



## A Model for Ranking Efficient Division Making Units in the Situation of Nonlinear Factors ( Case Study: Islamic Land University )

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### Abstract

In various applications of Data Envelopment Analysis (DEA), their major role was to assess performance. One problem is how these may be used to determine factors that are beyond the control of a Division Making Units (DMU)'s managers. Another problem is the lack of discrimination in DEA scores, i.e., efficient DMUs are not included. The objective of this paper is to present a model for ranking efficient DMUs in the presence of nonlinearity factors. A case study demonstrates the application of the proposed model.

**Key words:** Data envelopment analysis; Ranking; Nonlinear factors; Stochastic factors; Division making units.

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## 2. Introduction

The Development Analysis (DEA)'s popularity (Charnes *et al.*, 1978, 1980) was developed by Banker *et al.* (1984, 1986, 1989). It is an approach for evaluating the efficiency of Decision Making Units (DMUs). Degree of super-efficient DEA models, i.e., efficiency score equal to one or efficient DMUs and frontier are inefficient DMUs. In an inefficient DMU's ranking is given that efficient DMUs are not its peers. One problem that has been discussed depends on the DMUs ranking because, for that the lack of discrimination in DMUs applications, in particular when there are multiple efficient DMUs in the number of inputs and outputs is too high relative to the number of DMUs. The constraints on ranking efficient DMUs can be divided into the following three categories (Charnes *et al.*, 1980, 1984, 1985):

In the first issue, the research was conducted by Banker *et al.* (1984). In order to rank DMUs, the ranking of DMUs was based on a super-efficiency. In the second issue, the ranking of DMUs efficient DMUs is based on benchmarking, an approach initially developed by Thompson *et al.* (1986, 1979, 1986). They concluded that a DMU was highly ranked if it was above a benchmark by other other inefficient DMUs. In the third issue, basically, the Färe and Grosskopf (1987, 1994) study, who extend the research to stochastic and multicriteria performance such as statistical variance analysis and stochastic analysis to rank both efficient and inefficient DMUs. To increase efficiency discrimination among DMUs, in some of the later on DMUs, there have been proposed DEA  $\alpha$ -cut-off efficiency frontier rank DMUs of input outputs vectors are using and defining one of the input outputs vectors (DMUs) as constant (Banker *et al.*, 1986, 1989, Charnes, 1990, 1993, 1995; Färe and Grosskopf *et al.*, 1988, 1990, 1992, 1993, 1994, 1995, 1996; Kao *et al.*, 1991, 1993, 1994; Kneafsey *et al.*, 1994, 1995; Kneafsey & Cho, 1994, 1995, 1996; Kneafsey, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011; Kneafsey & Johnson, 2000, 2001,

2002). The last, on the other popular, research areas is ranking DMUs in order super-efficiency. An advantage of super-efficiency method is the capability to rank both efficient and inefficient DMUs. Here is presented a review paper.

The research in this area was first developed by Anderson & Petersen (1983, 1984, 1985). They proposed the idea of modifying the constraints. Linear Programming (LP) formulation so that the corresponding values of the DMUs being scored is increased from the inefficient ones. They (1983, 1984) pointed out that the model developed by Anderson and Petersen (1983) may result in inactivity when some inputs are close to zero. Thus, to avoid the problem, Murty *et al.* (1989, 2000, 2001, 2002, 2003) and Ghosh and Sengupta (2000, 2001, 2002, 2003) proposed.

Anderson *et al.* (1986, 1987, 1988) proposed a method for ranking extreme efficient frontier using only inefficient DMUs with constant and variable returns to scale. They explained the disadvantages and limitations. Anderson *et al.* (1988, 1991, 1992) using linear form method developed a method which is able to rank an efficient DMUs and inefficient DMUs.

Anderson *et al.* (1989, 2000, 2001) introduced a method for ranking DMUs using convex set of weights (Kao, 1996). Anderson & Sengupta (1994, 1995) proposed a ranking method which basically differs from previous methods. In the ranking method, DMUs are compared against a full efficiency frontier. The method can be used to rank all DMUs to get relative information about the inputs, and also to rank only efficient DMUs (see Ghosh and Sengupta, 2000).

Anderson *et al.* (1990, 1992, 1993) described a new DEA ranking approach. In this, i.e., Kao, Anderson *et al.* (1988, 1989, 1990) introduced the technique used for ranking DEA model and constant returns to ranking is change when some inputs of some inefficient DMUs change without changing the change in the new Production Frontier) for (1990). They modified DEA model to the this problem without stage.

In order to obtain a complete ranking of efficient DMUs when the two objectives are related, Chen (2004, 2012) proposed a modified super-efficiency DEA model to enhance the identifying power and to correctly capture the super-efficiency represented by the input saving in the output space. Chen (2004, 2012) suggested using both super-oriented and input-oriented super-efficiency models to determine the super-efficiency characteristics.

Andriantiatsaholainaina *et al.* (2004, 2007) proposed a natural based on using global loss for ranking DMUs. Wang *et al.* (2004, 2007) developed two DEA models, one is based on virtual ideal frontier making (VIM) (2004) and the other is frontier cross-frontier (FCM) (Wang, 2007) (2004). The former shows DMUs using the best possible relative efficiency and can be used to identify DEA-efficient units, while the latter estimates DMUs using the best possible relative efficiency and can be used to identify those DEA inefficient units. The two relative efficiency can be improved using a relative efficiency index, which provides the overall performance assessment of each DMU relative to the best or the least of comparing and ranking DMUs.

Yuan *et al.* (2005, 2006) suggested a modification to BCC model and proved that the assumed weakly always feasible and the taking  $\lambda_i$  to 0.0, unlike the previous models, this model is both input and output oriented simultaneously.

Works introduced in my earlier literature have not yet completely dealt with nonhomogeneous inputs or outputs that are beyond the context of a DMU's management. How efficiency can be generalized?

Barrett and Zhou (2004, 2007) provided the first of these DEA models, by including the nonhomogeneous variables in the model and defining efficiency ratios in the discriminatory inputs only the through oriented version. Charnes, Banker and Morey's model can be considered as a standard model for the analysis of nonhomogeneous inputs or nonhomogeneous outputs in DEA. The new important advantage of Barrett and Zhou's model lies in the nonhomogeneous identification in

the case DEA programs of all the variables through a hierarchy.

Barrett *et al.* (2004) provided an alternative model by including the nonhomogeneous variables with separate the nonhomogeneous variables and used nonhomogeneous analysis to highlight the advantages of his model over the Barrett and Morey model. A weakness of Barrett's model was its tendency to identify DMUs as efficient by default on the number of homogeneous factors. Barrett, Barrett (2004, 2005) extended this model to allow multiple nonhomogeneous inputs. The model requires three steps and uses regression analysis to derive an aggregate index capturing the influence of the nonhomogeneous factors.

Wang *et al.* (2004, 2007) showed that applying additional measures to make a nonhomogeneous efficiency is equivalent to expansion of the homogeneous inputs with additional factors that are nonhomogeneous. Because intensity and nonhomogeneous efficiency are involved and defined.

To assess relative efficiency of 14 public providers, Liu (2004, 2011) utilized Barrett and Morey's model. Model (2004, 2007) provides an alternative three-stage model to assess the effect that nonhomogeneous inputs have on production. Like the first stage in Barrett (2004, 2005), this model considers only discriminatory inputs and outputs in the first stage. The model, however, focuses not only on the nonhomogeneous of efficiency but also the remaining data, the results after non-homogeneous properties in the second stage. Moreover, by using only DEA methods, it is the advantage that there is no need to assume any functional form in any of the steps.

Barrett (2004, 2007) analyzed the effect of nonhomogeneous efficiency and nonhomogeneous factors on identification of the two relative efficiency is separately combined with the nonhomogeneous inputs, by using DEA efficiency estimates, will be found upward fit, to effectively handle the problem, a correct measure is necessary.

Yuan (2004, 2012) showed the importance of nonhomogeneous factors and suggested a generalized model for

incorporating different types of inputs and outputs in DEA. In this respect, two approaches in the literature of stochastic nonconvexity factors are noteworthy, one proposed by Banker and Maini (1986), (1987) and the other by Coelli (1988), (1989) and Haganer (1988), (1989). The approaches were compared theoretically, on the basis of economic systems, and empirically, on the basis of examples and simulated data. To verify the properties of the different models, computationally, a generalized DEA model allowing for the possibility was proposed.

Paul & Sautter (1988, 1989) evaluated the performance of the conventional frontier of a large Canadian bank using DEA. They introduced nonconvexity factors to reflect specific aspects of the stochastic process in operating its, such as the real economy growth rate of the region. Banker and Maini (1986, 1987) have proposed a methodology for testing nonconvexity in DEA frontiers. Maini, Haganer & Coelli (1988, 1989) compared the performance of the various models that allow for nonconvexity factors. The research (1988, 1989) was by

including the alternative models developed by Maini (1987, 1989).

To the best of author's knowledge, there is not any reference that presents the model for testing efficient DMUs in the situation of nonconvexity factors. The objective of this paper is to propose a model which tests efficient DMUs in the situation of nonconvexity factors.

This paper presents a follow-up to Section 2, proposed model which tests efficient DMUs in the situation of nonconvexity factors is presented. Classification and sensitivity results are discussed in Section 3 and 4 respectively.

## 1. Background

Suppose that there is a set of a DMUs,  $(DMU_j)$ ,  $j = 1, 2, \dots, n$ , which produce multiple outputs  $y_1, y_2, \dots, r$  by utilizing multiple inputs  $x_1, x_2, \dots, m$ . In particular,  $DMU_j$ ,  $j = 1, 2, \dots, n$ , the amount of input  $i$ , is denoted by  $x_{ij}$ ,  $i = 1, \dots, m$ , the amount of output  $r$ , denoted by  $y_{rj}$  corresponding to  $DMU_j$ , the DMU score corresponding to the best DMU is denoted as follows:  $DMU^* = 1$  or  $DMU^* = 0$ .

$$\begin{aligned} \min \quad & w_0 + \beta \\ \text{s.t.} \quad & \sum_{j=1}^n \lambda_j x_{ij} \leq x_i + w_i \lambda, \quad i = 1, \dots, m \\ & \sum_{j=1}^n \lambda_j y_{rj} \geq x_r - w_r \lambda, \quad r = 1, \dots, R \\ & \lambda_j \geq 0, \quad j = 1, \dots, n \end{aligned} \quad (1)$$

where  $w_0$  and  $\beta$  are variables and  $\lambda$  is a scalar of size. Model (1) by decreasing inputs and increasing outputs of the DMU under consideration the equal data, input  $i$  on the domain. Simultaneous changes in input and output are equal to one because otherwise they are giving different preference to them, the problem becomes a multi-objective

programming one and hence yielding a complex program.

Since the inputs and outputs are not homogeneous and units of different functions in model (1) is dependent on the units of measurement of inputs and output data, and independence is allowed by normalization. E.g. dividing each input and output by the

types of flows as one of the techniques for reformulation.

In the literature, with respect to governmental advantages of Baker and Moore's model, Baker and Moore's reformulated model is a standard model for the solution of transportation-type problems (see Chao and Moore, 1988, p. 10-11).

Suppose that the supply variables may be partitioned into subsets of distinguishable (or indistinguishable) (or) variables. Thus,

$$S = \{S_1, \dots, S_m\} = S_1 \cup S_2 \cup \dots \cup S_p \cup S_{p+1} = \emptyset$$

When a DMR is under evaluation, then,

$$\begin{aligned} \max \quad & \sigma + \alpha \left( \sum_{i \in I} r_i + \sum_{j \in J} r_j \right) \\ \text{s.t.} \quad & x_i = \sum_{j \in J} x_{ij} \mu_j + C_i, \quad i \in I_{1, \dots, m} \\ & \theta_i = \sum_{j \in J} \theta_{ij} \mu_j - C_i, \quad i \in D \\ & z_i = \sum_{j \in J} z_{ij} \mu_j - C_i, \quad i \in N \\ & r_i = 0, \quad i \in N \\ & \mu_j \in [0, 1], \quad j \in I_{1, \dots, m} \\ & C_i \geq 0, \quad i \in I_{1, \dots, m} \\ & C_i \geq 0, \quad i \in I_{1, \dots, p} \end{aligned} \quad (2)$$

where  $\mu_j \in [0, 1]$  is value of DMR's loading, denoting "how greater" (or) the DMR being evaluated, the capacity  $C_i$  is needed (or) of supply  $r_i$  and  $C_i$  is excess demand (or)  $r_i$ .

The higher the value of objective function of problem (2), the less efficient the DMR.

By varying value of variable  $\alpha$  within the proposed model is presented as follows:

$$\begin{aligned} \text{max } & \varphi = \alpha_1 + (1 + \alpha_2) \left( \frac{1}{n} \sum_{i=1}^n x_i + \frac{1}{m} \sum_{j=1}^m y_j \right) \\ \text{st. } & \sum_{i=1}^n (x_i \mu_i + \alpha_3) + C = \alpha_4, & \forall i = 1, \dots, n \\ & \sum_{j=1}^m (y_j \mu_j + \alpha_3) + C = \alpha_5, & \forall j = 1, \dots, m \\ & \sum_{i=1}^n (x_i \mu_i + \alpha_3) + C = \alpha_6, & \forall i = 1, \dots, n \\ & \alpha_1 \geq 0, & \forall i = 1, \dots, n \\ & \mu_i \geq 0, & \forall j = 1, \dots, m \\ & \alpha_3 \geq 0, & \forall i = 1, \dots, n \\ & \alpha_4 \geq 0, & \forall i = 1, \dots, n \\ & \alpha_5 \geq 0, & \forall j = 1, \dots, m \\ & \alpha_6 \geq 0, & \forall i = 1, \dots, n \end{aligned} \quad (3)$$

The higher the value of objective function of model (3), the less efficient the EMH. Model (3) seeks efficient EMHs in the situation of multidimensional target.

#### 4. Case study

To apply the proposed model (3), records (reports of history taking) covering 1943 (in

Tehran county) was selected. In 1411, there are 7 emergency services (EMHs). Two reports and 2 important variables (Table 1) shows the data for inputs and outputs. Besides of patients, for each consultation, is a multidimensional target. Table 1 describes consultation data.

Table 1. Inputs and outputs (1943-1998)

EMH	Inputs		Outputs	
	Number of patients	Number of assistant physicians and higher	Number of patients	Number of published books
EMH1	171	17	1	1
EMH2	125	17	1	1
EMH3	115	15	1	1
EMH4	100	15	1	1
EMH5	100	14	1	1

Table 3. Normalized data set

DMU	Inputs		Outputs	
	Number of instructors	Number of students per instructor	Number of papers	Number of published books
Italy	20	1.0	1	1.0
Central Europe	20	1.0	1	1.0
Indonesia	20	1.0	1	1.0
South Africa	20	1.0	1	1.0
South Korea	20	1.0	1	1.0

In Table 3, the efficiency results by using model (3), have been displayed. Research outputs of Italy, Central Europe, and South Africa are efficient.

Table 4. Efficiency results

DMU	Efficiency
Italy	1
Central Europe	1
Indonesia	1
South Africa	0.77
South Korea	0.7

To rank efficient DMUs, model (4) has been used. In Table 5, the ranking results by using model (4), have been displayed. The research outputs have been ranked in increasing order of their objective values. As Table 4 shows, Central Europe is the most efficient research output.

Table 5. Final ranking

DMU rank	Research Output	Objective Value
1	Central Europe	1
2	Italy	1.001
3	Indonesia	1.002

## 5. Concluding remarks

Ranking efficient DMUs in the situation of nondisposability factors is one of the least applied topics. This paper proposed an alternative method for ranking efficient DMUs in the situation of nondisposability factors.

The authors consider the discussion as a useful stage of investigation and more further investigations be distributed on the results of this paper. Some references are follows:

Further research can be reported for the cases of input-output disposability and generally, testing efficient DMUs under disposability when some factors are nondisposability.

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