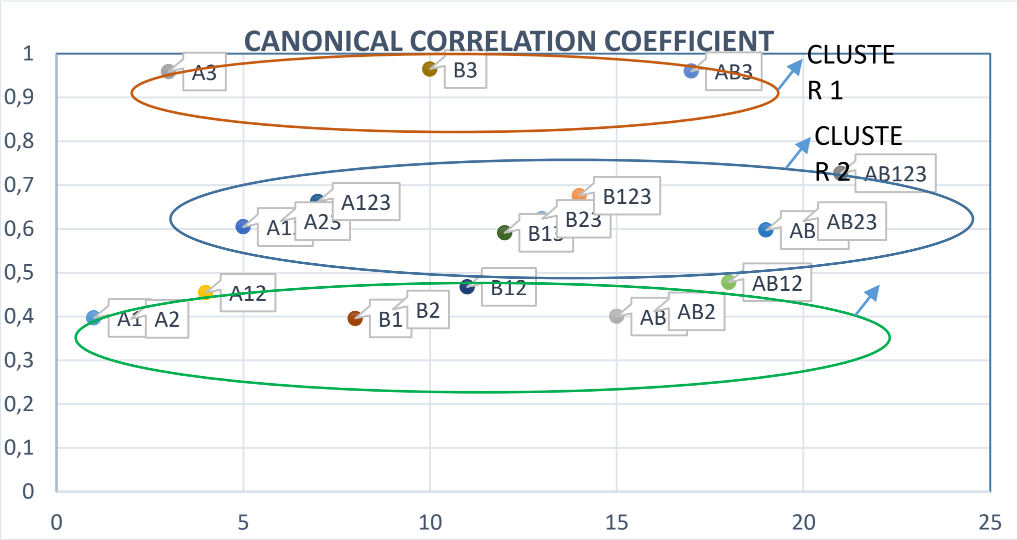

Figure 1. Cluster Analysis for Canonical Correlation Analysis Results

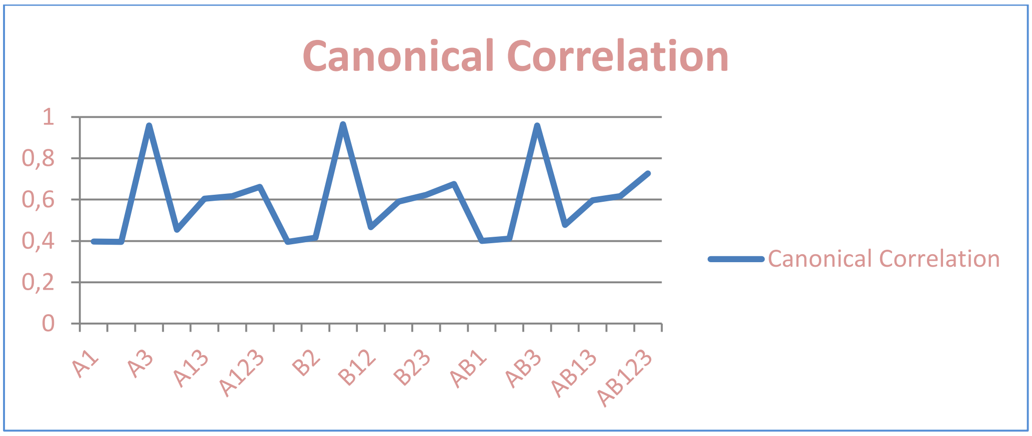

Figure 2. Canonical Correlation Values

As will be apparent from the graph; A3, B3, AB3 models having the highest canonical correlation values. And A1, A2, A12, B1, B2, B12, AB1, AB2, AB12 models having the lowest canonical correlation values. We can now see in which way DMU 1 is different from DMU 6. They both achieve the same efficiency score under the complete model AB123. But DMU 1 plots on the effective side of the first cluster, indicating that it values output Y3, while DMU 6 plots towards the uneffective side of the first cluster, indicating that models that ignore output Y3 will favour this DMU. If output Y3 was to be considered important by decision makers, DMU 1 would be preferred to DMU 6.

The clusters in Figure 1 confirm the conclusions obtained when models were discussed. Models group neatly into three clusters. One group is formed by models AB3, B3, and A3. All these models achieve their highest value in DMU A3, B3, AB3 and contain only output Y3, indicating that models achieves 100% efficiency by attaching high weights to output Y3. The remaining models split into two groups. One cluster points towards the input X1 and X2 and the other cluster points towards the input X1, X2 and output Y3. The difference between the two groups concerns the presence or absence or output Y3 in the specification. The models that do not contain output Y3 point downwards, and those that contain output 3 point upwards. Thus, output 3 is crucial in the modelling procedure.

The procedure to select a model is now clear. In the present case, it is to be first decided whether output 3 should or should not be included in the specification. This is a crucial decision. Models AB3, B3, and A3 do not appear to be reasonable since they show the remaining DMUs in bad efficiencies scores, a fact that can be confirmed by inspecting Table 2. If it is decided to leave output 3, in the specification, then any model among B23, A13, B13, AB23, B123, A23, B123, A123, AB123 could be chosen.

3. RESULT AND DISCUSSION

This paper has presented a benefical method for model selection in DEA based on multivariate statistical analysis. The methodology requires evaluating efficiencies for all possible input/output combinations. It is clear that such methodology produces much redundancy, but also generates valuable information. The matrix of efficiencies by models is then analysed by means of data reduction techniques, such as CCA. Further understanding of the data can be gained by applying HCA in this data set.

It has been shown that there are advantages with calculating efficiencies under all possible specifications of the DEA model, and then performing multivariate analysis on the results obtained. CCA has been the chosen technical approach, although Multidimensional Scaling would have been equally appropriate. For this purpose, possible 21-DEA model was created for 51 airports in Turkey. The relationship between the 21 model variables were measured by correlation analysis. The results obtained by CCR that was investigated by canonical correlation analysis. In this paper, the effect on the efficiency scores of input-output variables were investigated.

This methodology permits the joint graphical representation of models and DMUs, and thus it makes it possible to explain up to what point two models are equivalent, and if they are not equivalent, why they are not equivalent. The relationship between models and DMUs becomes clarified. By using CCA, the representations with the results of DEA techniques, it is possible to assess why a particular DMU achieves high efficiency scores under some models and low efficiency scores under other models. Extreme DMUs and models are easily identified. Finally, this method is guiding in model selection and also input-output combination selection.

CONFLICT OF INTEREST

No conflict of interest was declared by the authors

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