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Deriving Common Set of Weights in the Presence of the Undesirable Inputs: A DEA based Approach

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Abstract

Data Envelopment Analysis (DEA) as a non-parametric method for efficiency measurement allows decision making units (DMUs) to select the most advantageous weight factors in order to maximize their efficiency scores. In most practical applications of DEA presented in the literature, the presented models assume that all inputs are fully desirable. However, in many real situations undesirable inputs are part of the production process. In order to deal with undesirable inputs, this paper changes the undesirable inputs to be desirable ones by reversing, then a compromise solution approach is proposed to generate a common set of weights under DEA framework. The DEA efficiencies obtained with the most favorable weights to each DMU are treated as the target efficiencies of DMUs. Based on the generalized measure of distance, three types of DEA-based efficiency score programming can be derived. The proposed approach is then applied to real-world data set that characterize the performance of seven types of chemical activities.

Keywords: Data Envelopment Analysis (DEA), Efficiency, Undesirable Input, Compromise solution.

1. Introduction

Data Envelopment Analysis (DEA) is a non- parametric technique for evaluating the relative efficiency of a set of homogeneous decision making units (DMUs) by using a ratio of the weighted sum

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of outputs to the weighted sum of inputs. Specifically, it determines a set of weights such that the efficiency of a target DMU relative to the other DMUs is maximized. This flexibility in the selection of input and output weights often causes more than one DMU being evaluated as efficient, leading to them being unable to be fully discriminated. As the methods of DEA are run for each DMU separately, the set of weights will typically be different for the various DMUs. Also, in some cases it may be considered unacceptable that the same factor is accorded widely different weights. A possible answer to this difficulty lies in the specification of a common set of weights (CWS). To derive a common set of weights for DMUs, a number of approaches have been proposed in the DEA literature. For example, Kao and Hwang [7] proposed the compromise solution approach to generate a common set of weights for all DMUs. The efficiency scores calculated from the standard DEA model is the ideal solution for each DMU to achieve. The common set of weights which is able to produce a vector of efficiency scores closest to the ideal solution is desired. This vector of efficiency scores is called the compromise solution. Based on the generalized measure of distance, a family of compromise solutions with parameter p, $1 < p < \infty$, can be generated. As another method, Roll and Golany[10] suggested a method including running a general unbounded DEA model to obtain different sets of weights and then taking their average or weighted average with DEA efficiencies as the weights, maximizing the average efficiency of DMUs and assigning low weights to less important factors and maximal feasible weights to important ones. Chen et.al [4] proposed a linear multi –criteria programming which can be boil down to a single-objective linear programming by combining the DEA and the compromise solution programming. Zohrebandian et.al [12] presented a multi-objective linear programming to generate the common weights. Also see Belton and Vickers [2] and Li and Reevese [8].in all above mentioned literatures multiple desirable inputs were applied to generate multiple outputs. However, in some real occasions, both desirable and undesirable inputs may be applied. The most important example of undesirable inputs returns to recycled system process. The garbage can be considered as undesirable inputs which need to be reconstituted and re-entered to production process. The existing DEA researches mainly deal with undesirable outputs in four different divisions. The first group is hyperbolic measure approach, a non-linear DEA model introduced by Fare et.al [6] using reciprocal measure to evaluate the efficiency of undesirable outputs. Seiford ad Zhu [11] changed the undesirable outputs to be positive desirable outputs by a linear monotone decreasing transformation. The last one is directional distance function approach which is proposed by Chung et.al [5]. This approach evaluates and improves DMUs' efficiency according to the given direction. The researchers have made some contributions to deal with undesirable outputs into DEA models. However, analysts are sometimes interested in additionally estimating the weights in presence of undesirable inputs. In this paper we aim to search one common set of weights to estimate the absolute efficiency of each DMU if undesirable inputs are used in production process. The method for selecting common set of weights is based on the approach presented by Kao and Hwang [8].

The structure of this paper is organized as follows. In the next section we shall introduce standard DEA model with presence of undesirable inputs. In the section to follow the compromise solution for generating common set of weights under the DEA framework with undesirable inputs will be applied. Then a real-world problem is solved by the compromise solution approach to show that the developed models can illustrate the evaluations. Conclusions are offered in section 5.

2. DEA Frameworks

Consider a set of DMUs indexed by J . For all $j \in \{1,...,n\}$, DMU_j uses inputs x_{ij} $(i=1,...,M)$ to produce outputs y_{rj} $(r=1,...,S)$. Also, for each $j \in J$ $X_j > 0$ and $Y_j > 0$. The input-oriented technical efficiency of DMU_o , $o \in \{1,....,n\}$ can be measured by the BCC model below Banker et.al., 1984) [1].

$$
\begin{aligned}
& Min \quad \theta \\
& s.t. \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io} \quad , i = 1,...,M, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro} \quad , r = 1,....,S, \qquad\qquad (1) \\
& \sum_{j=1}^{n} \lambda_j = 1 \ , \\
& \lambda_j \ge 0 \ \ j = 1,...,n
\end{aligned}
$$

The model (1) tries to focus on each individual DMU to select the weights attached to the inputs and outputs, and to locate the envelopment surface. A set of weights for the inputs and outputs is determined by the BCC program to show each DMU in its most favorable light as long as the efficiency scores of all $DMUs$ calculated from the same set of weights do not exceed unity. The dual formulation of model (1) is as follows:

$$
\begin{aligned}
& Max \quad \sum_{r=1}^{S} u_r y_{ro} - u_o \\
& s.t. \\
& \sum_{r=1}^{S} u_r y_{rj} - \sum_{i=1}^{M} v_i x_{ij} - u_o \le 0 \quad , \ j = 1,\dots,n, \\
& \sum_{i=1}^{M} v_i x_{io} = 1 \ , \\
& u_r, \ v_i \ge 0 \quad , r = 1,\dots,S \ \ , i = 1,..,M \\
& u_o \ \text{ is free in sign}
\end{aligned}
\tag{2}
$$

Applying model (2) each DMU is allowed to select the most advantageous weights for maximizing its efficiency score. Thus, the resulting score is the best attainable efficiency level for each DMU. In fact, the linear model above is an equivalent form of the following fractional model. That is to say, applying Charnes-Cooper transformation [2], model (2) is attained. The fractional model is as follows:

$$
\begin{aligned}
& Max \quad \frac{\sum_{r=1}^{S} u_r y_{ro} - u_o}{\sum_{i=1}^{M} v_i x_{io}} \\
& s.t. \\
& \frac{\sum_{r=1}^{S} u_r y_{rj} - u_o}{\sum_{i=1}^{M} v_i x_{ij}} \le 1 \ , \ j = 1,\dots,n, \\
& u_r, \ v_i \ge 0 \quad , r = 1,\dots,S \ \ , i = 1,..,M \\
& u_o \ \text{ is free in sign}
\end{aligned}
\tag{3}
$$

3. Compromise weight solution with undesirable inputs

As far as we are aware, the standard CCR and BCC model assume that all inputs and outputs can be taken real –valued quantities. Also all consumed inputs and produced outputs are assumed desirable. However, in some real occasions, there are undesirable inputs. For example, in garbage recycling, trash can be considered as an undesirable input. Assume that each DMU_j consumes M desirable inputs x_{ij} $(i = 1,\dots.,M)$ and K undesirable inputs as $\bar{x}_{tj}\,(t = 1,\dots,K)$ to generate S outputs as y_{rj} $(r = 1,\dots,S)$ In order to tackle the efficiency measurement of DMU_o, according to Seiford and Zhu [11], the following model can be presented:

$$
\begin{aligned}
&\theta_o = Min \quad \theta \\
&s.t. \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io} \quad , i = 1,\dots, M, \\
&\sum_{j=1}^{n} \lambda_j \bar{x}_{tj} \le \theta \bar{x}_{to} \quad , t = 1,\dots, K, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro} \quad , r = 1,\dots, S, \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&\lambda_j \ge 0 \quad , j = 1,\dots, n
\end{aligned} \tag{4}
$$

In which $\bar{x}_{tj} = -x_{tj} + v$, and v is a chosen vector such that $\bar{x}_{tj} > 0$ for all $j = 1,\dots, n.$

Definition1: The optimal value of problem model (4) is called the efficiency index of DMU_o. if θ_o= 1 we say DMU_o is (at least) weakly efficient.

Considering the dual format of model (4), we have the following linear problem:

$$
\begin{aligned}
&Max \quad \sum_{r=1}^{S} u_r y_{ro} - u_o \\
&s.t. \\
&\sum_{i=1}^{M} v_i x_{io} + \sum_{t=1}^{K} \gamma_t \bar{x}_{to} = 1 \\
&\sum_{r=1}^{S} u_r y_{rj} - \sum_{i=1}^{M} v_i x_{ij} - \sum_{t=1}^{K} \gamma_t \bar{x}_{tj} - u_o \le 0 \quad j = 1,\dots, n \\
&u_r, v_i, \gamma_t \ge 0 \ \text{ for all } r, i, t \\
&u_o \ \text{ is free in sign}
\end{aligned} \tag{5}
$$

The fractional format of model (5) can be rewritten as follows:

$$
\begin{aligned}
&E_O^* = Max \ \frac{\sum_{r=1}^{S} u_r y_{ro} - u_o}{\sum_{i=1}^{M} v_i x_{io} + \sum_{t=1}^{K} \gamma_t \bar{x}_{to}} \\
&s.t. \\
&\frac{\sum_{r=1}^{S} u_r y_{rj} - u_o}{\sum_{i=1}^{M} v_i x_{ij} + \sum_{t=1}^{K} \gamma_t \bar{x}_{tj}} \le 1 \quad , \quad j = 1,\dots, n \\
&u_r, v_i, \gamma_t \ge 0 \ \text{ for all } r, i, t \\
&u_o \ \text{ is free in sign}
\end{aligned} \tag{6}
$$

Suppose that the optimal solution of model (6) is denoted by $(U^*, V^*, \gamma^*, u_o^*)$. The objective function of model (6) tries to determine the efficiency under the constraints that the efficiency score of all units are less than or equal to one when the same weights are applied. The optimal objective value of model (6) denoted by $E_o^* = \dfrac{\sum_{r=1}^{S} u_r^* y_{ro} - u_o^*}{\sum_{i=1}^{M} v_i^* x_{io} + \sum_{t=1}^{K} \gamma_t^* \bar{x}_{to}}$. This value is the best attainable efficiency level for DMU_j . Any other set of weights would result in an efficiency score which is less than or equal to E_O^*.

Definition 2. DMU_o Is said to be efficient if the objective value of model (6) is unity, $E_o^* = 1$.

In order to generate a common set of weights for all $DMUs$, we can consider $E^* = (E_1^*, E_2^*, .., E_n^*)$ as target vector or ideal solution to achieve. MOLP program can be proposed to achieve the closest weights to the ideal vector. Consequently, in presence of undesirable input a common set of weights can be achieved from the following model:

$$Max \quad \frac{\sum_{r=1}^{S} u_r y_{r1} - u_o}{\sum_{i=1}^{M} v_i x_{i1} + \sum_{t=1}^{K} \gamma_t \bar{x}_{t1}}$$

$$Max \quad \frac{\sum_{r=1}^{S} u_r y_{r2} - u_o}{\sum_{i=1}^{M} v_i x_{i2} + \sum_{t=1}^{K} \gamma_t \bar{x}_{t2}}$$

.

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$$Max \quad \frac{\sum_{r=1}^{S} u_r y_{rn} - u_o}{\sum_{i=1}^{M} v_i x_{in} + \sum_{t=1}^{K} \gamma_t \bar{x}_{tn}}$$

$$s.t$$

$$\frac{\sum_{r=1}^{S} u_r y_{rj} - u_o}{\sum_{i=1}^{M} v_i x_{ij} + \sum_{t=1}^{K} \gamma_t \bar{x}_{tj}} \le 1 \quad j = 1, \ldots, n \qquad (7)$$

$$u_r, v_i, \gamma_t \ge 0 \quad \text{for all } r, i, t$$

$$u_o \quad \text{is free in sign}$$

In order to solve the MOLP program, the proposed approach by Kao and Hung [8] seems acceptable. The proposed compromise method determine the closest distance between E_j^* and the efficiency value attainable calculated from the common weights denoted as the vector $E(u,v,\gamma)$. The program can have the following format:

$$
\begin{aligned}
& Min \ \left(\sum_{j=1}^{n} \left(E_j^* - \frac{\sum_{r=1}^{S} u_r y_{ro} - u_o}{\sum_{i=1}^{M} v_i x_{io} + \sum_{t=1}^{K} \gamma_t \bar{x}_{to}}\right)^p\right)^{\frac{1}{p}} \qquad 1 \le p \le \infty \\
& s.t. \\
& \frac{\sum_{r=1}^{S} u_r y_{rj} - u_o}{\sum_{i=1}^{M} v_i x_{ij} + \sum_{t=1}^{K} \gamma_t \bar{x}_{tj}} \le 1 \qquad j = 1,\dots,n \qquad\qquad (8) \\
& u_r, v_i, \gamma_t \ge 0 \qquad \text{for all } r,i,t \\
& u_o \ \text{is free in sign.}
\end{aligned}
$$

In the model above E_j^* is the ideal or target efficiency score obtained from model (6). In model (8) for the smallest value of $p = 1$, every deviation $E_j^* - E_j$ is weighted equally. As p increases, more weights are given to the larger deviations. There are three values of p, viz., $p = 1,2$ and ∞, which have special mathematical properties and worthy of some discussion. For different values of p, three compromise solution approaches with undesirable inputs are achieved.

1. If $p = 1$, model (8) is referred to as a city block measure of distance. In other words, model (8-1) finds a set of weights that results in the minimal total deviation between $E_j(u,v,\gamma)$ and E_j^*. The model has the formulation as follows:

$$
\begin{aligned}
& Min \ \left(\sum_{j=1}^{n} \left(E_j^* - \frac{\sum_{r=1}^{S} u_r y_{ro} - u_o}{\sum_{i=1}^{M} v_i x_{io} + \sum_{t=1}^{K} \gamma_t \bar{x}_{to}}\right)\right) = Min \quad \sum_{j=1}^{n} (E_j^* - E_j(u,v)) \\
& s.t. \\
& \frac{\sum_{r=1}^{S} u_r y_{rj} - u_o}{\sum_{i=1}^{M} v_i x_{ij} + \sum_{t=1}^{K} \gamma_t \bar{x}_{tj}} \le 1 \qquad j = 1,\dots,n \qquad\qquad (8\text{-}1) \\
& u_r, v_i, \gamma_t \ge 0 \qquad \text{for all } r,i,t \\
& u_o \ \text{is free in sign.}
\end{aligned}
$$

Since $\sum_{j=1}^{n} E_j^*$ is a constant, it has no effect on the optimal solution (u,v,γ). Thus the objective function is equivalent to $Min \ \sum_{j=1}^{n} E_j(u,v,\gamma)$.

2. If $p=2$, the objective function of model (8) is to find the set of weights (u,v,γ). which results in the shortest distance between $E_j(u,v,\gamma)$ and E_j^*. Thus it suffices to solve the following programming:

$$
\begin{aligned}
& Min \ \sum_{j=1}^{n} (E_j^* - \frac{\sum_{r=1}^{S} u_r y_{ro} - u_o}{\sum_{i=1}^{M} v_i x_{io} + \sum_{t=1}^{K} \gamma_t \bar{x}_{to}})^2 \\
& s.t. \\
& \frac{\sum_{r=1}^{S} u_r y_{rj} - u_o}{\sum_{i=1}^{M} v_i x_{ij} + \sum_{t=1}^{K} \gamma_t \bar{x}_{tj}} \le 1 \quad j=1,\ldots,n \qquad\qquad (8\text{-}2) \\
& u_r, v_i, \gamma_t \ge 0 \quad \text{for all } r,i,t \\
& u_o \text{ is free in sign.}
\end{aligned}
$$

As the model presents the constraints can be rewritten in the linear format as $\sum_{r=1}^{S} u_r y_{rj} - \sum_{i=1}^{M} v_i x_{ij} - \sum_{t=1}^{K} \gamma_t \bar{x}_{tj} - u_o \le 0 \quad , \ j=1,\ldots,n$, but the objective function is nonlinear. For $p=\infty$, the objective is reduced to minimize the maximum of individual deviations. So, model (8) can be transformed into the following programming:

$$
\begin{aligned}
& Min \ \ z \\
& s.t. \\
& E_j^* - (\frac{\sum_{r=1}^{S} u_r y_{rj} - u_o}{\sum_{i=1}^{M} v_i x_{ij} + \sum_{t=1}^{K} \gamma_t \bar{x}_{tj}}) \le z \quad j=1,\ldots,n \\
& \qquad \frac{\sum_{r=1}^{S} u_r y_{rj} - u_o}{\sum_{i=1}^{M} v_i x_{ij} + \sum_{t=1}^{K} \gamma_t \bar{x}_{tj}} \le 1 \qquad\qquad (8\text{-}3) \\
& u_r, v_i, \gamma_t \ge 0 \quad \text{for all } r,i,t \\
& u_o \text{ is free in sign.}
\end{aligned}
$$

For $p = \infty$, the objective function means that the maximal dissatisfaction of the DMUs is decreased to be minimal. However, it is better to investigate all three values of p and make a subjective judgment. Top of all, $p = 2$ seems to be better choice, because the objective function indicates the conventional Euclidean distance between the ideal target E^* and $E_j(u, v, \gamma)$. Also from the statistical point of view this deviation has the smallest variance.

4. Numerical Example

The applicability of the proposed approach is illustrated by an empirical data set consisting of seven DMUs. In order to investigate the effect of temperature on chemical instances, each unit uses two sets of inputs: desirable and undesirable to produce two categories of outputs. Desirable inputs includes ionic liquid and undesirable inputs consists of temperature. What's more, higher temperature seems more acceptable during experiment. The outputs characterized as time (calculated per min) and the percentage of the material which yielded. Applying model (6), BCC fractional model, the efficiency scores are obtained. Table (1) summarizes the date set.

Table1: The Chemical Data Set

DMU	Desirable Input	Undesirable Input	Output1	Output2
1	0	40	240	56
2	5	25	75	65
3	3	40	30	75
4	10	40	10	96
5	10	25	40	89
6	10	55	8	90
7	15	40	15	88

Employing $v = 10$ to corresponding component in undesirable inputs, Table (2) presents the efficiency scores by Model (6). What's more, this score is used as ideal or target vector in different distance estimations.

Table2: The results for BCC model

DMU	1	2	3	4	5	6	7
E_o^*	1	0.16	0.29	0.39	1	0.43	1

It can be seen that in presence of undesirable inputs, three DMUs are satisfied in efficiency definition. That is, their efficiency scores are unity. The objective is to find such compromise weights for both desirable and undesirable inputs to be closest to the ideal solution vector E_o^*. To determine the degree of closeness, three distance measure are used to indicate the compromise weights. In Model (8) p represents the distance parameter. For $p = 1$, the deviation $E_j^* - E_j$ is weighted equally. Hence model (8) boils down to model (8-1). For $p = 2$, the objective is to find the set of weights which results in shortest distance between E^2 and E^* in the conventional Euclidean space. To solve model (8) for $p = 2$, it suffices to solve model (8-2). For $p = \infty$, the objective is to minimize the maximum of individual deviations. Hence model (8) can be transformed to model (8-3). The most prominent characteristic features of these models is to allow each unit to select the most favorable weights in calculating efficiency under the envelopment constraints. What's more, referring to decision maker, every distance measure can be selected to reflect the shortest deviation in each point of view. Table (3) reports the results of utilizing the three proposed model to data set of Table (1). Likewise, selects the results in Table (2) as ideal vector to compromise.

Table (3): Efficiency scores calculated from different methods of common weights

DMU	E_o^*	Model(8-1)	Model(8-2)	Model(8-3)
		$p = 1$	$p = 2$	$p = \infty$
1	1	10.1318(1)	8.3332(1)	1.9845(1)
2	0.16	4.2518(7)	5.0760(7)	1.1445(7)
3	0.29	5.1618(6)	5.7474(6)	1.2745(6)
4	0.39	5.8618(5)	6.1940(5)	1.3745(5)
5	1	10.1318(2)	8.3332(2)	1.9845(2)
6	0.43	6.1418(4)	6.3612(4)	1.4145(4)
7	1	10.1318(3)	8.3332(3)	1.9845(3)

The associated ranking calculated from three different methods of common weights are shown in parenthesis. As Table (3) presents efficiency score calculated from Model (8-1) the largest efficiency score is obtained (10.1318), whereas, Model (8-2) and Model (8-3) have smaller values of 5.0760 and 1.1445. However, there is no differences between efficient units but also detect some information in presence of undesirable inputs. The common set of weights generated from these three models are shown in Table (4).

Table (4): Common set of weights from different models

Method	Desirable Input	Undesirable Input	Output 1	Output 2
Model(8-1)	0.0100	0.0100	0.0100	0.0591
Model(8-2)	0.0100	0.0100	0.0100	0.0591
Model(8-3)	0.0617	0.0239	0.0100	0..684

As Table (4) shows the resultant weights are same for Model (8-1) and Model (8-2). However, they reflect the technical rates of substitution, but the results are same. As Kao and Hwang [8] argues it is inappropriate to say which weights are correct and which are not. Also, the ranking of these three models are consistent with those of the BCC model, indicating that the results are reasonable. The compromise solution approach of Model(8) is to use different distance measures to generate a linear production frontier such that the efficiency scores of the DMUs calculated from this production frontier are closest to the target efficiency scores.

5. Conclusion

Standard DEA models suffers flexibility in selecting weights for inputs and outputs in calculating the efficiency scores. This shortcoming of this flexibility highlights when it hampers a common base for comparison in presence of undesirable inputs. This paper researches one common set of weights that is the most favorable for determining the absolute efficiency for DMUs in presence of undesirable inputs. The paper proposes the compromise solution approach to generate a common set of weights for all DMUs. Based on generalized measure of distance, three DEA-based model are generated to obtain a common set of weights. The practical application of this methodology is aimed at evaluating a group of DMUs characterizes the performance of 7 real-chemical activities with undesirable inputs.

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