Socio-Economic Planning Sciences 48 (2014) 169–174

Contents lists available at ScienceDirect

Socio-Economic Planning Sciences

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

An application of data envelopment analysis to evaluate the efficiency level of the operational cost of Brazilian electricity distribution utilities

Marcus Vinicius Pereira de Souza [a,*], Reinaldo C. Souza [c], José Francisco M. Pessanha [b], Carlos Henrique da Costa Oliveira [a], Madiagne Diallo [c]

[a] CEFET/RJ – Centro Federal de Educação Tecnológica Celso Suckow da Fonseca – UnED Angra dos Reis/RJ, Brazil
[b] UERJ – Universidade do Estado do Rio de Janeiro, Brazil
[c] PUC-Rio – Pontifícia Universidade Católica do Rio de Janeiro, Brazil

ARTICLE INFO

Article history:
Available online 12 April 2014

Keywords:
Data envelopment analysis
Weight restrictions
Influential observations
Economic regulation

ABSTRACT

This paper shows efficiency indices for 60 Brazilian electricity distribution utilities. The efficiency scores are gauged by three DEA models. For both models, these quantities are evaluated under different contexts. One treats with respect to the regulator perspective. The others examine an alternative approach based on cluster analysis and restrictions on factor weights. It is worth pointing out that these developments can reduce the information asymmetry and improve the regulator's skill to compare the performance of the utilities, a fundamental in incentive regulation schemes.

1. Introduction

For many years, the Brazilian Electrical Sector (SEB) had natural monopolistic features. However, since the mid-1990s, the National Electrical Energy Agency (ANEEL), responsible to determine the regulatory reforms in the SEB, has implemented profound restructuring whose goals are, for example, to provide efficiency improvement of the transmission and distribution sectors as well as the introduction of a competitive market in electricity trading activities.

Taking into account the previous consideration, it is worth mentioning that the supply of energy tariffs is periodically revised within a period of 4 to 5 years, depending on the distributing utility contract. On the very year of the periodical revision, the tariffs are brought back to levels compatibles to its operational costs and to guarantee the adequate payback of the investments made by the utility, therefore, maintaining its Financial and Economical Equilibrium (EEF).

In agreement with the above, in the first cycle of tariff revisions in Brazil, the ANEEL adopted the methodology of "Reference Utility" which starts with the identification of all processes related to the activities of a distribution utility considering the commercial and technical aspects, then moves to the definition of the efficient costs to each one of these processes and ends with an estimate for the total efficient costs [4,5]. Therefore, it constitutes a complex approach and clearly open opportunities to the regulator to get involved in a kind of micro-management of the utility under revision, which is not at all recommended as a good regulation practice.

To avoid the complexity of the "Reference Utility" approach and in order to produce an objective way to obtain efficient operational costs, ANEEL envisages the possibility of using benchmarking techniques, among them, the efficient frontier method, as adopted by the same ANEEL to quantify the efficient operational costs of the Brazilian transmission lines utilities [6]. The frontier is the geometric locus of the optimal production. The straightforward comparison of the frontier with the position of the utilities allows the quantification of the amount of improvement each utility should work on in order to improve its performance with respect to the others.

In this sense, the review conducted by Jamasb and Pollitt [26] showed that the most important benchmarking approaches used in regulation of the electricity services provided by utilities are based on: (i) Data Envelopment Analysis (DEA); (ii) Stochastic Frontier Analysis (SFA); and (iii) Corrected Ordinary Least Square (COLS). Zhu [49] reported that DEA explores mathematical programming techniques and models to evaluate the performance of peer units. With respect to SFA and COLS, both the methodologies

* Corresponding author. Tel.: +55 3284369695.
E-mail addresses: marcusvpsouza@yahoo.com.br, mvinic@engenharia.ufjf.br (M. V. Pereira de Souza).

http://dx.doi.org/10.1016/j.seps.2014.03.002
0038-0121/

Table 1
Basic primal DEA models.

Input-oriented CCR primal	Input-oriented BCC primal
$\underset{\theta,\lambda}{\text{Min}}\ \theta$ Subject To : $\ge \boldsymbol{y}_0 \theta \boldsymbol{x}_0 - \boldsymbol{X}\lambda \ge 0 \lambda \ge 0$ $\boldsymbol{Y}\lambda$	$\underset{\theta,\lambda}{\text{Min}}\ \theta$ Subject To : $\le \boldsymbol{y}_0 \theta \boldsymbol{x}_0 - \boldsymbol{X}\lambda \le 0 \overrightarrow{1}\lambda = 1 \lambda \ge 0$ $\boldsymbol{Y}\lambda$

use econometric models and require specification of a production or cost function (for a more detailed discussion of this issue see, e.g. Ref. [30]). As stated by Souza et al. [42]; the above methods have distinct assumptions and each has its advantages and disadvantages depending on the specific application. Therefore, there is no such statement as the best overall frontier method.

By now, it is worthwhile to point out that the pioneer works, in a DEA modeling context, were introduced by Färe et al. [20,21] and Charnes et al. [13]. Subsequently, between 1992 and 1998, many empirical studies were developed. For instance, Milliotis [32] described about DEA models to gauge the efficiency scores of 45 electricity distribution districts in Greece. Bagdadioglu [8] discussed the performance evaluation of public and private electricity firms in Turkey. Similarly, Goto and Tsutsui [25] compared the DEA scores for electricity companies in U.S and Japan; in this case, they argued that the latter performed better results. With regard to Norwegian distributing utilities, Førsund and Kittelsen [23] carried out optimization techniques to estimate the productivity improvement of these industries during the time period from 1983 to 1989.

Following, Korhonen and Luptacik [29] suggested a procedure for adding undesirable outputs in order to measure the efficiency scores of power plants and Cherchye and Post [15] conducted a survey to assess the Dutch electricity sector.

In conformity with what has been already exposed, studying cases of the SEB, authors such as Resende [37], Vidal and Tavora [46], Pessanha et al. [36] and Sollero and Lins [39] used different DEA models to evaluate the efficiency of the Brazilian distributing utilities. On the other hand, Zanini [48] and Arcoverde et al. [2] also obtained efficient indices for the Brazilian distributing utilities using SFA models. To complete, Souza et al. [40–43] developed several parametric and nonparametric techniques to compute the estimates of cost efficiency. In particular, it is remarkable that Souza et al. [40,42,43] proposed a method regarding the Bayesian Markov Chain Monte Carlo (MCMC) algorithm (for further details see, Refs. [24,28] and references cited therein).

Here, it is noteworthy to inform that this research presents the efficiency scores obtained by three DEA models. For both models, these quantities are evaluated under different contexts. One treats with respect to the regulator perspective. The others examine an alternative approach based on cluster analysis and restrictions on factor weights.

The plan of this article is as follows: The next section outlines the basic theoretical DEA formulations. The third section discusses the role of weight restrictions, while the fourth section present main empirical results obtained by these methodologies. The fifth section concludes.

2. Data envelopment analysis (DEA)

The use of DEA has become widespread to calculate the relative technical efficiency in many empirical applications (see, for example Ref. [14]). According to Zhu [49]; one of the reasons for this argumentation could be that DEA performs well in a multiple inputs and multiple outputs set, without the usual information on market prices. In addition, another meaningful question is that no a priori functional forms on the frontier technology are required.

At this point, let us now consider that each Decision Making Unit (DMU_j, $j = 1,\ldots,n$) transforms an input vector $\boldsymbol{x}_j = \begin{bmatrix} x_{1j} & \ldots & x_{mj} \end{bmatrix}^{\mathbf{T}} \cdot \in \mathbf{R}_+^m$ into an output vector (or production vector) $\boldsymbol{y}_j = \begin{bmatrix} y_{1j} & \ldots & y_{sj} \end{bmatrix}^{\mathbf{T}} \cdot \in \mathbf{R}_+^s$. The union of all possible ways of transforming x in y forms the Production Possibility Set (PPS for short), defined by:

$$T = \left\{ (\boldsymbol{x}, \boldsymbol{y}) \in \mathbf{R}_+^{m+s} | \boldsymbol{x} \text{ can produce } y \right\} \tag{1}$$

Adopting the resources conservation approach (input orientation), the technical efficiency of a particular DMU (DMU_0) is defined as the maximum radial contraction of the input vector that allows the production of the same quantities of output, i.e.:

$$\text{Technical efficiency} = \mathbf{Min}\{\theta | (\theta \boldsymbol{x}, \boldsymbol{y}) \in T(\boldsymbol{x}, \boldsymbol{y})\} \tag{2}$$

In conformity with what is mentioned up to here, a DMU is technically efficient if and only if the optimal $\theta^* = 1$ and all slack variables constraints are nil. On the other hand, if there is an excess of input that has to be reduced ($\theta < 1$) or $\theta^* = 1$ but having any constraint excess positive, then the DMU is regarded as technically inefficient. In addition, the reference set (benchmarks) of some inefficient DMU is formed by the DMUs associated to the optimal coefficients $\lambda_j^* > 0$ (i.e. λ in Table 1).

Based on these results and assuming the hypothesis of Constant Returns-to-Scale (CRS) and convex technology, [12] proposed the DEA-CCR model. In this model, the efficiency is formulated as a linear programming problem whose objective function is the maximum concentration of input (input orientation) and the constraints represent the PPS. Later on, Banker et al. [9] added a convex combination constraint to the CCR model, and proposed a model that includes a hypothesis of Variable Return to Scale (VRS), denoted by DEA-BCC. In Table 1, the input-oriented DEA models on both approaches, CCR and BCC are presented [14]:where λ is a semipositive vector in $\mathbf{R}^n$, $\overrightarrow{1}$ is the $(1 \times n)$ unit vector, $\boldsymbol{X}$ is the $(m \times n)$ input matrix, $\boldsymbol{Y}$ is the $(s \times n)$ output matrix, $\boldsymbol{x}_0$ is a $(m \times 1)$ vector of inputs and $\boldsymbol{y}_0$ is a $(s \times 1)$ vector of outputs for DMU_0 under evaluation. Concerning the input-oriented BCC primal model (see

Table 2
Basic dual DEA models.

Input-oriented CCR dual	Input-oriented BCC dual
$\underset{\boldsymbol{u},\boldsymbol{v}}{\text{Max}}\ \boldsymbol{u}^{\text{T}}\boldsymbol{y}_0$ Subject To : $\le 0 \boldsymbol{v}^{\text{T}} \ge 0 \boldsymbol{u}^{\text{T}} \ge 0$ $\boldsymbol{v}^{\text{T}}\boldsymbol{x}_0 = 1$ $-\boldsymbol{v}^{\text{T}}\boldsymbol{X} + \boldsymbol{u}^{\text{T}}\boldsymbol{Y}$	$\underset{\boldsymbol{u},\boldsymbol{v}}{\text{Max}}\ \boldsymbol{u}^{\text{T}}\boldsymbol{y}_0 - \boldsymbol{u}_0$ Subject To : $\le 0 \boldsymbol{v}^{\text{T}} \ge 0, \boldsymbol{u}^{\text{T}} \ge 0 \boldsymbol{u}_0$ free in sign. $\boldsymbol{v}^{\text{T}}\boldsymbol{x}_0 = 1$ $-\boldsymbol{v}^{\text{T}}\boldsymbol{X} + \boldsymbol{u}^{\text{T}}\boldsymbol{Y} - \boldsymbol{u}_0 \overrightarrow{1}$