Ecological Indicators 51 (2015) 59–66

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Closest targets in environmental efficiency evaluation based on enhanced Russell measure

Qingxian An [a,b], Zhiqiang Pang [c,*], Haoxun Chen [b], Liang Liang [a]

[a] School of Management, University of Science and Technology of China, Hefei 230026, China
[b] Industrial Systems Optimization Laboratory, Charles Delaunay Institute and UMR CNRS 6281, University of Technology of Troyes, Troyes 10004, France
[c] School of Statistics, Lanzhou University of Finance and Economics, Lanzhou 730020, China

ARTICLE INFO

Article history:
Received 27 April 2014
Received in revised form 27 August 2014
Accepted 1 September 2014

Keywords:
Environmental efficiency
Closest target
Data envelopment analysis
Enhanced Russell measure

ABSTRACT

As environmental problems become more and more serious all over the world, environmental efficiency evaluation has drawn increasing interests of many scholars and governments' decision makers. Data envelopment analysis (DEA) as a non-parametric approach for evaluating the relative efficiency of a group of decision making units (DMUs) has been widely extended and applied in many areas. Among various DEA models, enhanced Russell measure (ERM) model can measure the inefficiencies from input orientation and output orientation simultaneously. In this paper, we proposed a new non-orientation DEA approach based on enhanced Russell measure for measuring the environmental efficiency of a DMU and meanwhile, provided the closest target for the evaluated DMU to efficient with less effort. At last, our approach was applied to a practical example about thermal power enterprises. The results show that our model can provide a much easier way for the inefficient enterprises to improve their efficiencies than the enhanced Russell measure method. Moreover, the provided benchmarks for enterprises through our model can be used to further rank the efficient ones.

1. Introduction

Data envelopment analysis (DEA) is a programming based technique for measuring the relative efficiency of a group of homogenous decision making units (DMUs) (Cook and Seiford, 2009). It does not require assumptions on the production function form and can well measure the efficiency of a system with multiple inputs and multiple outputs. Besides, it can provide the benchmarking information for the DMUs, which plays a vital role in practice because this information show keys for inefficient DMUs to improve their performance. So far, DEA has been extensively applied in many areas, such as schools, hospitals, banks, transportations and so on (Nicky, 2012 Zhu, 2014). The first DEA model was proposed by Charnes et al. (1978), so it is also known as CCR model. Then, another important DEA model, BCC model, was proposed by Banker et al. (1984) under the assumption of variable returns to scale. Many works are developed based on these two models, see Cook and Seiford (2009) and Zhu (2014). These traditional DEA models are either input-oriented or output-oriented, which measure the efficiency of the evaluated DMU from either input side or output side. Färe and Lovell (1978) proposed an efficiency measure to provide a solution to this problems, which was later widely called "Russell measure" for R.R. Russell, who subsequently contributed to its further development in Russell (1988, 1990). Russell measure model simultaneously minimizes the input efficiency measure and maximizes the output inefficiency measure. The original Russell measure model is non-linear programming, Sueyoshi and Sekitani (2007) proposed a reformulation of the Russell measure by a second-order cone programming (SOCP) model and applied the primal-dual interior point algorithm to solve the Russell measure. Even though this algorithm can solve the problem, it is complicated. Moreover, Cooper et al. (1999) expressed that this measure cannot be easily understood because Russell measure is a weighted average of arithmetic and harmonic means. Pastor et al. (1999) extended the Russell measure model and built an enhanced Russell measure model (ERM). These Russell measure models can well discriminate the efficient and inefficient DMUs, but they usually bring the farthest target for the evaluated DMU to be efficient. Because of this, ERM cannot give a reasonable target for the evaluated DMUs in some scenarios. We will illustrate this in details through a practical example in Section 4.

Meanwhile, the issue of finding the closest targets for DMUs to be efficient has attracted increasing interests of many scholars in DEA area. There are two ways for finding the closest targets, one is minimizing the selected distance and the other one is minimizing

* Corresponding author. Tel.: +86 13893603765.
E-mail address: zqpanglufe@126.com (Z. Pang).

http://dx.doi.org/10.1016/j.ecolind.2014.09.008
1470-160X/

(or maximizing) the chosen efficiency measure. In the former category, Frei and Harker (1999) gave the closest targets by minimizing the Euclidean distance to the efficient frontier. Furthermore, Baek and Lee (2009), Amirteimoori and Kordrostami (2010) and Aparicio and Pastor (2014a) applied the weighted versions of the Euclidean distance to obtain the closest targets. Gonzalez and Alvarez (2001) minimized the sum of input contractions required to reach the frontier of the technology so as to gain the relative targets in the context of input-oriented technical efficiency assessment. Portela et al. (2004) determined the targets for the DMUs through a directional distance function approach. Jahanshahloo et al. (2012) presented a method for obtaining the minimum distance of DMUs from the frontier of the PPS by $||\bullet||_1$. Briec and Lemaire (1999), and Briec and Leleu (2003) used Hölder distance functions to obtain the evaluated DMU's minimum distance to the frontier. Ando et al. (2012) pointed out that least distance measures based on Hölder norms meet neither weak nor strong monotonicity on the strongly efficient frontier and further provided a method to guarantee the function is weak monotonicity. Recently, two important works were given to provide a measure that satisfies the strong monotonicity property. Aparicio and Pastor (2014b) provided a solution for output-oriented models based on an extended production possibility set which is strongly monotonic and suggested by Lim and Zhu (2013) and Räty (2002). Another work is Fukuyama et al. (2014), who applied least distance p-norm inefficiency measures that satisfy strong monotonicity over the strongly efficient frontier to obtain the targets. In the latter category, Silva et al. (2003) maximized the BRWZ measure proposed by Brockett et al. (1997) to obtain the closest targets. Aparicio et al. (2007) and Aparicio and Pastor (2013) proposed several mathematical programming problems to find the closest targets where efficiency measure (such as range adjusted measured, Russell measure) was chosen as the criterion of similarity. These programming problems, which are easily solved, can guarantee the evaluated DMU to reach the closest projection point on the Pareto-efficient frontier.

Furthermore, the pollutions, waste and other undesirable outputs are usually produced in the production. So far, in DEA literature, there are mainly three categories of methods for addressing the undesirable outputs. The first one is based on the weakly disposable assumption of undesirable outputs which was firstly mentioned in the work of Färe et al. (1989). In this category, undesirable outputs are treated in their original forms under this assumption. For some extensions on this method, see Färe et al. (2005) and Zhou et al. (2012). The second category is based on strong disposable assumption of undesirable output. Two ways for treating undesirable outputs under this assumption are given. One way treats undesirable outputs as inputs for processing (Hailu and Veeman, 2001; Mahlberg and Sahoo, 2011; Macpherson et al., 2013; Wu et al., 2014), which only requires the information on whether the output is desirable or undesirable. This way can provide the shadow price of undesirable outputs (Hailu, 2003). The other way is transformation way which contains a non-linear monotonic decreasing transformation (Scheel, 2001) or a linear monotonic decreasing transformation (Seiford and Zhu, 2002). Scheel (2001) treated the reciprocal of undesirable outputs as DEA outputs. Seiford and Zhu (2002) suggested undesirable outputs by adding a big enough positive scalar to the opposite additive transformation of the undesirable outputs. The third category is a ratio model based on penalty index proposed by You and Yan (2011). In their model, the undesirable outputs are not treated as both inputs and outputs. A penalty index is used instead of undesirable outputs. The new outputs of the system are formed by the desirable outputs divided by the penalty index. It should be noted that each way has its own strengths and weaknesses, and all of them can be used to address the undesirable outputs as long as they reflect the meaningful economic trade-offs among undesirable outputs, desirable outputs and inputs, that is, one cannot reduce undesirable outputs for free. In this paper, the strong disposable assumption of undesirable outputs is chosen for building the new models because it is easily understood and also widely used in DEA literature.

Even many closest targets methods have been proposed, however, no closest targets model is proposed based on the enhanced Russell measure which has a remarkable advantage in evaluating the efficiency of decision making units. As providing the closest targets is very meaningful for guiding the DMUs to achieve the efficient status, this paper combines enhanced Russell measure and closest targets for the first time to form a new approach for measuring the environmental efficiency and providing the closest targets.

This paper unfolds as follows: in Section 2, we will briefly review Russell measure model and enhanced Russell measure model. In Section 3, we will extend enhanced Russell measure model in the presence of undesirable output for discriminating the efficient and inefficient DMUs. Then, based on these efficient DMUs, the closest target model will be built, which combines the ERM and closest targets method to obtain the benchmarks for the DMUs and the environmental efficiency based the closest targets. An empirical example about thermal power enterprises will be analyzed by our approach in Section 4. Finally, Section 5 will summarize the findings and implications of this study.

2. Enhanced Russell measure

Assume that there are a set of n DMUs, and each DMUj, (j = 1, 2, ..., n) produces s different outputs using m different inputs which are denoted as y_{rj} (r = 1, 2, ..., s) and x_{ij} (i = 1, 2, ..., m), respectively. Denote input vector of DMUj by x_j and output vector of DMUj by y_j.

The Russell measure of technical efficiency is a non-orientation efficiency measure firstly proposed by Färe and Lovell (1978), where it was expressed by a combination of the input and output measures of technical efficiency. Because of the computational and interpretative difficulties of Russell measure model, Pastor et al. (1999) built an enhanced Russell measure model for measuring the efficiency, shown as follows:

$$\begin{aligned}
&E_{\mathrm{CRS}} = \min \frac{1/m\Sigma_{i=1}^{m}\alpha_i}{1/s\Sigma_{r=1}^{s}\beta_r}\\
&s.t.\sum_{j=1}^{n}\lambda_j x_{ij} \le \alpha_i x_{i0},\\
&0 \le \alpha_i \le 1, i = 1, \ldots, m.\\
&\sum_{j=1}^{n}\lambda_j y_{rj} \ge \beta_r y_{r0},\\
&\beta_r \ge 1, r = 1, \ldots, s.\\
&\lambda_j \ge 0, j = 1, \ldots, n.
\end{aligned} \tag{1}$$

E_{CRS} is the efficiency of DMU0. When it is equal to 1, DMU0 is an efficient DMU. When the value is smaller than 1, DMU0 is an inefficient DMU. α_i means that how much proportion the ith input should reduce to. β_r means that how much proportion the rth output should increase to. λ_j stands for unknown variables (often referred to as "structural" or "intensity" variables) for connecting the input and output vectors by a convex combination. In this model, it is implicit that y is desirable output. All efficient DMUs form the efficient production frontier. This model is under the assumption of constant returns to scale (CRS) and its production possibility set (PPT) is $T_{\mathrm{CCR}} = \left\{(x, y)|\Sigma_{j=1}^{n}\lambda_j x_j \le x, \Sigma_{j=1}^{n}\lambda_j y_j \ge y\right\}$. Referring to the CRS technology, we can easily extend this model to non-decreasing, non-increasing and variable returns to scale assumptions (respectively, NDRS, NIRS and VRS) by adding $\Sigma_{j=1}^{n}\lambda_j \le 1, \Sigma_{j=1}^{n}\lambda_j \ge 1$ and $\Sigma_{j=1}^{n}\lambda_j = 1$ in the constraints of Model (1), respectively. Through Charnes–Cooper transformation