Electric Power Systems Research 190 (2021) 106675

Contents lists available at ScienceDirect

Electric Power Systems Research

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

Benchmarking the operational expenditures of Brazilian transmission utilities by using DEA models

José F.M. Pessanha*, Albert C.G. Melo

CEPEL/UERJ, Rio de Janeiro, Brazil

ARTICLE INFO

Keywords:
Data envelopment analysis
Economic regulation
Efficiency frontier
Operational expenditure
Transmission utilities

ABSTRACT

In Brazil, the transmission assets are remunerated for their availability regardless of the full utilization of their capacities. The annual allowed revenue for each transmission utility is determined by the Brazilian Electricity Regulatory Agency (ANEEL). ANEEL has been using Data Envelopment Analysis (DEA) to define the regulatory operational expenditure (OPEX) for each utility, a key element for the annual allowed revenue assessment. Based on the ANEEL's DEA model this work proposes improvements in representing the quality of service, transmission capacity and transmission network length in the DEA model. Furthermore, this paper presents a more robust methodology to evaluate the regulatory operational expenditure of transmission utilities by applying several distinct DEA models; then a global efficiency score is defined by the geometric mean of the efficiency scores resulting from the set of DEA models analyzed. The performance of the proposed approach is illustrated with real data of the Brazilian transmission utilities.

1. Introduction

In several countries the economic regulation of transmission companies (TRANSCOS) takes place by controlling their revenues. For example, in Brazil, the transmission utilities are remunerated for their availability regardless of the full utilization of their capacities. In order to overcome the asymmetry of information between the regulator and the TRANSCOS the Brazilian Electricity Regulatory Agency (ANEEL) has utilized the Data Envelopment Analysis (DEA), a technique based on Linear Programming [1], to define the regulatory operational expenditure (OPEX) for each utility, a key element for the annual allowed revenue assessment [2–4].

The DEA approach provides an ideal framework for implementing regulation strategies based on benchmarking [5], for example, the ANEEL's DEA model quantifies an efficient frontier that indicates the lowest OPEX level for a given size of the transmission utility and compute an efficiency score for each utility based on its distance to the efficient frontier. The efficient frontier is the benchmarking for the inefficient utilities; so, the DEA approach identifies the best performance standards (benchmarks and peer sets) to be followed by the inefficient utilities.

Since 2007 the methodology adopted by ANEEL to define the efficient operating expedinture levels for the Brazilian distribution and transmission utilities has been based on the DEA approach [6]. During this time the ANEEL's DEA model has been evolved by incorporating improvements from public hearings. Despite the advances achieved, some aspects can still be improved.

The objective of this work is to propose a more robust methodology to evaluate the regulatory operational expenditure of transmission companies by applying several DEA models with distinct return to scale (RS) assumptions (constant - CRS, variable - VRS and non-decreasing - NDRS) [1] as well as the cross efficiency analysis (Cross DEA approach [7,8]). A global efficiency score is defined as the geometric mean of the efficiency scores obtained from the set of DEA models analyzed. In addition, a more appropriately representation of the quality of service, transmission capacity and transmission network length in the DEA model is suggested. The proposed approach is applied to the transmission utilities database provided by ANEEL for the period 2013 to 2016.

The outline of the paper is as follows. Section II introduces the classical DEA models CRS, VRS and NDRS. Next, section III presents the Cross DEA approach. Section IV describes the main aspects of the ANEEL's DEA model. The proposed model and the main results achieved are discussed in sections V and VI respectively, Finally, section VII presents the main conclusions.

* Corresponding author.
E-mail addresses: francisc@cepel.br, pessanha@ime.uerj.br (J.F.M. Pessanha), albert@cepel.br, albert.melo@ime.uerj.br (A.C.G. Melo).

https://doi.org/10.1016/j.epsr.2020.106675
Received 3 October 2019; Received in revised form 11 May 2020; Accepted 1 August 2020
Available online 06 August 2020
0378-7796/

2. Classical DEA models

2.1. Constant return to scale – CRS

Proposed by Charnes, Cooper and Rhodes [9], the DEA approach is a technique widely used to assess the efficiency of organizations (Decision Making Unit - DMU) in a same economic sector and that convert quantities of multiple inputs to produce quantities of multiple outputs. In the general case, a DMU uses multiple inputs $X = (x_1,\ldots,x_s)$ to produce multiple outputs $Y = (y_1,\ldots,y_m)$. Under the resource conservation assumption (input orientation), the efficiency score θ $(0 \le \theta \le 1)$ of a DMU is defined as the maximum radial contraction of the input vector X that can produce the same vector of outputs Y:

$$\text{Efficiency} = \text{Min}\{\theta \mid (\theta X, Y) \in \text{ production possibility set}\} \tag{1}$$

The optimization problem in (1) is modeled by the linear programming problem (LPP) in (2), where the variables X and Y correspond, respectively, to the input and output data from N DMUs, and $j0$ is the index of the evaluated DMU.

$$\text{Efficiency} = \underset{\lambda,\theta}{Min}\,\theta \tag{2}$$

s.t.

$$\theta X_{j_0} \ge \sum_{j=1}^{N} \lambda_j X_j$$

$$Y_{j_0} \le \sum_{j=1}^{N} \lambda_j Y_j$$

$$\lambda_j \ge 0 \;\forall\, j = 1, \ldots j_0, \ldots, N$$

The LPP in (2) is called CRS DEA model in the input-oriented envelopment formulation. The DMU_{j0} is efficient if and only if $\theta = 1$ and all slacks variables are equal to zero. However, if $\theta = 1$ and any slack variable is non-zero, DMU_{j0} is weakly efficient [10]. If $\theta < 1$ DMU_{j0} is inefficient, in this case the efficient DMUs are associated with the dual variables $\lambda_j > 0 \;\forall\, j = 1,N$ and form the peer set of the DMU_{j0}.

Alternatively, the efficiency score can be defined by the following ratio:

$$\text{Efficiency} = \theta = (u_1 y_1 + \ldots + u_m y_m)/(v_1 x_1 + \ldots + v_s x_s) \tag{3}$$

where $U = (u_1,\ldots,u_m)$ and $V = (v_1,\ldots,v_s)$ correspond to the weight vectors assigned to the outputs and inputs, respectively.

From the linear programming duality theory and based on (3), we have that the dual of the LPP (2) is the LPP in (4), which corresponds to the input-oriented CRS DEA model in the multipliers formulation. LPP (2) or LPP (4) must be solved for each DMU in order to calculate its efficiency score. In the case of LPP (4), the DMU_{j0} is fully efficient if $\theta = 1$ and all weights in U and V are positive in the optimal solution. However, if $\theta = 1$, but some weights are zero, DMU_{j0} is considered weakly efficient; otherwise if $\theta < 1$ the DMU_{j0} is inefficient.

$$\text{Efficiency} = \theta = \underset{u,v}{Max} \sum_{i=1}^{m} u_i y_{i,j_0} \tag{4}$$

s.t.

$$-\sum_{i=1}^{s} v_i x_{ij} + \sum_{i=1}^{m} u_i y_{ij} \le 0 \;\forall\, j = 1, \ldots j_0, \ldots, N$$

$$\sum_{i=1}^{s} v_i x_{i,j_0} = 1$$

$$u_i \ge 0,\;\; v_j \ge 0 \;\forall\, i = 1, m, \forall\, j = 1, s$$

2.2. Variable return to scale - VRS

The CRS DEA model was originally developed for comparing a set of reasonably homogenous DMUs and then faces difficulty to be applied to the Brazilian transmission utilities due to the existence of larger and smaller DMUs, thus forming a heterogeneous set [11]. The DEA model with variable returns to scale (VRS) [12] overcomes this difficulty [13] by introducing a convexity constraint $(\lambda_1 + \lambda_2 + \ldots + \lambda_N = 1)$ in LPP (2) or by including an unconstrained variable in LPP (4). Nevertheless, the VRS model classifies as efficient the DMUs with the lowest input levels or the highest output levels at least in one variable. For example, in the DEA VRS model, it is enough for a transmission utility to present the largest network extension to be classified as efficient, regardless of its OPEX. However,the fact that an utility has the largest network or the largest installed capacity does not mean that it is efficient.

2.3. Non-Decreasing return to scale - NDRS

A criticism of the DEA VRS model is that, due to the convexity hypothesis, the VRS efficiency frontier is not characterized by constant or increasing returns to scale across the entire frontier, but decreasing returns to scale if the level of activity increases beyond the optimal scale. Such characteristic of the VRS frontier can lead to optimistic efficiency assessments, making it difficult to meet the objectives of an incentive regulation scheme, whose purpose is to build mechanisms that stimulate productivity gains [6].

An alternative is the non-decreasing return to scale model - NDRS, a variant of the VRS model where the convexity constraint $\lambda_1 + \lambda_2 + \ldots + \lambda_N = 1$ is replaced by the inequality $\lambda_1 + \lambda_2 + \ldots + \lambda_N \ge 1$. The NDRS DEA model recognizes that smaller DMUs operating in the range of increasing returns to scale (operate on a suboptimal scale) should not be penalized by imposing the CRS frontier. For these utilities the frontier is defined by the VRS model. In other hand, for larger DMUs (operating in the range of decreasing returns to scale), the NDRS model imposes the CRS frontier as a way of encouraging their cost reduction.

2.4. Frontiers according to CRS, VRS and NDRS models

Classic DEA models assume that the production possibility set (PPS) is convex. As illustrated in Fig. 1 for the case with one input and one output, the shape of the PPS under the efficiency frontier depends on the assumptions for the return to scale regime. The point D in the interior of the PPS represents an inefficient DMU under all assumptions for the return to scale. The DMU at point C is efficient only under VRS assumption, while DMU at B is efficient under NDRS or VRS assumptions. Under CRS assumption only DMU at point A is efficient. This

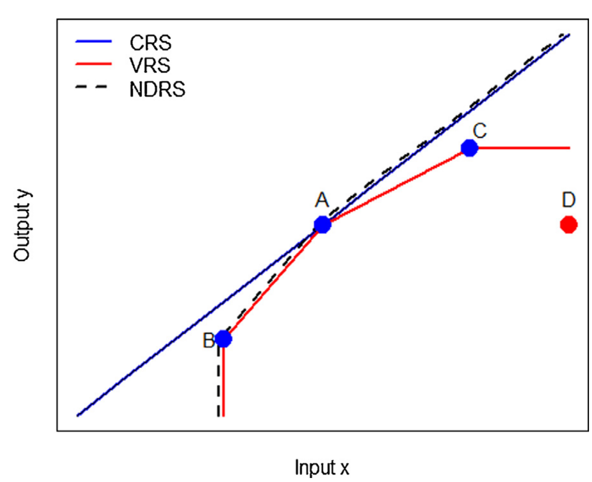

Fig. 1. Efficiency frontier for different return to scale assumptions.

simple example shows that $\theta_{\mathrm{VRS}} \geq \theta_{\mathrm{NDRS}} \geq \theta_{\mathrm{CRS}}$.

3. Cross-Evaluation - CEA

The classical DEA models described in section II can assign zero or unrealistic weights to inputs and outputs and it may result in over-estimated efficiencies [7]. One way to mitigate this problem is to include weight constraints in the DEA LPP model. However, the weight constraints intrinsically bring with some degree of arbitrariness and relies on the discretion of the regulator to interpret the relative importance of each variable. An alternative is the Cross Efficiency Analysis (CEA) [7,8], where the efficiency of a DMU is assessed according to the optimal weight schemes of the other DMUs, i.e., efficiency scores are assessed from the point of view of the other utilities (peer appraisal evaluation). In this case, the cross-efficiency of a DMU q based on the weights of a DMU k is defined by the following ratio:

$$E_{kq} = \sum_{i=1}^{outputs} u_{ik} y_{iq} / \sum_{j=1}^{inputs} v_{jk} x_{jq} \tag{5}$$

where u_{ik} and v_{jk} are the optimal weights for DMU k applied to the y_{iq} outputs and x_{jq} inputs of the DMU q.

In a set with N DMUs, the efficiency scores calculated by the CRS model and the cross-efficiency can be arranged in a matrix, as shown in Table 1. The resulting efficiencies from the CRS model are arranged in the diagonal. The k-th row shows the cross-efficiencies scores computed with the weights for DMU k , while the k-th column holds the cross-efficiencies scores of the k-th DMU calculated with the weights of the other DMUs.

In order to improve the discrimination between DMU efficiencies, aggressive formulation [14] is recommended. The same formulation was used to assess the efficiency of Taiwan's electricity distribution utilities [15] and to evaluate the efficient operating expenditure of the Brazilian distribution utilities [16]. In the aggressive formulation, the cross-efficiency score for the DMU q, under the point of view of DMU k (E_{kq}), is based on the weights u and v determined by the optimal solution of the LPP (6). Note that LPP (6) considers the DMU efficiency score (E_{kk}) calculated by the DEA CRS model. The constraint (6.1) is part of the linearization of the CRS model, the constraint (6.2) is the linearization of Eq. (5) for $q = k$, the constraints (6.3) ensure that all cross-efficiencies are less than or equal to 1 and constraints (6.4) guarantee non-negative weights. The benevolent version of cross-assessment corresponds to the maximization of LPP (6).

$$\underset{u,v}{Min} \sum_{i}^{outputs} u_{ik} \left(\sum_{q=1, q\neq k}^{N} y_{iq} \right) \tag{6}$$

s.t.

$$\sum_{j}^{inputs} v_{jk} \left(\sum_{q=1, q\neq k}^{N} x_{jq} \right) = 1 \tag{6.1}$$

$$\sum_{i}^{outputs} u_{ik} y_{ik} - E_{kk} \sum_{j}^{inputs} v_{jk} x_{jk} = 0 \tag{6.2}$$

$$\sum_{i}^{outputs} u_{ik} y_{iq} - \sum_{j}^{inputs} v_{jk} x_{jq} \leq 0 \;\forall\; q \neq k \tag{6.3}$$

$$u_{ik},\, v_{jk} \geq 0 \tag{6.4}$$

Table 1
Cross-efficiency matrix.

DMU	1	2	3	…	k	…	N
1	E_{11}	E_{12}	E_{13}	…	E_{1k}	…	E_{1N}
2	E_{21}	E_{22}	E_{23}	…	E_{2k}	…	E_{2N}
…	…	…	…	…	…	…	…
k	E_{k1}	E_{k2}	E_{k3}	…	E_{kk}	…	E_{kN}
…	…	…	…	…	…	…	…
N	E_{N1}	E_{N2}	E_{N3}	…	E_{Nk}	…	E_{NN}

In the CEA approach, the efficiency of a DMU k corresponds to the average of all values in column k of the cross-efficiency matrix, but without taking into account the self-efficiency E_{kk}, i.e., the average of cross-efficiencies in (7). The efficiencies resulting from the CEA approach are generally lower than those obtained by the classical DEA models.

$$e_k = \frac{1}{N-1} \sum_{i=1, i\neq k}^{N} E_{ik} \tag{7}$$

4. ANEEL's DEA model

The first tariff review cycle of the Brazilian transmission utilities was in 2007 [6,11]. Since then four tariff review cycles have passed while the ANEEL has been improved the DEA model for the definition of efficient operating expenditure levels of the transmission utilities [11]. Basically, the operational cost drivers of a transmission utility are related to the operation and maintenance actions to keep the transmission capacity available, represented by the amounts of four physical assets: transformation capacity (MVA), network length (km), number of substation equipment (power transformers and reactors) and number of switching modules. These physical assets characterize the size of the transmission network, a proxy of the available capacity, which is the main output of a TRANSCO. For a given output level, a TRANSCO should produce it at the lowest operational expenditures (OPEX). Therefore, in order to achieve an efficiency score that indicates how much each TRANSCO should reduce its OPEX, ANEEL proposed an input-oriented DEA model, in which the total OPEX is the only input and the quantities of the physical assets mentioned above are the outputs [6,11]. With respect to return to scale, ANEEL has adopted non-decreasing return to scale (NDRS).

The DEA model proposed in the first tariff review of transmission utilities has been improved through successive tariff review cycles. Nevertheless, the latest version described in Technical Note ANEEL 204/2019 [4] preserves the key features of the first DEA model. Basically, the main differences between the current DEA model and the model adopted in the first tariff review cycle lie in the following points [11]:

- Introduction of the total duration of outages to represent the quality of service as an output variable. Previously ANEEL used the interrupted power as a quality proxy [2].
- The installed capacity is represented by two variables: the total MVA (transformers) and total MVAr (reactor powers, series and shunt capacitor banks, synchronous and static compensators and filter banks). Previously ANEEL used the sum of MVA and MVAr [2].
- Breakdown of the transmission network length in two output variables: total length of networks with voltage up to 230 kV and total length of networks with voltage equal or greater than to 230 kV.
- Breakdown of the number of switching modules in two output variables: total number of switching modules with voltage up to 230 kV and total number of switching modules with voltage equal or greater than to 230 kV.
- Breakdown of the number of substations equipment in two output variables: total number of substation equipment with voltage up to 230 kV and number of substation equipment with voltage equal or greater than to 230 kV.
- Introduction of weights constraints [11].
- The efficiency scores are obtained by a two-stage process.
- The rule to normalize the efficiency scores

Table 2
Inputs and outputs statistics - ANEEL´s model.

Variable		Unit	Min	Mean	Max
Total duration of outages		min/year	71	35,354	212,779
Network extension	< 230 kV	km	0	880	6,533
	≥230 kV	km	687	6,388	17,759
Reactive Power		MVAr	0	7,610	37,734
Substation equipment	< 230 kV	units	0	97	376
	≥230 kV	units	24	263	661
Switch modules	< 230 kV	units	6	425	1,676
	≥230 kV	units	20	344	982
Transformation capacity		MVA	1,407	24,376	93,031
OPEX		1000 R$	12,295	364,143	1,394,273

Then the current DEA model adopted by ANEEL has eight outputs variables and only one input variable (OPEX), as illustrated in Table 2.

The outages compromise the transmission capacity availability; then the total duration of outages is an undesirable output, i.e. an output that should be minimized. There are several approaches for including undesirable outputs in a DEA model [17]. In the ANEEL's approach the total duration of outages is a non-discretionary input [13].

The latest version of the DEA model proposed by ANEEL catch the effect of transmission line voltage levels by classifying the transmission lines in two voltage classes: lines with voltage up to 230 kV and lines with voltage equal or greater than to 230 kV. Therefore, the network length, the number of switching modules and the number of substation equipment are computed separately in each voltage range. This approach creates some output variables with null values as illustrated in Table 2, a feature that conflicts with the assumption of positivity of input and output variables in the DEA model [13]. In addition, in order to avoid null and unrealistic weights ANEEL introduced the constraints (8) to (15) on the ratios of input and output weights. Unfortunately, the limits are based on information not disclosed by the regulatory agency [11].

$$0.5 \leq \frac{u_{reactive\ power}}{u_{transformation\ capacity}} \leq 2 \tag{8}$$

$$1 \leq \frac{u_{substation\ equippment\ \geq 230\ kV}}{u_{switch\ modules\ \geq 230\ kV}} \leq 10 \tag{9}$$

$$0.2 \leq \frac{u_{network\ extension < \ 230\ kV}}{u_{network\ extension\ \geq 230\ kV}} \leq 0.75 \tag{10}$$

$$0.2 \leq \frac{u_{switch\ modules\ <\ 230\ kV}}{u_{switch\ modules\ \geq 230\ kV}} \leq 0.75 \tag{11}$$

$$0.2 \leq \frac{u_{substation\ equipment\ <\ 230\ kV}}{u_{substation\ equipment\ \geq 230\ kV}} \leq 0.75 \tag{12}$$

$$800 \leq \frac{v_{OPEX}}{u_{transformation\ capacity}} \leq 2,000 \tag{13}$$

$$2,500 \leq \frac{v_{OPEX}}{u_{network\ extension\ \geq 230\ kV}} \leq 8,500 \tag{14}$$

$$15,000 \leq \frac{v_{OPEX}}{u_{switch\ modules\ \geq 230\ kV}} \leq 75,000 \tag{15}$$

Finally, ANEEL began defining efficiency scores through a two-stage process [13]: in the first one, the weight-constrained DEA NDRS model computes an efficiency score for each TRANSCO; next, in the second stage, a regression model is fitted in which the dependent variable is the efficiency score resulting from DEA model and the explanatory variables are environmental variables [11].

5. Proposed DEA model

Despite the advances in the DEA model adopted by ANEEL, the authors believe that there is room for further improvements. The results from first stage is of paramount importance once it determines the subsequent results. In this sense, the proposal presented in this work aims to improve the first stage of the DEA model.

Table 3
Coefficients per voltage level.

Voltage	Weight
69 kV	1.0000
88 kV	1.0013
138 kV	1.2906
230 kV	1.7657
345 kV	2.2472
440 kV	3.0369
500 kV	3.5946
600 kV	3.9621
750 kV	4.8070

In the DEA model adopted by ANEEL the transmission lines are segregated into two voltage ranges: <230 kV and ≥ 230 kV. However, some TRANSCOS do not operate in voltage levels below 230 kV; thus, some DMUs present null value for the output variable network length < 203 kV, which conflicts with the assumption of positivity of the input and output variables. Therefore, in order to avoid this problem, it is proposed to replace the output variables network length below and above 230 kV by only one output variable defined by the Weighted Sum of Network Length (WSNL):

$$WSNL = \sum_{i=69\ kV}^{750\ kV} \left(\frac{construction\ cost\ per\ km\ at\ i\ kV}{construction\ cost\ per\ km\ at\ 69\ kV} \right) km_i \tag{16}$$

where km_i is the network length at voltage level $i\ \forall\ i\ =\ 69$ kV,…, 750 kV.

In (16) the transmission lines lengths (km) are weighted by the coefficients in Table 3 [6] whose values are based on the reference costs for construction by voltage levels in Fig. 2.

Furthermore, the output variables corresponding to the number of substation equipment and number of switching modules, in the voltage ranges <230 kV and ≥ 230 kV, are replaced by only two variables: the total number of substation equipment and total number of switching modules. This also avoid output variables with null values.

The second proposal aims to improve the representation of the outages duration (quality) in the DEA model. The outage is a typical example of undesirable output [17]. As illustrated in Table 2 there is a DMU with null value in the output variable reactive power lower than 230 kV. Then, we propose replace the variables transformation capacity (MVA) and reactive power (MVAr) by the Expected Installed Capacity (EIC) in (17) where we introduce an unavailability factor based on the total outage duration.

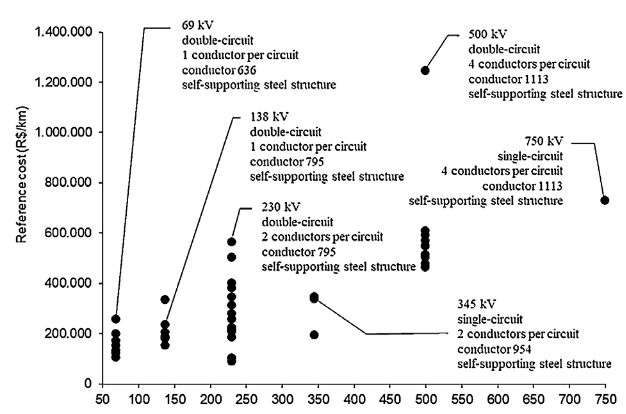

Fig. 2. Reference costs for construction, adapted from [6].

$$EIC = \left(\begin{matrix} tranformation \\ capacity \end{matrix} + \begin{matrix} reactive \\ power \end{matrix}\right)\left(1 - \frac{\Delta}{8,\,760\ horas}\right) \tag{17}$$

In (17) Δ is the total outage duration (hours) in the period of study and the 8,760 corresponds to the total hours in a year. Then, the ratio Δ/8,760 is an unavailability factor. The sum of transformation capacity and reactive power in a single variable means that implicitly the proposed DEA model assigns the same weights for these two output variables. Thus, the proposed DEA model has only one input - the OPEX, and four outputs - weighted sum of network length (16), expected installed capacity (17), number of switching modules and number of substation equipment.

Finally, in order to overcome the lack of information to define the limits of the weight constraints we propose to include the cross-evaluation (CEA) in the computation of a global efficiency score defined as the geometric mean of the efficiency scores obtained from the set of DEA models analyzed.

6. Results

The proposed approach is applied to the annual panel data over the period 2013–2016 provided by ANEEL [4] for 14 Brazilian TRANSCOS. The DEA models analyzed include the CRS, VRS, NDRS, and CEA models. In this case study, each TRANSCO in a given year correspond to one DMU. Thus, for example, the performance of a utility in 2016 is compared with the performance of its counterparts over the four years and also with its own performance in the remaining years. In all, 56 DMUs were analyzed. This approach allows the analysis of the evolution of each utility, considering that significant technological change was not observed over the analyzed period, a plausible hypothesis for the electricity transmission business [6].

Tables 4–6 show the efficiency scores from the CRS, VRS and CEA models respectively. The results were generated with the aid of the Benchmarking and MultiplierDEA packages available for the R project [18].

The efficiency scores from NDRS model are similar to the results shown in Table 4, as illustrated by the high correlation between the results from CRS and NDRS models in Table 7.

It is noteworthy that in the CEA approach a constant return of scale is considered [19]. Figs. 3 and 4 show the boxplots and histograms of the efficiency scores from different DEA models. As illustrated in Fig. 3, the VRS model presented the most optimistic efficiency estimates, while the CEA provides the most pessimistic ones. Table 7 shows the negative correlation between the OPEX and the efficiency score, but in the VRS model this correlation has no statistical significance. It shows the extremely optimistic behavior of VRS models. Additionally, there is a large similarity between the results from the CRS and NDRS models, this shows that few DMUs operate in the efficiency frontier region with increasing returns to scale and that they are evaluated with higher efficiency score by the NDRS model. The histograms in Fig. 4 highlight the differences between the scores computed by the CEA and VRS model and the similarity between the results from CRS and NDRS

Table 4
Efficiency scores from DEA/CRS model.

Utility	2013	2014	2015	2016
A	0.603	1.000	0.929	0.949
B	0.583	0.784	0.769	1.000
C	0.922	0.849	0.994	1.000
D	0.865	0.821	0.667	0.594
E	0.591	0.672	0.789	1.000
F	0.421	0.467	0.464	0.475
G	0.456	0.619	0.606	0.528
H	0.893	0.891	1.000	0.879
I	0.387	0.398	0.404	0.288
J	0.322	0.443	0.417	0.399
K	0.341	0.426	0.416	0.446
L	0.910	0.963	0.785	0.859
M	0.402	0.452	0.852	0.861
N	0.620	0.766	0.953	1.000

Table 5
Efficiency scores from DEA/VRS model.

Utility	2013	2014	2015	2016
A	0.603	1.000	0.929	0.958
B	0.584	0.785	0.770	1.000
C	0.923	0.850	0.996	1.000
D	0.866	0.841	0.667	0.599
E	0.601	0.686	0.795	1.000
F	0.721	0.851	0.969	1.000
G	0.457	0.620	0.607	0.529
H	0.900	0.896	1.000	1.000
I	0.421	0.430	0.433	0.318
J	0.375	0.542	0.544	0.529
K	0.788	0.948	0.937	1.000
L	0.945	1.000	0.833	0.931
M	0.479	0.498	1.000	1.000
N	0.632	0.773	0.953	1.000

Table 6
Efficiency scores from CEA model.

Utility	2013	2014	2015	2016
A	0.543	0.900	0.836	0.814
B	0.313	0.426	0.420	0.542
C	0.741	0.694	0.793	0.807
D	0.621	0.614	0.494	0.442
E	0.546	0.623	0.735	0.948
F	0.336	0.376	0.364	0.383
G	0.377	0.506	0.495	0.435
H	0.773	0.774	0.870	0.761
I	0.300	0.309	0.316	0.247
J	0.269	0.367	0.350	0.342
K	0.289	0.358	0.350	0.374
L	0.733	0.782	0.625	0.680
M	0.309	0.353	0.657	0.665
N	0.496	0.604	0.759	0.799

Table 7
Correlation between OPEX and efficiency scores.

	CRS	VRS	NDRS	CEA	OPEX
CRS	1.0000				
VRS	0.7285	1.0000			
NDRS	0.9999	0.7278	1.0000		
CEA	0.9362	0.6990	0.9354	1.0000	
OPEX	−0.6531	−0.0675	−0.6546	−0.5994	1.0000

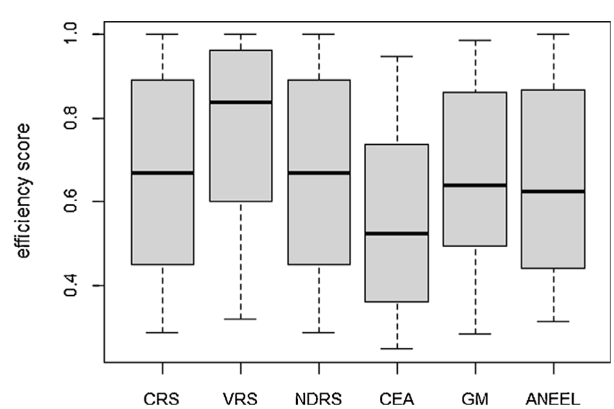

Fig. 3. Boxplots of the efficiency scores of the 56 DMUs.

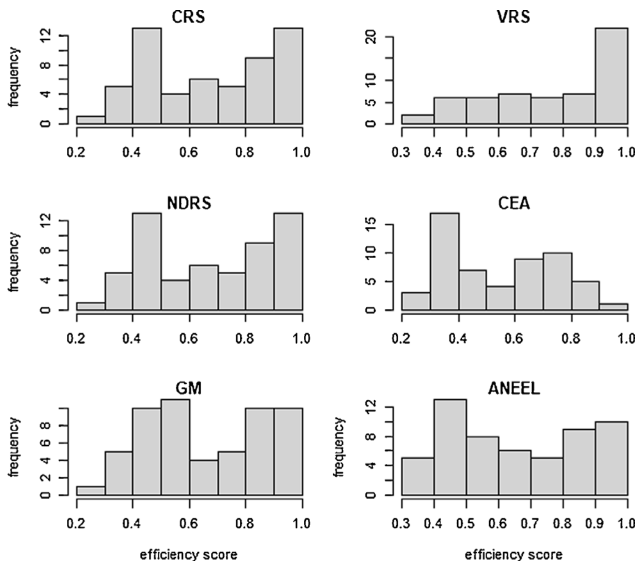

Fig. 4. Histograms of the efficiency scores for the 56 DMUs.

Table 8
Geometric mean of efficiency scores.

Utility	CRS	VRS	NDRS	CEA	GM
A	0.854	0.856	0.854	0.759	0.830
B	0.770	0.771	0,771	0.417	0.661
C	0.939	0.940	0.939	0.757	0.890
D	0.728	0.734	0.734	0.537	0.678
E	0.748	0.757	0.748	0.698	0.737
F	0.456	0.878	0.456	0.364	0.508
G	0.548	0.549	0.549	0.450	0.522
H	0.914	0.948	0.914	0.793	0.890
I	0.366	0.397	0.366	0.292	0.353
J	0.393	0.492	0.393	0.330	0.398
K	0.405	0.915	0.405	0.341	0.476
L	0.877	0.925	0.877	0.703	0.841
M	0.604	0.699	0.604	0.467	0.587
N	0.820	0.826	0.820	0.653	0.776

models. Table 8 shows the proposed global efficiency score, i.e., the geometric means (GM) of the efficiency scores for each DMU.

From a pragmatic point of view, it is often difficult to justify the most appropriate return to scale regime. In these situations, a good approach is to compute the geometric mean (GM) of efficiency scores from the different DEA models in order to combine the results in a unique efficiency score for each TRANSCO. This proposal was successfully used when analyzing railway performance in Europe [20]. As illustrated by Figs. 3 and 4 there is a similarity between the efficiency scores from ANEEL´s DEA model and the geometric mean (correlation 0.972) of the efficiency scores from CRS, VRS, NDRS and CEA models.

The final efficiency scores from the different approaches are summarized in Fig. 5 where we can observe the extremely optimistic efficiency scores from VRS model to DMUs F and K, the two DMUs have the highest values in at least one output. In the same Fig. 5 we observe that the CEA approach are very pessimist for all DMUs, in special for DMU B. However, the geometric mean mitigates the extremely optimistic and pessimistic views of the VRS and CEA approaches respectively. Thus, the geometric mean of the efficiency scores from the four DEA models leads to a more robust and practical methodology, where the risk of unduly rewarding agents and penalizing efficient ones is minimized.

The efficiency scores from geometric mean and the ANEEL's DEA model [4] for the first stage are presented in Table 9 per TRANSCO across the years. The results achieved are comparable with the efficiency scores from ANEEL`s DEA model before the 2nd stage and normalization [4], but in the proposed approach the assumption of positive

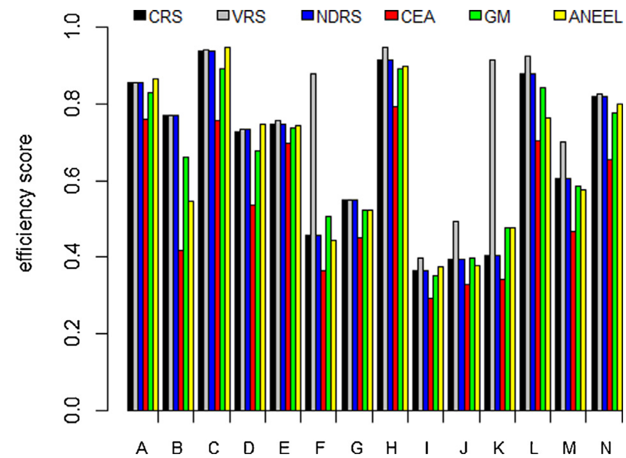

Fig. 5. Efficiency averages for each TRANSCO over 2013–2016.

Table 9
Efficiency scores.

Utility	Geometric Mean	ANEEL 1st stage
A	0.830	0.865
B	0.661	0.547
C	0.890	0.947
D	0.678	0.747
E	0.737	0.744
F	0.508	0.443
G	0.522	0.522
H	0.890	0.899
I	0.353	0.375
J	0.398	0.379
K	0.476	0.476
L	0.841	0.764
M	0.587	0.576
N	0.776	0.799

outputs is met and the weight constraints are not necessary.

7. Conclusion

In order to improve the Data Envelopment Analysis model adopted by ANEEL in the regulation of the operational expenditures of the Brazilian transmission utilities, the present work propose an alternative specification. Initially, new definitions for the output variables related to the installed capacity and network extension were proposed in order to incorporate the effects of the quality of service and voltage levels. In addition, the efficiency score were computed considering the different returns to scale regimes, i.e., the CRS (constant), VRS (variable) and NDRS (non-decreasing) models. In order to overcome the problem of unrealistic weighting assigned to the outputs variables without the need to include weight constraints, the cross-evaluation technique was used. Then, the efficiency scores were computed by four DEA models. Aiming a more robust methodology, the final efficiency scores for each utility are defined by the geometric mean of the efficiency scores resulting from the four analyzed models. The results achieved are comparable with the efficiency scores from ANEEL`s DEA model before the 2nd stage DEA model and normalization, but the assumption of positive outputs is now met. Finally, the proposed approach offers a practical alternative to the DEA model with weights constraints.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] A. Mardani, D. Streimikiene, T. Balezentis, M.Z.M. Saman, K.M. Nor, S.M. Khoshnava, Data envelopment analysis in energy and environmental economics: an overview of the state-of-the-art and recent development trends, Energies 11 (8) (2018) 2002, , https://doi.org/10.3390/en11082002 https://doi.org/10.3390/en11082002.

[2] ANEEL, "NT 160/2017-SRM/ANEEL (Original in Portuguese)", 2017. [Online]. Available: www.aneel.gov.br.

[3] ANEEL, "NT 204/2018-SRM/ANEEL (Original in Portuguese)", 2018. [Online]. Available: www.aneel.gov.br.

[4] ANEEL, "NT 012/2019-SRM/ANEEL (Original in Portuguese)", 2019. [Online]. Available: www.aneel.gov.br.

[5] P. Bogetoft, Performance Benchmarking: Measuring and Managing Performance, Performance Benchmarking: Measuring and Managing Performance, Springer, New York, 2012.

[6] J.F.M. Pessanha, M.A.R. Figueira de Mello, M. Barros, R.C. Souza, Avaliação dos custos operacionais eficientes das empresas de transmissão do setor elétrico brasileiro: uma proposta de adaptação do modelo DEA adotado pela ANEEL, Pesquisa Operacional 30 (3) (2010) 521–545, https://doi.org/10.1590/S0101-74382010000300002 https://doi.org/10.1590/S0101-74382010000300002.

[7] J. Chu, Improvement Methods for Data Envelopment Analysis (DEA) Cross-Efficiency Evaluation, Université Paris-Saclay and University of Science and Technology of China, 2018. [Online]. Available: https://hal.inria.fr/tel-02015680v1

[8] Q. Si, Z. Ma, DEA cross-efficiency ranking method based on grey correlation degree and relative entropy, Entropy 21 (10) (2019), https://doi.org/10.3390/e21100966 https://doi.org/10.3390/e21100966.

[9] A. Charnes, W.W. Cooper, E. Rhodes, Measuring the efficiency of decision-making units, Eur. J. Oper. Res. 2 (6) (1978) 429–444, https://doi.org/10.1016/0377-2217(78)90138-8 https://doi.org/10.1016/0377-2217(78)90138-8.

[10] W.D. Cook, J. Zhu, Modelling Performance Measurement: Applications and Implementations Issues in DEA, Modelling Performance Measurement: Applications and Implementations Issues in DEA, Springer, New York, 2005.

[11] A.V. Silva, M.A. Costa, H. Ahn, A.L.M. Lopes, Performance benchmarking models for electricity transmission regulation: caveats concerning the Brazilian case, Utilities Policy 60 (2019), https://doi.org/10.1016/j.jup.2019.100960 https://doi.org/10.1016/j.jup.2019.100960.

[12] R.D. Banker, A. Charnes, W.W. Cooper, Some models for estimating technical and scale Inefficiencies in data envelopment analysis, Manage. Sci. 30 (9) (1984) 1078–1092, https://doi.org/10.1287/mnsc.30.9.1078 https://doi.org/10.1287/mnsc.30.9.1078.

[13] T.J. Coelli, D.S.P. Rao, C.J. O'Donnell, G.E. Battese, An Introduction to Efficiency and Productivity Analysis, An Introduction to Efficiency and Productivity Analysis, Springer, New York, 2005.

[14] W. Liu, Y.M. Wang, S. Lv, An aggressive game cross-efficiency evaluation in data envelopment analysis, Ann. Oper. Res. 259 (2017) 241–258, https://doi.org/10.1007/s10479-017-2524-1 https://doi.org/10.1007/s10479-017-2524-1.

[15] T.Y. Chen, An assessment of technical efficiency and cross-efficiency in Taiwan's electricity distribution sector, Eur. J. Oper. Res. 137 (2) (2002) 421–433, https://doi.org/10.1016/S0377-2217(01)00101-1 https://doi.org/10.1016/S0377-2217(01)00101-1.

[16] S.M. Rezende, J.F.M. Pessanha, R.M. Amaral, Cross evaluation of electric distribution utilities, Production 24 (4) (2014) 820–832, https://doi.org/10.1590/S0103-65132014005000004 https://doi.org/10.1590/S0103-65132014005000004.

[17] G. Halkos, K.N. Petrou, "A Critical Review of the Main Methods to Treat Undesirable Outputs in DEA", MPRA Paper 90374, University Library of Munich Germany, 2018 [Online]. Available: https://mpra.ub.uni-muenchen.de/90374/.

[18] R CORE TEAM, R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Viena: Austria, 2020 [Online]. Available: http://www.R-project.org/.

[19] J.C.C.B. Soares de Mello, L. Angulo-Meza, J.Q. Silveira, E.G. Gomes, About negative efficiencies in cross evaluation BCC input-oriented models, Eur. J. Oper. Res. 229 (3) (2013) 732–737, https://doi.org/10.1016/j.ejor.2013.02.020 https://doi.org/10.1016/j.ejor.2013.02.020.

[20] T. Coelli, S. Perelman, A comparison of parametric and non-parametric distance functions: with applications to European railways, Eur. J. Oper. Res. 117 (2) (1999) 326–339, https://doi.org/10.1016/S0377-2217(98)00271-9 https://doi.org/10.1016/S0377-2217(98)00271-9.