Universidade Federal de Minas Gerais - UFMG

School of Engineering

Production Engineering Graduate Program

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BENCHMARKING MODELING FOR COST INCENTIVE REGULATION OF BRAZILIAN ELECTRICITY COMPANIES

BELO HORIZONTE

2019

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Benchmarking modeling for cost incentive regulation of Brazilian electricity companies

Doctoral Thesis presented as partial requirement for obtaining the title of Doctor in Production Engineering, conceded by the Production Engineering Graduate Program of the Universidade Federal de Minas Gerais (UFMG).

Supervisor: Prof. Dr. Marcelo Azevedo Costa

Belo Horizonte

2019

S586b Silva, Aline Veronese da
Benchmarking modeling for cost incentive regulation of Brazilian electricity companies/ Aline Veronese da Silva. – 2019.
1 recurso eletrônico (106 f. : il., color.): pdf.

Orientador: Marcelo Azevedo Costa.

Tese (Doutorado) – Universidade Federal de Minas Gerais, Escola de Engenharia.

Bibliografia: f. 100-106.
Exigências do sistema: Adobe Acrobat Reader.

1. Engenharia de produção - Teses. 2. Análise Envoltória de Dados - Teses. 3. Benchmarking (Administração) - Teses. 4. Energia elétrica - Transmissão - Teses. I. Costa, Marcelo Azevedo. II. Universidade Federal de Minas Gerais. Escola de Engenharia. III. Benchmarking modeling for cost incentive regulation of Brazilian electricity companies.

CDU 658.5(043)

Ficha catalográfica: Biblioteca Prof° Mário Werneck, Escola de Engenharia da UFMG

UNIVERSIDADE FEDERAL DE MINAS GERAIS

PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA DE PRODUÇÃO

UFMG

FOLHA DE APROVAÇÃO

Benchmarking modeling for cost incentive regulation of Brazilian electricity companies

ALINE VERONESE DA SILVA

Tese submetida à Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação em ENGENHARIA DE PRODUÇÃO, como requisito para obtenção do grau de Doutor em ENGENHARIA DE PRODUÇÃO, área de concentração PESQUISA OPERACIONAL E INTERVENÇÃO EM SISTEMAS SOCIOTÉCNICOS, linha de pesquisa Modelagem Estocástica e Simulação.

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Belo Horizonte, 31 de outubro de 2019.

Acknowledgements

Ao fim dessa jornada, agradeço àqueles que me apoiaram e que me deram o suporte necessário para que essa pesquisa fosse realizada.

Agradeço ao professor Marcelo Azevedo Costa pela orientação durante o Mestrado e o Doutorado, não medindo esforços para o sucesso da pesquisa. Sua dedicação ao novo e à busca por melhores resultados são inspiração que levo para além da Academia.

Agradeço à professora Ana Lúcia Miranda Lopes, que também deu suporte incondicional para o desenvolvimento dessa pesquisa, e do meu Doutorado. Aos colegas e professores orientadores da Technische Universität Braunschweig, pelo suporte e apoio.

Agradeço aos professores da UFMG, que buscando a excelência, deixaram um pouco de si na minha formação.

Agradeço meus colegas da Engenharia de Produção e da Faculdade de Ciências Econômicas, que tornaram os dias no campus mais leves, e o aprendizado mais divertido.

Agradeço aos meus colegas do setor elétrico, em especial à "vanguarda da regulação brasileira", grupo com o qual aprendi muito. À amiga Andréa Damico de Sampaio Gonzaga, que sintetiza a relação de companheirismo e de troca de conhecimentos desse grupo. Sou grata por ter recebido tanto suporte de vocês.

Agradeço à minha família, em especial meus pais Amaro e Deonilce e meus irmãos Alessandra e Maurício, que sempre deram suporte às minhas escolhas e apoiaram meus projetos.

Por fim, agradeço ao meu esposo Matheus, que durante essa longa jornada esteve ao meu lado. Obrigada por ter acreditado que eu era capaz de fazer coisas incríveis, e por ter também me levado a acreditar e fazer.

Und jedem Anfang wohnt ein Zauber inne,
Der uns beschützt und der uns hilft, zu leben.
E todo começo contém uma mágica
Que nos protege e nos ajuda a viver.
Hermann Hesse

Abstract

Regulation plays an important role in natural monopoly markets, such as energy electricity distribution and transmission. A robust regulatory process assures the economic-financial balance of the system utilities while sets fair tariffs to consumers. In order to achieve these objectives, the Brazilian Energy regulator (ANEEL) has been using benchmarking models to define the efficient operational costs of distribution and transmission companies. These benchmarking models affect a significant portion of the companies' revenues and the electricity tariff. Although regulators worldwide use benchmarking techniques for the same purposes, the Brazilian case is especially challenging, due to its specific features. The continental dimension of the country and the dissimilarities among the compared companies require the use of specific solutions in the modeling process to assure reliable efficiency scores. In this context, omitted variables may cause great damage in the final results. Thus, the objective of this study is to evaluate the benchmarking modeling for cost incentive regulation of Brazilian distribution and transmission companies. First, we present a proposal for including environmental variables in the benchmarking modeling of distribution companies. To do that, we propose a compound error second-stage Data Envelopment Analysis (DEA) approach. Nevertheless, this solution is not suitable for the benchmarking modeling of transmission system operators (TSOs). To better model this latter segment, we first analyze the effectiveness of the incentive cost regulation implemented by the regulator in the previous tariff review cycles. We point out the main mechanisms which were successful to incentive the cost reduction. Then, we present a detailed analysis of the benchmarking model used to regulate Brazilian TSOs and propose methodological improvements. A final proposal regards an approach to include environmental variables in the model through the correction of the input variable. All these evaluations help to better understand the problems within the benchmarking modeling process of Brazilian utilities. The proposed methods improve the reliability of the efficiency scores, ensuring a fair regulatory process.

Key-words: Data Envelopment Analysis (DEA). Environmental Variables. Energy regulation. Benchmarking modeling.

Resumo

A regulação tem um papel importante em mercados classificados como monopólios naturais, tais como a distribuição e a transmissão de energia elétrica. Um processo regulatório robusto assegura o balanço econômico-financeiro das empresas do sistema, e ao mesmo tempo define tarifas justas para o consumidor. Para atingir esses objetivos, o regulador de energia brasileiro (ANEEL) tem usado modelos de *benchmarking* para definir os custos operacionais eficientes das empresas de distribuição e transmissão. Esses parâmetros compõem uma parte significativa das receitas das empresas e da tarifa de energia. Embora reguladores do mundo todo também utilizem modelos de *benchmarking* para o mesmo propósito, o caso brasileiro tem especificidades que o tornam notadamente desafiador. As dimensões continentais do país e as dissimilaridades entre as empresas comparadas requerem o uso de soluções específicas no processo de modelagem, a fim de assegurar a geração de escores de eficiência confiáveis. Nesse contexto, variáveis ocultas no processo podem causar um grande dano aos resultados finais. Sendo assim, o objetivo desse trabalho é avaliar a modelagem de *benchmarking* usada para a regulação por incentivos para custos das empresas brasileiras do setor elétrico. Primeiro, apresentamos uma proposta para inclusão de variáveis ambientais no modelo de *benchmarking* das distribuidoras de energia. Para isso, utilizamos um modelo de erro composto em uma abordagem de *Data Envelopment Analysis* (DEA) em dois estágios. Essa solução, contudo, não se mostra aplicável ao caso das transmissoras de energia elétrica. Para modelar adequadamente esse último segmento, nós primeiro analisamos a efetividade da regulação por incentivos para custos implementada pelo regulador nos últimos 17 anos. Apontamos os principais mecanismos que foram bem-sucedidos em incentivar a redução de custos. Na sequência, apresentamos uma detalhada análise do modelo de *benchmarking* utilizado para regular as transmissoras brasileiras, e propusemos melhorias conceituais ao modelo. Uma última proposta diz respeito a uma abordagem para a inclusão dos efeitos das variáveis ambientais na modelagem por meio da correção da variável de entrada do DEA. Todas estas avaliações ajudam a ter um melhor entendimento do problema de modelagem de *benchmarking* das empresas brasileiras de energia elétrica. As contribuições que propomos ajudam a melhorar a confiabilidade dos escores de eficiência, garantindo um processo regulatório justo.

Palavras-chave: *Data Envelopment Analysis* (DEA). Variáveis ambientais. Regulação de mercados de energia. Modelagem de *Benchmarking*.

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1 Introduction

An industry is a natural monopoly if the provision of a particular good or service by a single firm minimizes the system cost [Cabral, 2000]. Electricity distribution and transmission are classical examples of natural monopolies since these activities have no close substitutes. Besides, the high fixed costs required to execute these services exclude the alternative of direct competition.

In such markets, regulation plays an important role, preventing companies from setting high and unfair prices. According to Bogetoft and Otto [2010], the regulator acts as a *proxy* of the consumer, imposing operation contracts and verifying the quality of the services. The regulator is responsible for applying incentives for costs reduction and quality improvement.

In the electricity markets, incentive regulation is a broadly studied topic. The great reforms which have been occurring in the energy sector since the 1980s have led to the development of a great number of regulatory schemes. Pollitt [2004] highlights that the regulation process is iterative and requires time to be tested and improved. In this context, regulators from emerging markets which started their reforms in the final years of the 1990s are still facing a learning process.

The Brazilian energy regulator (*Agência Nacional de Energia Elétrica* — ANEEL) uses incentive schemes to regulate costs and quality of generation, distribution and transmission operators. With respect to the cost regulation, the Distribution System Operators (DSOs) and the Transmission System Operators (TSOs) are indirectly compared with their counterparts and required to reduce costs to the sector efficiency level.

Like most of the energy regulators, ANEEL applies benchmarking models to indirectly compare DSOs and TSOs. A popular benchmarking method among the regulators and also applied by ANEEL is the non-parametric Data Envelopment Analysis (DEA). This method was introduced by Charnes et al. [1978] and uses linear programming to estimate the relative efficiency scores of a comparable set of units. The DEA's result is an efficiency scores that can be used to ranking companies. The the regulator uses it to define the portion of the efficient operational costs of DSOs and TSOs that should be passed to the companies as part of their revenues. This amount composes a significant part of the energy tariff.

The benchmarking modeling is a critical step within the regulatory process. A misspecified model may lead to wrong regulatory signs to the market, failing in incentiving the costs reduction and the innovation. Moreover, if the the energy tariff is set at a very high level, the final consumers are penalized. On the opposite, if the energy tariff is too low, the economic balance of the service operators may be injured, causing their bankruptcy.

Furthermore, the electricity sector is critical to the development of an emerging country. The lack of investments in this field can make the electricity a bottleneck to the industrial and technological progress. Thus, the regulated environment needs to be reliable and predictable in order to attract and retain investors. The benchmarking modeling represents an important portion of the signs that the regulator sends to the market, and because of that it must represent the real problems faced for the companies and send the correct incentives to them.

1.1 Objectives

The general objective of this study is to propose enhancements to the modeling of benchmarking techniques used for the cost incentive regulation of Brazilian electricity companies. The study is centered in the benchmarking modeling of distribution and transmission companies.

The specific objectives of this study are:

1. To describe and document particular features of the distribution and transmission markets in Brazil;
2. To analyze the effectiveness of the incentive regulation for costs, especially regarding the transmission segment, highly affected by governmental interventions;
3. To investigate the impact of the environmental variables in the benchmarking modeling of Brazilian DSOs and TSOs;
4. To propose alternatives to consider the effects of the environmental variables in the efficiency scores.

1.2 Structure of the thesis and chapter contents

This thesis is structured as a set of independent papers, presented in each chapter. The studies are complementary among them, because they identify the pattern in the benchmarking modeling followed by ANEEL and suggest improvements which are complementary. The papers are presented in chronological order, considering the date of its publication. In the following paragraphs, the general purpose of each chapter is explained.

The first paper, presented in chapter 2, is an adapted version of the paper published by da Silva et al. [2019b] that proposes a second stage procedure for the DSOs' benchmarking modeling. In the 4$^{\text{th}}$ Tariff Review Cycle (TRC) of the DSOs, concluded in 2015, ANEEL claims that the environmental variables do not have relevant impact in the efficiency scores. However, the paper brings evidences that the environmental variables influence the efficiency scores.

Most of the studies regarding DEA second stage approaches are concerned in modeling the relation between the efficiency scores and the environmental variables. In the case of regression-based second stage, the test of the statistical significance of the variables is the most common output. To overcome the gap in the literature regarding the correction of the efficiency scores, this paper describes the adjustment procedures according to three regression-based second stage approaches: (*i*) Ordinary Least Squares (OLS), (*ii*) Tobit regression and (*iii*) compound error models.

With respect to the compound error models, we take a close look at the model proposed by Banker and Natarajan [2008], which was used by the Brazilian regulator in the 3$^{\text{rd}}$ TRC of DSOs. We show that the compound error equation proposed by the authors is actually a truncated version of the complete convolution of the inefficiency and random noise distributions. In addition, a more intuitive compound error model is proposed. The model is applied to the Brazilian DSOs' data and compared with the results of the Tobit adjustment.

In chapter 3, it is presented a general overview about the effectiveness of costs incentive regulation of TSOs, adapted from the paper published by da Silva et al. [2019c]. The study highlighs the most relevant changes in the Brazilian regulatory scheme and analyzes the responses of the firms in terms of costs reduction. Data of 17 years, which comprises the last tariff review cycles, show that some firms are less sensitive to cost reduction incentives than others. Nevertheless, the whole scene suggests that the costs are reducing in the transmission sector in recent years, despite some arbitrary changes imposed by the regulator.

Chapter 4 presents an adapted version of the paper published by da Silva et al. [2019a]. The authors make a detailed analysis of the benchmarking model proposed by the regulator in the 4^{th} TRC of TSOs, concluded in 2018. Caveats concerning three main issues are highlighted: the comparability of the companies, the weight restrictions modeling and the second stage procedure. The paper also presents alternatives to overcome the main problems raised.

The last paper, shown in chapter 5, presents a proposal for including the effects of the contextual variables in the efficiency scores of TSOs. This working-paper focuses on one of the three issues raised in the previous chapter, regarding the effectiveness of the second stage procedure of the Brazilian's 4^{th} TRC of TSOs. Econometric and regression-based techniques are difficult to be executed in the case of TSOs, due to the reduced quantity of compared companies and the large number of contextual variables. Thus, instead of a regression-based second stage, we propose a procedure to adjust the DEA input variable, considering the contextual variables.

The set of papers contributes to the benchmarking modeling study since we present alternatives to overcome issues regarding real data and problems. In addition, the study provides a comprehensive overview of the Brazilian regulatory model for the electricity market. The enhancements proposed in the papers become the modeling process more predictable and fair, contributing to the regulatory stability.

2 A close look at second stage Data Envelopment Analysis using compound error models and the Tobit model

Abstract

In 2014 the Brazilian Electricity Regulator (ANEEL) evaluated the efficiency of power distribution utilities using Data Envelopment Analysis (DEA). Estimated efficiencies range from 22.46% to 100%. Although environmental information is available in the data set, corrected efficiencies were not investigated. Different second stage models can be applied to adjust for environmental heterogeneity. Although statistical correlation among efficiencies and environmental variables can be easily estimated, corrected efficiencies are subject to the underlying structure of the second stage model. Therefore, different second stage models may achieve different corrected efficiencies. We provide a detailed statistical analysis of the Tobit model and compound error models for second stage analysis. Limitations are described and the corrected efficiencies using these models are evaluated. Potentially, Brazilian power distribution utilities may achieve substantial changes in estimated efficiencies if second stage analysis is used.

Keywords: Data Envelopment Analysis. Second Stage Analysis. Stochastic Frontier Analysis. Tobit regression. Environmental Variables.

2.1 Introduction

Data Envelopment Analysis (DEA) is a non-parametric frontier method, that uses Linear Programming techniques to define relative efficiency scores, or efficiencies, of comparable decision making units (DMUs). It is a deterministic method, that allows comparisons of multiple inputs and multiple outputs. To apply DEA, the DMUs must be comparable: they need to produce the same outputs, using the same inputs. Furthermore, it is important that the DMUs face similar environmental conditions. In practice, however, it is common to find situations in which DMUs within distinct environmental contexts must be compared. Second stage analysis was developed to deal with such problem. It allows correction of the efficiency scores using regression based models.

As pointed by McDonald [2009], Tobit regression and Ordinary Least Squares (OLS) are the simplest and most common methods for evaluating the linear correlation between DEA efficiency scores and environmental variables. Nonetheless, there is no consensus about the best second stage approach. Simar and Wilson [2007] claim that second stage analysis induces bias into the efficiency scores since environmental variables can be linearly correlated to first stage variables. However, second stage analysis is very intuitive for policy makers and regulators since it provides separate statistical evidence of the impact of environmental variables on the efficiency scores, estimated previously using DEA.

Compound error models for DEA second stage were proposed by Banker and Natarajan [2008] and Simar and Wilson [2007]. Although they share similarities with OLS and Tobit regression, they assume a data generating process (DGP) model. As a consequence, there are differences in the way the regression residuals are treated by each method. Furthermore, compound error models assume that the residuals of the model are decomposed into two unknown components: noise and technical inefficiency. Different statistical assumptions about the probability distribution of these components are proposed. Nonetheless, all methods use the residuals of the regression models to estimate the corrected efficiency scores. As a consequence, the corrected efficiencies are not correlated to the environmental variables and, therefore, it can be claimed that the original efficiency scores were adjusted in order to correct the environmental heterogeneity.

In this work, we evaluate the statistical properties of Tobit and compound error models for DEA second stage analysis. We show that the statistical significance of environmental variables is affected by the model. The model also affects corrected efficiency scores. Briefly, compound error models generally produce larger corrected efficiency scores as compared to Tobit and OLS. Furthermore, the estimates of the probability parameters of compound error are sensitive to initial conditions, optimization algorithms and sample sizes, which may lead to inaccurate estimates of the parameters.

The final application, and one of the main motivations of the paper, is the analysis of the Brazilian energy distribution utilities. The Brazilian regulator (ANEEL) used DEA models to estimate the efficiencies of the utilities in 2014. In addition to input and output variables, environmental variables are available in the data set. Nonetheless, the environmental information was not used to adjust the DEA efficiencies. This work evaluates the impact of the environmental information on the corrected efficiencies.

This paper is organized as follows. Section 2.2 presents the historical motivation of the work and reviews the DEA model and second stage analysis. In addition, OLS, Tobit regression and compound error models are described in this section. The adapted Stochastic Frontier Analysis (a-SFA) is presented in section 2.2.8. Section 2.2.9 presents the case study. Results are presented in section 2.3. Section 2.4 presents discussion and conclusion.

2.2 Materials and Methods

2.2.1 Background

In April 2015, the Brazilian regulator concluded the 4th Periodic Tariff Review Cycle (4PTRC) of the 61 Brazilian Electricity Energy Distribution utilities, hereafter named DSOs (Distribution Service Operators). To evaluate technical efficiencies, non-decreasing returns to scale, input-oriented data envelopment analysis model was applied. The input variable is operational costs (OPEX) and the output variables are number of consumers, weighted power consumption, high level network extension, low level network extension and underground network extension. In addition, two quality variables are included in the model as negative outputs: non-technical losses and duration of interruption of energy. These quality variables are included in the model as the difference between observed values and regulatory values. Weight restrictions are also included in the DEA model to reduce the number of DSOs with efficiency scores of 1 (100%). The complete

DEA model is described in Technical Note 66/2015-SRM [ANEEL, 2015]. Efficiency scores vary from 22.4% to 100%, and have a mean of 71.3%.

Despite the large range of the efficiency scores, and the environmental diversity faced by the Brazilian DSOs, the regulator did not adjust the efficiency scores using second stage analysis. Technical Note 407/2014-SRE/ANEEL [ANEEL, 2014b] claims that no statistical correlation was found between environmental variables and efficiency scores. Furthermore, Technical Note 407/2014-SRE/ANEEL provides environmental data that do not to support this claim. On the contrary, Bogetoft and Lopes [2014] present an exploratory analysis using Tobit regression models and 14 environmental variables, available from the regulator. Tobit regression results are statistically significant for four of the environmental variables: high vegetation index, precipitation index, average duration of interrupted energy and frequency of interrupted energy. The last two variables are quality KPI's (Key Performance Indicators), as described by the regulator.

It is worth mentioning that in the 2011 Periodic Tariff Review Cycle (3PTRC) the regulator proposed a second stage analysis to correct the DEA efficiency scores. Three methods are mentioned in Technical Note 101/2011 ANEEL [2011]: Tobit regression and the compound error models proposed by Simar and Wilson [2007] and Banker and Natarajan [2008]. This Technical Note 101/2011 ANEEL [2011] does not provide details about the application of the investigated second stage models. A closer look at the final corrected efficiencies revealed that the corrected scores were, most likely, estimated using a simpler OLS regression. Furthermore, corrected scores were not estimated as expected using OLS or Tobit models. There is evidence that the corrected scores were estimated using the regression equation rather than the residuals of the models.

The next Periodic Tariff Review Cycle (4PTRC) is expected to start in 2019. It is expected that the DEA model presented in April 2015 [ANEEL, 2014b] will be applied. Nevertheless, this work presents strong evidence that the environmental variables play an important role in DSOs efficiencies, that must not be ignored. Using the second stage models mentioned by the regulator in 2011 [ANEEL, 2011], this work evaluates the statistical significance of the environmental variables using the different second stage models and the efficiency changes due to second stage modeling. Further details about pros and cons are provided for each second stage model.

2.2.2 Data Envelopment Analysis

DEA is a popular benchmarking method introduced by Charnes et al. [1978] and then extended by Banker et al. [1984]. The original approach is based on previous studies by Farrell [1957], who proposed a technique to calculate relative efficiency scores of Decision Making Units (DSOs) with similar production contexts. DEA is a non-parametric approach, i.e., it does not require any previous knowledge about the functional form between the inputs and outputs that compose the Technology Production set. Through the minimal extrapolation principle, the frontier of fully efficient firms is composed of observed data [Agrell and Bogetoft, 2014].

Although previous knowledge about the functional form of the production frontier is not required, there are some assumptions that must be observed. Standard DEA models assume convexity and free disposability of inputs and outputs [Bogetoft, 2013]. These properties claim that it is always possible to absorb an extra amount of inputs, with no reduction in the amount of outputs [Mas-Colell et al., 1995].

The efficiency measured by DEA is a radial projection from the DSO to the frontier. Thus, the scale property is also important. According to Bogetoft [2013], it refers to how the production process responds to proportional increases in the input set. A Technology set may assume constant returns to scale (CRS), non-increasing returns to scale (NIRS), non-decreasing returns to scale (NDRS) or variable returns to scale (VRS).

Let the Production set T be composed of vector $\mathbf{w} = [w_1, ..., w_s]$ having s output variables and a vector $\mathbf{x} = [x_1, ..., x_m]$ having m input variables. The NDRS input-oriented efficiency of the reference DSO, known as DSO_0, is calculated using the linear programming problem shown in the linear problem 1, where α_r and γ_i are the weight parameters associated with the outputs and inputs, respectively. The ψ parameter is associated with the scaling property.

$$
\begin{aligned}
& \max \sum_{r=1}^{s} \alpha_r w_{r0} + \psi \\
& \text{s. t.:} \qquad \sum_{r=1}^{s} \alpha_r w_{rj} + \psi - \sum_{i=1}^{m} \gamma_i x_{ij} \leq 0, \quad j = 1, ..., n \\
& \qquad\qquad \sum_{i=1}^{m} \gamma_i x_{i0} = 1 \\
& \qquad\qquad \alpha_r, \gamma_i \geq 0 \\
& \qquad\qquad \psi \leq 0
\end{aligned}
\tag{1}
$$

The DEA model shown in Equation 1 is known as the primal equation and may include weight restrictions. Further details about DEA benchmarking modeling are found in Bogetoft and Otto [2010], Cook and Zhu [2008].

2.2.3 Second Stage Analysis

In general, input and output variables used in DEA are associated with controlled factors, i.e., production variables that can be managed by the decision maker in order to improve efficiency. Another set of variables - not necessarily less important - can affect production and are, generally, non-manageable. These variables are known as environmental or contextual variables. The inclusion of environmental variables in DEA analysis is not a new topic. Banker and Morey [1986] added exogenous variables in Equation 1. Econometric approaches were first proposed by Ray [1988] and Ray [1991] by adjusting linear regression models in which the dependent variable is the estimated DEA efficiency scores. This approach is known as second-stage analysis. Second stage analysis has become very popular as described by Simar and Wilson [2007].

In second stage analysis, DEA scores are managed as the dependent variables in a regression model [Ramalho et al., 2010]. In most empirical studies, linear regression, known as Ordinary Least Squares (OLS), or Tobit models are used.

According to McDonald [2009], two-stage analysis requires the specification of the underlying Data Generating Process (DGP), i.e., how the input and output variables, the production frontier and the environmental variables are correlated. Simar and Wilson [2007] and Banker and Natarajan [2008] were the first to propose DGP for second stage analysis. Both studies rely on different assumptions for the DGP. Banker and Natarajan [2008] present a less restrictive approach than Simar and Wilson [2007]. In addition, Ramalho et al. [2010] and Simar and Wilson [2007] claim that the model proposed by Banker and Natarajan [2008] is not consistent. Nonetheless, Banker and Natarajan [2008] claims that *the DEA-based procedure with OLS, maximum likelihood, or even Tobit estimation in the second stage perform as well as the best of the parametric methods in estimation of the impact of contextual variables on productivity.*

2.2.4 Ordinary Least Squares

The classic ordinary least squares statistical regression model assumes a linear relation between the dependent random variable Y and the independent variable z, as shown in Equation 2.

$$Y_i = \delta_0 + \delta_1 z_i + \epsilon_i \tag{2}$$

where ϵ_i is a random variable normally distributed with mean of zero and variance of σ^2, δ_0 is the intercept parameter and δ_1 is the slope parameter. For multiple independent variables, the vector representation can be used: $y_i = \mathbf{z}_i\delta + \epsilon$, where $\mathbf{z}_i = [1, z_{1i}, ..., z_{pi}]$ and $\delta = [\delta_0, \delta_1, ..., \delta_p]$. Estimates of the linear parameters are obtained using least squares minimization:

$$\hat{\delta}_0, \hat{\delta}_1 = arg \min_{\delta_0, \delta_1} \sum_{i=1}^{n} [y_i - (\delta_0 + \delta_1 z_i)]^2 \tag{3}$$

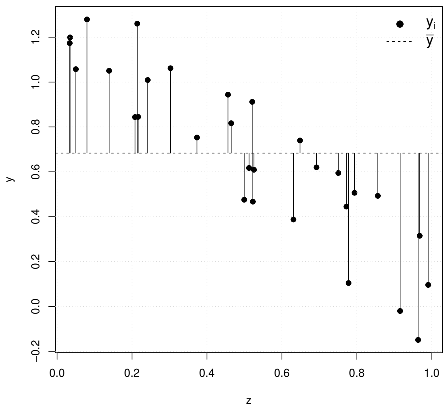
where n is the sample size.

2.2.4.1 Corrected dependent variable

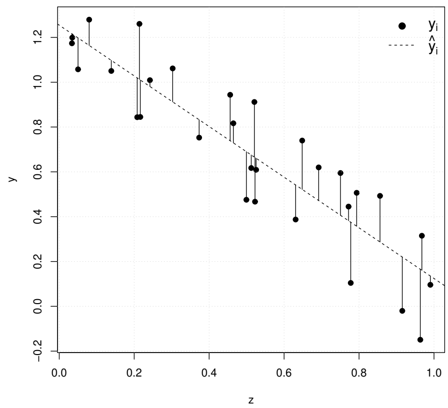
Second stage analysis can be seen as a regression analysis in which the final objective is to estimate a new dependent variable y_i^* which is not linearly correlated to the independent variable z_i. Using linear regression theory [Seber and Lee, 2012, Montgomery et al., 2012], this can be achieved using the *fundamental analysis-of-variance identity for a regression model*, show in Equation 4

$$\sum_{i=1}^{n} (y_i - \bar{y})^2 = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2 + \sum_{i=1}^{n} (y_i - \hat{y}_i) \tag{4}$$

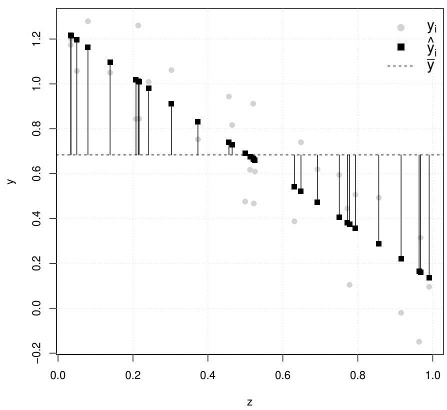
where $\hat{y}_i = \hat{\delta}_0 + \hat{\delta}_1 z_i$ is the fitted linear equation and $\bar{y}$ is the sample mean, $\bar{y} = \sum_i y_i/n$. The first term in Equation 4 is known as the *Total Sum of Squares* (TSS) and it represents the amount of variability in the observations y_i. The second term in Equation 4 is known as the *Explained Sum of Squares* (ESS) and it represents the component of the TSS associated with the fitted linear model. In other words, it represents the variability of the dependent variable linearly associated with the independent variable. Finally, the third term in Equation 4 is known as the *Residual*



(a) Total Sum of Squares (TSS)



(b) Residual Sum of Squares (RSS)



(c) Explained Sum of Squares (ESS)

Figure 1 – Fundamental analysis-of-variance identity for a linear regression model. TSS measures the total variability in the observations. RSS is the variability in the observations that is not linearly associated with the dependent variable. ESS is the variability in the observations that is linearly associated with the dependent variable.

Sum of Squares (RSS) and it represents the component of the TSS that is not linearly associated with the dependent variable. Figure 1 illustrates the analysis-of-variance identity.

Furthermore, the ESS can be written as: ESS $= \sum_i reg_i^2$, where $reg_i = (\hat{y}_i - \bar{y})$ is the component of the dependent variable linearly associated with the independent variable by means of the fitted regression. Therefore, the corrected dependent variable can be written as:

$$\begin{aligned} y_i^* &= y_i - reg_i \\ &= y_i - (\hat{y}_i - \bar{y}) \\ &= \bar{y} + \hat{\epsilon}_i \end{aligned} \tag{5}$$

where $\hat{\epsilon}_i$ is the residual of the linear model: $\hat{\epsilon}_i = y_i - \hat{y}_i$. Equation 5 shows an interesting property of the corrected dependent variable: the information of the dependent variable that is not linearly correlated to the independent variable is represented by the residuals of the regression model.

Therefore, using linear regression analysis, corrected variables are estimated using the sum of the sample mean of the dependent variable ($\bar{y}$) and the residuals of the regression model.

In addition, it is often of interest to calculate the *coefficient of determination* (R^2) which is defined as:

$$R^2 = \frac{ESS}{TSS} = 1 - \frac{RSS}{TSS} \tag{6}$$

The R^2 statistic ($0 \leq R^2 \leq 1$) represents the proportion of the variability in y explained by the regression model. On the contrary, as shown in Equation 5, the variability of the corrected dependent variable is associated with the RSS. Therefore, this work uses $1 - R^2$, which is the variability associated with the residuals of the regression model.

2.2.5 Tobit regression

The Tobit regression [Tobin, 1958] is commonly applied to estimate correlation between efficiency scores and contextual or environmental variables [Hoff, 2007]. As stated in McDonald [2009], the Tobit regression is used if the dependent variable is both continuous and discrete, which is the case of the DEA efficiency scores. Furthermore, the Tobit regression model has a latent linear structure as follows. Let Y_i be a latent dependent random variable defined as

$$Y_i = \delta_0 + \delta_1 z_i + \epsilon_i \tag{7}$$

where ϵ_i is a random variable normally distributed with mean of zero and variance of σ^2, δ_0 is the intercept parameter and δ_1 is the slope parameter, as previously defined in Equation 2.

The correlation between the efficiency scores (θ_i) and the latent random variable can be written as:

$$\theta_i = \begin{cases} 1, & \text{if } Y_i \geq 1; \\ Y_i, & \text{if } 0 < Y_i < 1; \\ 0, & \text{if } Y_i \leq 0. \end{cases} \tag{8}$$

In practice, most of the input-oriented efficiency scores estimated using DEA are above 0. Therefore, the lower bound of Equation 8 can be ignored. From Equations 7 and 8, the probability distribution of θ_i can be written as:

$$f(\theta_i|\mu_i, \sigma) = \left[\frac{1}{\sigma}\phi\left(\frac{\theta_i - \mu_i}{\sigma}\right)\right]^{d_i} \times \left[\Phi\left(\frac{\mu_i - 2}{\sigma}\right)\right]^{(1-d_i)} \tag{9}$$

where d_i is an indicator function, $d_i = I(\theta_i = 1) : d_i \in \{0, 1\}$, $\mu_i = \delta_0 + \delta_1 z_i$, $\phi(\cdot)$ is the standard normal density distribution and $\Phi(\cdot)$ is the standard normal cumulative distribution. From Equation 9, maximum likelihood (ML) estimates for δ_0, δ_1 and σ^2 are found.

2.2.5.1 *Corrected efficiency scores using Tobit regression*

If the Tobit model is used the corrected efficiency scores must be estimated using the latent variables Y_i. Nonetheless, the latent variables are unknown if $\theta_i = 1$ and, therefore, must be estimated. Equation 8 shows that $Y_i \geq 1$ if $\theta_i = 1$. Using probability theory and the Tobit model assumptions, shown in Equations 7 and 8, it can be shown that the conditional density of Y_i, given $\theta_i = 1$, is left truncated at 1 and normally distributed:

$$f(Y_i|\theta_i = 1, \mu_i, \sigma) = \frac{\phi\left(\frac{y_i - \mu_i}{\sigma}\right)}{\sigma\left[1 - \Phi\left(\frac{1-\mu_i}{\sigma}\right)\right]}, \quad Y_i > 1. \tag{10}$$

From Equation 10, point estimates for the latent variables can be calculated using the conditional mean:

$$E\left(Y_i|\theta_i = 1, \mu_i, \sigma\right) = \mu_i + \sigma \cdot \frac{\phi\left(\frac{1-\mu_i}{\sigma}\right)}{\left[1 - \Phi\left(\frac{1-\mu_i}{\sigma}\right)\right]} \tag{11}$$

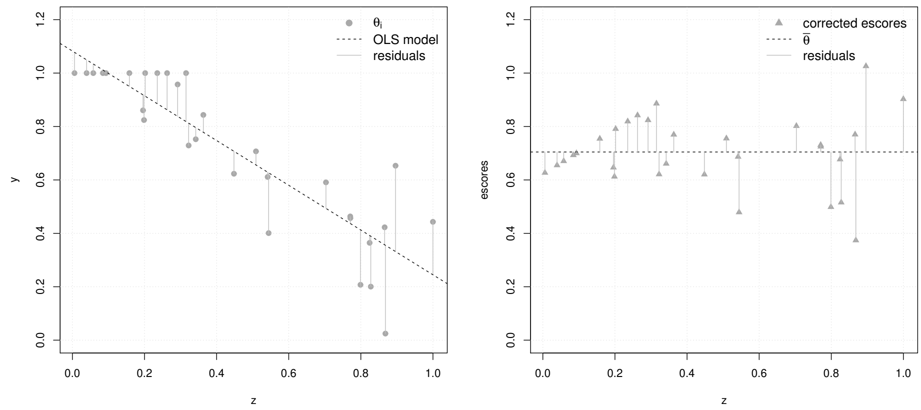
It is worth noticing the differences between corrected efficiency scores using OLS, in which the efficiency scores (θ_i) are used as the dependent variable in the regression model, and using Tobit, in which the latent variables (Y_i) are used to estimate the corrected scores. Figures 2 and 3 illustrate the differences using simulated data. If OLS is used then estimates of intercept and slope achieve minimum residuals between efficiency scores and regression equation, as shown in Figure 2 (a). Corrected scores are estimated using the mean value of the original scores and the residuals of the model, as shown in Figure 2 (b). As a consequence, DSOs which originally achieved efficiency scores of 100% are more likely to have efficiency scores below 1. On the contrary, using Tobit regression, the estimates of intercept and slope achieve minimum residuals between the latent dependent variables and the regression equation, even though the latent variables for DSOs with efficiency scores of 100% are missing. This is shown in Figure 3 (a). For the DSOs with efficiency scores of 1, the estimated latent variables are above 1. As a consequence, corrected efficiency scores for DSOs which originally achieved efficiency scores of 1 are more likely to be closer or equal to 1 using Tobit regression, as shown in Figure 3 (b). In addition, average values of corrected scores using OLS and Tobit regression are closer to the average value of the original scores.

2.2.6 Banker and Natarajan second stage model

The original output-oriented DGP model proposed by Banker and Natarajan [2008] is:

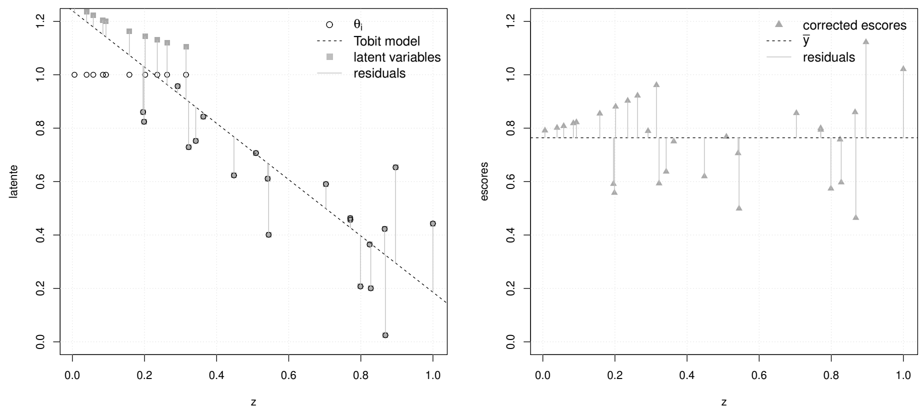
$$\mathbf{x} = \varphi\left(\mathbf{w}\right) \cdot e^{\mathbf{z}\delta + v - u} \tag{12}$$

where $\mathbf{x}$ and $\mathbf{w}$ are the input and output vectors, previously described, $\mathbf{z}$ is the vector of environmental variables, $\varphi(\cdot)$ is the best practice frontier, u is a positive random variable representing technical inefficiency and v is a random variable representing stochastic noise. It is assumed that the random variables u and v are independent. The density distribution of v,



(a) Fitted OLS regression. (b) Corrected scores using OLS.

Figure 2 – OLS fitted regression and corrected efficiency scores. OLS uses the efficiency scores as the dependent variable.



(a) Fitted Tobit regression. (b) Corrected scores using Tobit.

Figure 3 – Tobit fitted regression and corrected efficiency scores. Tobit uses the latent variable Y_i as the dependent variable.

$f_v(v)$, is a two-sided truncated normal distribution, $|v| \leq V^M$, with mean of zero and variance of σ^2. The density distribution of u, $f_u(u)$, is the Gamma distribution with the shape parameter equal to 2 and rate parameter λ.

$$f_u(u) = \frac{u \cdot e^{-u/\lambda}}{\lambda^2}, \quad u > 0, \quad \lambda > 0 \tag{13}$$

$$f_v(v) = \frac{1}{\sigma} \cdot \frac{\phi\left(\frac{v}{\sigma}\right)}{\Phi\left(\frac{V^M}{\sigma}\right) - \Phi\left(\frac{V^M}{\sigma}\right)}, \quad - V^M < \varepsilon < V^M \tag{14}$$

Equation 13 can be rewritten as

$$\frac{x}{\varphi(\mathbf{w})} = e^{\mathbf{z}\delta+v-u} \tag{15}$$

where $\varepsilon = v - u$ is the error attributable to noise and technical inefficiency in the output-oriented model.

It is worth mentioning that this work uses the input-oriented model in which the DGP is written as: $\mathbf{x} = \varphi(\mathbf{w}) \cdot e^{\mathbf{z}\delta+v+u}$. Thus, in the input-oriented model the error is written as $\epsilon = v + u$. It can be shown that the probability density of the input-oriented error ($\epsilon = v + u$) is related to the probability density of the output-oriented error ($\varepsilon = v - u$) as follows:

$$f_{v+u}(\epsilon) = f_{v-u}(-\epsilon) \tag{16}$$

Considering an input-oriented DEA model with one input, the ratio $\frac{x}{\varphi(\mathbf{w})}$ can be replaced by the estimated DEA input-oriented efficiency score, $\hat{\theta} = \hat{\varphi}(\mathbf{w})/x$, which leads to:

$$-\log\hat{\theta} = \mathbf{z}\delta + \epsilon \tag{17}$$

where $\epsilon = u + v$ is the input-oriented compound error, previously described, and $\mathbf{z}\delta$ is the linear component, $\mathbf{z}\delta = \sum_{i=1}^{k}\delta_i z_i$. The probability density of ϵ can be calculated using Equations 13 and 14. Banker and Natarajan [2008] show that the density of the output-oriented error model (ε) is:

$$f_\varepsilon(\varepsilon) = \frac{\sigma e^{(\sigma^2/2\lambda^2)+\varepsilon/\lambda}}{\lambda^2\left\{\Phi(V^M/\lambda) - \Phi(-V^M/\sigma)\right\}} \times \left[\left\{\phi(\varepsilon_1) - \phi(\varepsilon_2)\right\} + \varepsilon_1\left\{\Phi(\varepsilon_1) - \Phi(\varepsilon_2)\right\}\right] \tag{18}$$

where $\varepsilon_1 = \left(\frac{\varepsilon}{\sigma} + \frac{\sigma}{\lambda}\right)$ and $\varepsilon_2 = \left(\frac{V^M}{\sigma} + \frac{\sigma}{\lambda}\right)$. Therefore, using Equation 18, maximum likelihood estimates for σ, λ, V^M and $\boldsymbol{\delta}$ for the output-oriented model are found. In addition, using Equation 16, maximum likelihood estimates for σ, λ, V^M and $\boldsymbol{\delta}$ for the input-oriented model are found. It is also worth noticing that Equation 17 represents a linear regression model in which the dependent variable is the negative logarithm of the DEA efficiency scores.

2.2.6.1 Corrected efficiency scores for compound error models

In general, after estimating the parameters of the model, it is possible to estimate the residuals: $\hat{\epsilon}_i = -\log\hat{\theta}_i - \mathbf{z}_i\hat{\delta}$. In order to find final estimates of the corrected efficiency scores, $\hat{\hat{\theta}}_i$, it is necessary to estimate the technical inefficiency u. Using the Bayes Rule, the conditional density of u given ϵ can be written as:

$$f_{u|\varepsilon} = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{f_u(u)\cdot f_v(\varepsilon - u)}{f_\varepsilon(\varepsilon)} \tag{19}$$

The most often used point estimate for the corrected efficiency scores [Bogetoft and Otto, 2010] is the conditional mean $E(e^{-u}|\epsilon)$ presented in Equation 20.

$$\hat{\hat{\theta}}|\varepsilon = E(e^{-u}|\epsilon) = \int_0^{+\infty} e^u \cdot f(u|\varepsilon)du \tag{20}$$

In addition to Equation 20, an alternative conditional mean, $\log \hat{\hat{\theta}} = -E(u|\epsilon)$, and the conditional mode, $\log \hat{\hat{\theta}} = -M(u|\epsilon)$, can be used to provide point estimates of the corrected efficiency scores.

2.2.7 A close look at Banker and Natarajan compound error model

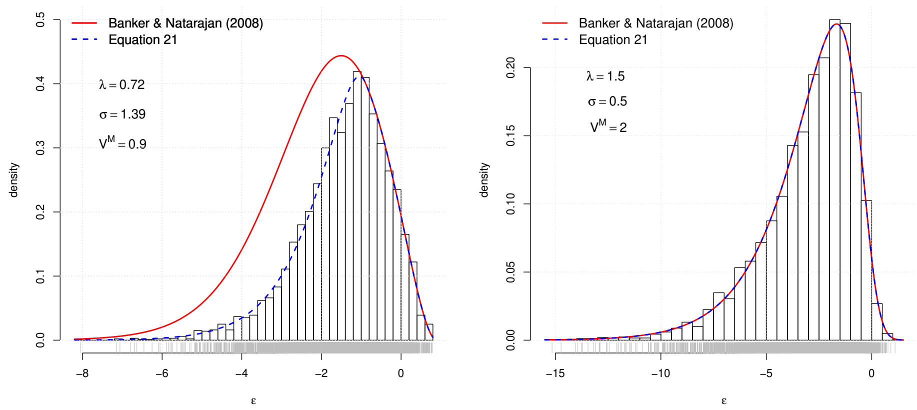
Given the model proposed by Banker and Natarajan [2008], in which the density distribution of the error follows a normal distribution and the density distribution of the technical inefficiency follows a Gamma distribution, the density distribution of the compound error, $\epsilon = u + v$, can be derived using probability theory [Feller, 1968]. Equation 21 shows the cumulative distribution function (cdf) of the compound error.

$$F_\epsilon(\epsilon) = \begin{cases} \int_{-V^M}^{+V^M} f_v(v)F_u(\epsilon - v)dv, & \epsilon > V^M \\ \int_{-V^M}^{\epsilon} f_v(v)F_u(\epsilon - v)dv, & -V^M < \epsilon \leq +V^M \end{cases} \tag{21}$$

The density distribution of ϵ, $f_\epsilon(\epsilon)$, is the derivative of Equation 21 with respect to the ϵ variable, $\frac{dF_\epsilon(\epsilon)}{d\epsilon}$, shown in Equation 22.

$$f_\epsilon(\epsilon) = \begin{cases} K\frac{\sigma}{\lambda^2}e^{\frac{-\epsilon}{\lambda}+\frac{\sigma^2}{2\lambda^2}}\left(\epsilon - \frac{\sigma^2}{\lambda}\right) \times \\ \quad \times \left\{\left[\Phi\left(\frac{+V^M}{\sigma} - \frac{\sigma}{\lambda}\right) - \Phi\left(\frac{-V^M}{\sigma} - \frac{\sigma}{\lambda}\right)\right] - \sigma\left[\Phi\left(\frac{-V^M}{\sigma} - \frac{\sigma}{\lambda}\right) - \Phi\left(\frac{+V^M}{\sigma} - \frac{\sigma}{\lambda}\right)\right]\right\}, \\ \quad \text{for } \epsilon > V^M; \\ K\Phi\left(\frac{\epsilon}{\sigma}\right) - Ke^{\frac{-z}{\lambda}+\frac{\sigma^2}{2\lambda^2}}\Phi\left(\frac{\epsilon}{\sigma} - \frac{\lambda}{\sigma}\right) + \\ \quad +K\sigma\frac{\epsilon}{\lambda^2}e^{\frac{-\epsilon}{\lambda}+\frac{\sigma^2}{2\lambda^2}}\left[\Phi\left(\frac{\epsilon}{\sigma} - \frac{\sigma}{\lambda}\right) - \Phi\left(\frac{-V^M}{\sigma} - \frac{\sigma}{\lambda}\right)\right] + \\ \quad +K\frac{\sigma^2}{\lambda^2}e^{\frac{-\epsilon}{\lambda}+\frac{\sigma^2}{2\lambda^2}}\left[\Phi\left(\frac{\epsilon}{\sigma} - \frac{\sigma}{\lambda}\right) - \Phi\left(\frac{-V^M}{\sigma} - \frac{\sigma}{\lambda}\right)\right] + \\ \quad +K\frac{\sigma^3}{\lambda^3}e^{\frac{-\epsilon}{\lambda}+\frac{\sigma^2}{2\lambda^2}}\left[\Phi\left(\frac{-V^M}{\sigma} - \frac{\sigma}{\lambda}\right) - \Phi\left(\frac{z}{\sigma} - \frac{\sigma}{\lambda}\right)\right], \\ \quad \text{for } -V^M < \epsilon \leq +V^M. \end{cases} \tag{22}$$

where $K = \frac{1}{\sigma} \cdot \frac{1}{\Phi(\frac{V^M}{\sigma}) - \Phi(\frac{-V^M}{\sigma})}$. Figure 4 compares the input-oriented density distribution of Banker and Natarajan [2008] with the density distribution shown in Equation 22 for different values of λ, σ and V^M. Data was generated using truncated Normal and Gamma random number generators. Figure 4 shows that the density distribution presented in Banker and Natarajan [2008] is a density approximation which fails to fit the data, as shown in Figure 4 (a). Numerical integration results show that $\int_{-\infty}^{V^M} f_\epsilon(\epsilon)d\epsilon = 1.535883$, for the example presented in Figure 4 (a) using the Banker and Natarajan density distribution, whereas $\int_{-\infty}^{V^M} f_\epsilon(\epsilon)d\epsilon = 1.000001$ using Equation 22. For Figure 4 (b) both methods achieve numerical integration close to 1. It is worth mentioning that Banker and Natarajan [2008] present a simulation study in which the noise variable v follows a truncated normal distribution with upper and lower bounds at



(a) Simulated values: $\lambda = 0.72$, $\sigma = 1.39$, $V^M = 0.9$

(b) Simulated values: $\lambda = 1.5$, $\sigma = 0.5$, $V^M = 2$

Figure 4 – Comparison of Banker and Natarajan error density distribution and the density distribution shown in Equation 22.

$+V^M = 6\sigma$ and $-V^M = -6\sigma$. For such large values of V^M, the approximation presented in Equation 18 is well behaved. In practice, the value of V^M is unknown and must be estimated. If the true unknown value of V^M is small, then Equation 18 [Banker and Natarajan, 2008] is a very poor approximation of the compound error density distribution. On the other hand, Maximum Likelihood estimates using Equation 22 also present numerical problems, mainly because the density function is highly complex and discontinuous at $\epsilon = V^M$.

2.2.8 Adapted SFA compound error model

The DGP presented by Banker and Natarajan [2008] may assume different density distributions. Such distributions have been investigated for the technical inefficiency, u. Meeusen and Van den Broeck [1977] use an exponential distribution, Aigner et al. [1977] use half-normal distribution, Stevenson [1980] uses truncated normal distribution, among others. Nonetheless, assuming v as normal distribution, $v \sim N(0, \sigma_v^2)$, and u as a half-normal distribution, $u \sim N^+(0, \sigma_u^2)$, the distribution of $\epsilon = v + u$ can be written as shown in Equation 23.

$$\begin{aligned} f_\varepsilon(\varepsilon) &= \frac{2}{\sqrt{2\pi}\sigma}\Phi\left(\frac{\lambda\varepsilon}{\sigma}\right) e^{-\frac{1}{2}\cdot\frac{\varepsilon^2}{\sigma^2}} \\ &= \frac{2}{\sigma}\phi\left(\frac{\varepsilon}{\sigma}\right)\Phi\left(\lambda\frac{\varepsilon}{\sigma}\right) \end{aligned} \tag{23}$$

where $\sigma^2 = \sigma_u^2 + \sigma_v^2$ is known as scale parameter, and $\lambda = \sigma_u/\sigma_v$, is hereafter known as shape parameter. Equation 23 is a particular case of the Skew-Normal distribution [Azzalini, 2013]. Aigner et al. [1977] claim that this representation is very convenient, since λ represents the ratio between inefficiency and noise. $\lambda^2 \to 0$ implies that $\sigma_v^2 \to \infty$ and/or $\sigma_u^2 \to 0$, i.e., the noise component dominates the error ϵ_i. As a consequence, the corrected efficiency scores are 1 (100%). Otherwise, if $\sigma_v^2 \to 0$, the error is dominated by the inefficiency and, therefore, corrected scores are the original first stage scores.

The error density distribution presented in Equation 23 is used in Stochastic Frontier Analysis (SFA), which is a parametric stochastic benchmarking method proposed by Aigner et al. [1977]. Since the SFA error density is used with the Banker and Natarajan [2008] DGP, the model is hereafter named *adapted* SFA, or simply *a*-SFA.

Similar to the linear regression model, Equation 24 shows the technical inefficiency coefficient of determination (R_u^2) [Llorca et al., 2014].

$$R_u^2 = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2} = \frac{\lambda^2}{1+\lambda^2} \tag{24}$$

2.2.8.1 *Sensitivity analysis of the λ parameter in the adapted SFA model*

Newton Raphson algorithm and variants, such as BFGS [Nocedal and Wright, 2006], are the most common algorithms to estimate the parameters of compound error models, using maximum likelihood estimation. For example, let $\Theta = [\lambda, \sigma^2, \delta]$ be the parameter vector of the a-SFA compound error model. Equation 25 shows the Newton Raphson parameter update equation

$$\Theta^{k+1} = \Theta^k - \left[\frac{\partial^2 l(\Theta^k)}{\partial \Theta^2}\right]^{-1} \frac{\partial l(\Theta^k)}{\partial \Theta} \tag{25}$$

where $l(\Theta)$ is the compound error log-likelihood function and k is the algorithm iteration.

Initial conditions, $\Theta^0 = [\lambda^{[0]}, \sigma^{2[0]}, \delta^{[0]}]$, are required to run the algorithm. In general, initial estimates for σ^2 and δ are found using ordinary least squares, which represent the compound error maximum log-likelihood solution if λ is fixed at 0. For the λ parameter, Bogetoft and Otto [2010] propose $\lambda^{[0]} = 1$.

It is worth noticing that λ is the ratio between σ_u and σ_v and, therefore, it is a critical parameter to estimate the corrected efficiency scores. Furthermore, despite its nice properties, for moderate sample size, the maximum likelihood estimate for λ may be infinite with positive probability [Azzalini and Arellano-Valle, 2013, Sartori, 2006]. Thus, we propose a sensitivity analysis for the λ parameter. Equation 26 shows the maximum log-likelihood function for fixed λ values. We investigate the maximum log-likelihood function for different values of λ.

$$g(\lambda) = \max_{\delta, \sigma^2} \sum_i \log\left[\frac{2}{\sigma}\phi\left(\frac{\varepsilon_i}{\sigma}\right)\Phi\left(\lambda\frac{\varepsilon_i}{\sigma}\right)\right] \tag{26}$$

2.2.9 Case Study

As previously mentioned, this work evaluates second stage analysis using a public data set available from the Brazilian regulator during the 2015 Periodic Tariff Review Cycle (4PTRC). The data comprises DEA efficiency scores estimated using an input-oriented DEA-NDRS model with weight restrictions. Average values for seven output variables and one input variable were calculated using yearly data from 2011 to 2013, for the 61 Brazilian energy distribution utilities. The input variable is the mean operational cost for each utility and the output variables are: underground network, overhead network, high voltage network, total number of consumers, weighted energy market, non-technical losses and consumer-hour interrupted energy. The weighted energy market is the weighted sum of high-, medium- and lower-voltage energy consumption in which the weights are proportional to the amount of consumption in the high- , medium-, and lower-voltage markets of each DSO. The last two output variables are, in fact, contextual variables, which were included in the model as negative outputs [Bogetoft and Otto, 2010].

In addition to input and output variables, 13 environmental variables are available: density of consumers, network density, complexity index, precipitation index, lightning rate, low vegetation index, medium vegetation index, high vegetation index, mean declivity index, proportion of paved roads, concession area (km^2), average duration of interrupted energy (DIE) and frequency of interrupted energy (FIE).

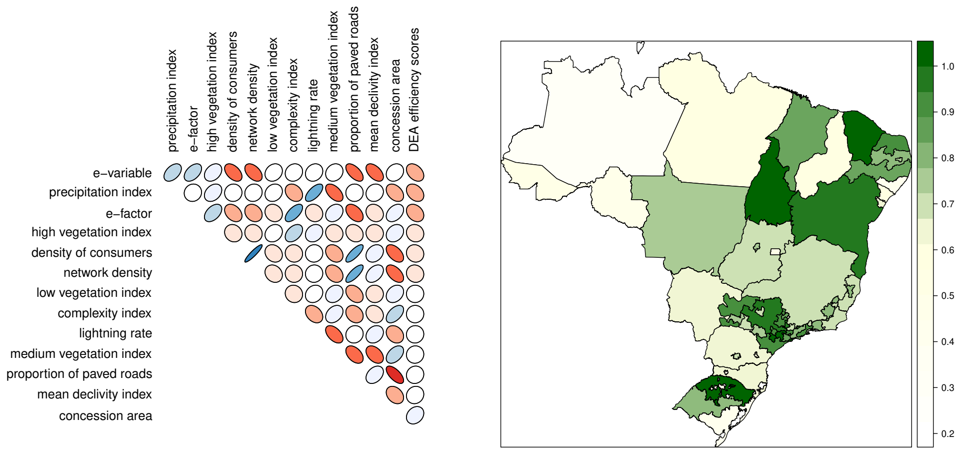
Since it could be argued that average duration of interrupted energy (DIE) and frequency of interrupted energy (FIE) are not purely environmental variables, these variables were replaced by two estimated variables. The environmental index, named as *e-index*, proposed by Gil [2016], was estimated using a penalized linear model in which FIE is the dependent variable and the purely environmental variables are the independent variables. The environmental factor, named as *e-factor*, is the first factor of a statistical Factor Analysis [Johnson et al., 2002] using the original 13 variables.

2.3 Results

Figure 5 (a) shows the Spearman [Spearman, 1904] correlation matrix using the proposed environmental variables and the DEA efficiency scores. Positive correlations are represented by ellipses with positive slopes. Negative correlations are represented by ellipses with negative slopes. The larger (or lower) the correlation the narrower the ellipse. The last column shows the correlation among the first stage DEA efficiency scores and the environmental variables. It can be seen that the *e-variable* has the larger correlation followed by the precipitation index and *e-factor*. Figure 5 (b) shows the DEA efficiency scores across the Brazilian territory. It can be seen that most of the lower efficiency scores are concentrated in the north region, in the upper left part of the map.

Table 1 shows the ordinary least squares (OLS) and Tobit model results. Each model was adjusted using one environmental variable. In this case, the dependent variable is the DEA efficiency scores. Both OLS and Tobit results show that *e-variable*, *e-factor*, precipitation index, high vegetation index and network density are the statistically significant variables, using P-value ≤ 0.10.

Figure 6 shows the Tobit corrected efficiency scores of the Brazilian utilities, sorted in increasing order of the first stage DEA efficiency scores. Each boxplot comprises corrected scores of five Tobit models, each model using one of the five selected environmental variables shown in Table 1. In general, the utilities: AME, CERON, ELETROACRE, CELPA, CEMAT and CEMAR have corrected scores much larger than their original first stage scores. These utilities are located in the northern part of Brazil. It is worth mentioning that, in general, average values



(a) Correlation matrix of the enviromental variables and the DEA efficiency scores.

(b) Brazilian map of the first stage DEA efficiency scores.

Figure 5 – Exploratory analysis of the correlation among efficiency scores and environmental variables (a), and the Brazilian map of the efficiency scores (b).

Table 1 – Ordinary Least Squares and Tobit regression results using the DEA efficiency scores as the dependent variable

	Ordinary Least Squares		Tobit model	
Environmental variable	Coefficient	P-value	Coefficient	P-value
e-variable	-0.01068	0.00038	-0.01101	0.00039
e-factor	-0.06684	0.00718	-0.07179	0.00635
precipitation index	-0.00020	0.00841	-0.00019	0.01614
high vegetation index	-0.49652	0.02084	-0.51690	0.02376
network density	-0.01321	0.08469	-0.01352	0.10026
proportion of paved roads	0.12279	0.29810	0.16177	0.21702
concession area (km^2)	0.00000	0.28811	0.00000	0.34611
lightning rate	-0.00548	0.51613	-0.00467	0.61270
complexity index	-0.10631	0.67510	-0.13303	0.63058
density of consumers	0.00003	0.80473	0.00003	0.82994
medium vegetation index	-0.04034	0.80618	-0.02203	0.90343
low vegetation index	-0.06812	0.86041	-0.02550	0.95225
mean declivity index	0.00054	0.93143	0.00026	0.97038

of original (first stage) and corrected efficiency scores using the Tobit model are closer. As a consequence, most of the Brazilian utilities have boxplots close to original first stage scores. Table 4 shows the corrected efficiencies using the Tobit model for each environmental variable, the average corrected efficiency and the difference between the average corrected efficiencies and the first stage efficiencies (DEA). DSOs with the largest differences are highlighted. Results show that AME is the DSO with the largest change (Diff= 0.2660) in efficiency, followed by CELPA, ELETROACRE, CERON and CEMAT. Most utilities have negative change in the corrected efficiency. This is because the Tobit model generates corrected efficiencies with mean value close to the mean value of the first stage efficiencies, as previously described.

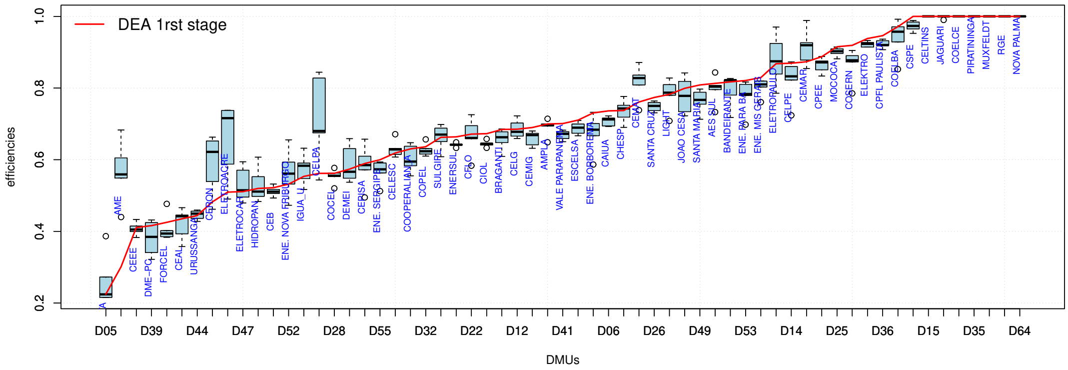


Figure 6 – Corrected scores using the selected Tobit models.

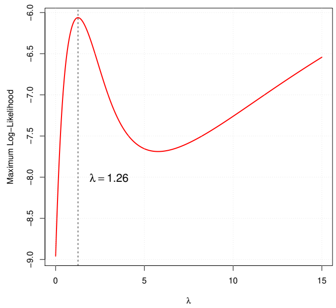
Table 2 – Ordinary Least Squares and adapted SFA regression results using the negative logarithm of DEA efficiency scores as the dependent variable.

	Ordinary Least Squares			adapted SFA		
Environmental variable	Coefficient	P-value	$1 - R^2$	Coefficient	P-value	R_u^2
e-variable	0.01917	0.00005	0.75543	0.01475	0.00833	0.61357
e-factor	0.10794	0.00661	0.88157	0.06402	0.14690	**0.99329**
precipitation index	0.00034	0.00483	0.87307	-0.00002	0.17000	**0.99558**
high vegetation index	0.86916	0.01106	0.89553	-0.06969	0.67900	**0.99558**
network density	0.02667	0.02823	0.92102	-0.00445	0.26500	**0.99558**

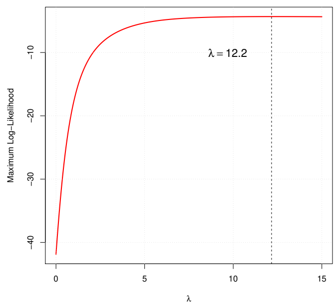
Table 2 shows the ordinary least squares (OLS) and a-SFA results using the five previously selected environmental variables. OLS results use the negative logarithm of the first stage DEA scores as the dependent variable, as proposed in the input-oriented DGP of Banker and Natarajan [2008]. It can be seen that the OLS estimates are positive, as expected. Furthermore, the a-SFA estimates of the *e-variable* and *e-factor* are also positive, as expected. On the contrary, the estimates of the precipitation index, high vegetation index and network density are negative. These estimates also present larger values of the R_u^2 coefficient (shown in boldface) and, consequently, larger estimated values of $\hat{\lambda}$.

Figure 7 presents the sensitivity analysis of the λ parameter using the a-SFA model for each environmental variable. The λ parameter was varied from 0 to 15. For the *e-variable*, the maximum likelihood estimate is $\hat{\lambda} = 1.26$. For the *e-factor*, the maximum likelihood estimate is $\hat{\lambda} = 12.2$, which is a very large value. For precipitation index, high vegetation index and network density the estimated λ parameter is the maximum value of $\hat{\lambda} = 15$. Therefore, the sensitivity analysis shows that maximum likelihood estimate of λ is biased. This conclusion is also supported by the signs of the estimated a-SFA coefficients which are negative, as opposed to the previous positive OLS results. Bias prevention of maximum likelihood estimates for λ are presented in the literature [Azzalini and Arellano-Valle, 2013, Sartori, 2006]. As previously described, large λ means that the technical inefficiency component dominates the error. Consequently, corrected scores are the original first stage scores. This is an unlikely result for *e-factor*, precipitation index, high vegetation index and network density. Therefore, if a proper rate between technical inefficiency and noise is selected then proper inference for the a-SFA coefficients are generated.

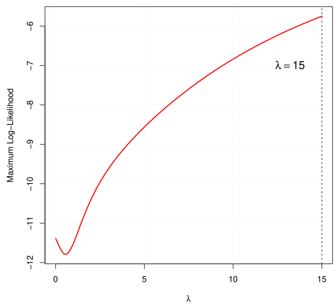
Interestingly, the *e-variable* model did not present maximum likelihood bias for λ. The



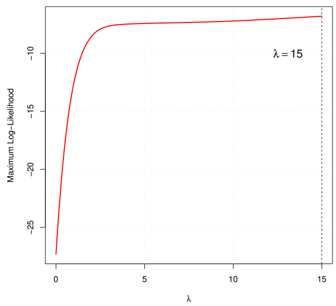
(a) *e-variable*



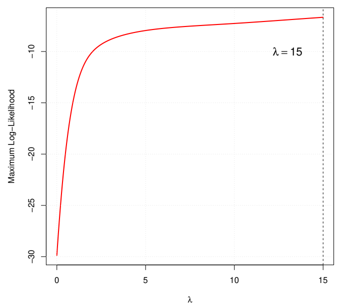
(b) *e-factor*



(c) Precipitation index



(d) High vegetation index



(e) Network density

Figure 7 – Maximum Log-Likelihood sensitivity analysis for λ using a-SFA model.

e-variable combines the information of all environmental variables. Therefore, one may claim that the unbiased λ estimates for the *e-factor*, precipitation index, high vegetation index and network density variables will be close to $\hat{\lambda} = 1.26$ ($R_u^2 = 61.36\%$). Furthermore, R_u^2 is the ratio between technical inefficiency and the sum of technical inefficiency and error in the a-SFA model. Similarly, $1 - R_{ols}^2$ represents the inefficiency component in the OLS model. We propose to use $1 - R_{ols}^2$ to calculate our initial value of λ. This proposal is not supported by mathematical proofs or simulation studies. However, it is worth mentioning that initial values for the a-SFA optimization algorithm are the OLS estimates. Therefore, we use OLS results to create a new

Table 3 – Maximum likelihood estimates for a-SFA using fixed values of λ ($\tilde{\lambda}$).

Environmental variable	Coefficient	P-value	$1 - R^2_{ols}$	$\tilde{\lambda}$	LogLikelihood
e-factor	0.10689	0.00525	0.88157	2.7283	-8.0805
precipitation index	0.00047	0.05380	0.87307	2.6227	-9.8691
high vegetation index	0.75211	0.00418	0.89553	2.9278	-7.6765
network density	0.01718	0.06400	0.92102	3.4149	-8.5734

estimate for λ, as shown in Equation 27:

$$\tilde{\lambda} = \sqrt{\frac{1 - R^2_{ols}}{R^2_{ols}}} \tag{27}$$

Equation 27 is based on Equation 24 in which R^2_u is replaced by $1 - R^2_{ols}$. Equation 27 assumes that the ratio between the technical inefficiency (σ_u) and noise (σ_v) is similar to the ratio between the variability associated with the residuals of the OLS model and the Total Sum of Squares (TSS). As previously described, the OLS residuals are used to estimate the corrected dependent variable.

Given $\tilde{\lambda}$, maximum likelihood estimates for δ are shown in Table 3 for *e-factor*, precipitation index, high vegetation index and network density. It worth noticing that the signs of the estimated coefficients are now positive, as expected.

Figures 8, 9 and 10 show corrected efficiency scores using the conditional means: $E(e^{-u}|\epsilon)$ and $e^{-E(u|\epsilon)}$, and the conditional mode $e^{-M(u|\epsilon)}$ for a-SFA models with selected environmental variables and using $\tilde{\lambda}$ (except for *e-variable*). Using the conditional mean $E(e^{-u}|\epsilon)$, corrected efficiency scores are larger than first stage scores except for utilities which achieved first stage scores close to 1 (100%). This is because the upper bound of the probability distribution of $e^{-u|\epsilon}$ is 1 and the conditional mean is unlikely to generate a corrected score at the upper bound of the distribution. Similar results are found using the conditional mean $e^{-E(u|\epsilon)}$ (see Figure 9). In practice, using conditional means, it is unlikely that any utilities will achieve a corrected efficiency score of 100%, including those which achieved a first stage score of 100%.

In general, using the conditional mode (see Figure 10) utilities with a first stage score of 100% may achieve a corrected efficiency score of 100%. In addition, corrected efficiency scores for all utilities are equal or larger than the first stage scores using the conditional mode. Table 5 shows the corrected efficiencies using the conditional mode for each environmental variable, the average corrected efficiencies and the difference between the average corrected efficiencies and the first stage efficiencies. DSOs with the largest differences are highlighted. Results show that AME is the DSO with the largest change (Diff= 0.2292) in efficiency, followed by CELPA, ELETROACRE, CERON and CEMAT. As compared to Table 4, DSOs with the largest changes are the same. However, changes using a-SFA are positive to most of the DSOs.

Table 6 shows the operational costs (OPEX), the first stage efficiencies (DEA), the efficient costs (OPEX $\times$ DEA), and the average changes in the efficient costs due to second stage analysis using Tobit and a-SFA (conditional mode). DSOs with the largest changes using a-SFA are highlighted. CELPA is the only DSO with larger changes in both efficiency and efficient costs. CEMIG, ELETROPAULO, COPEL and CELESC achieved larger changes in efficient costs

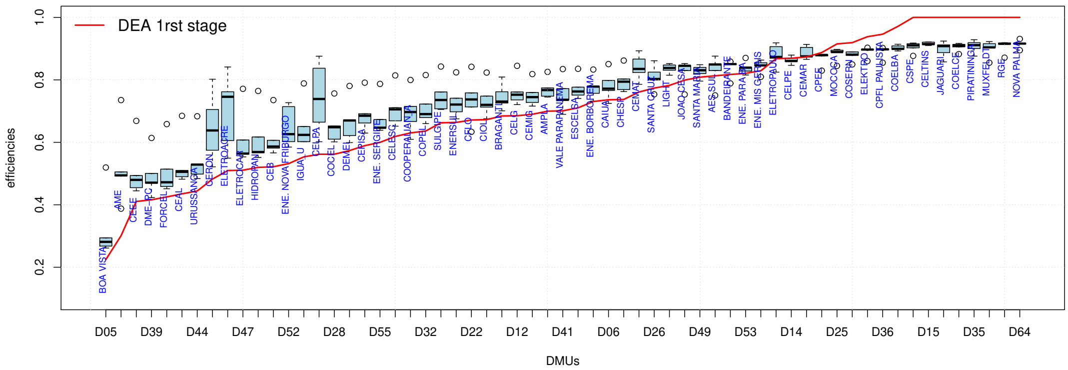


Figure 8 – Corrected scores using the a-SFA model and the conditional mean $E(e^{-u}|\epsilon)$.

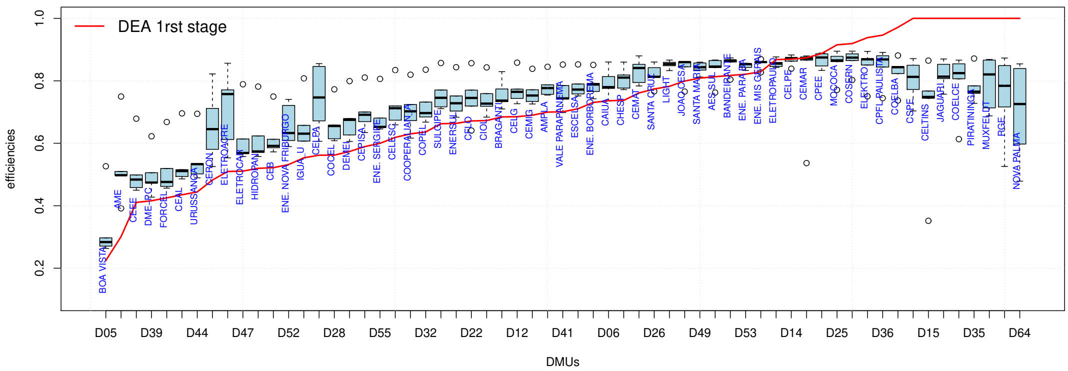


Figure 9 – Corrected scores using the a-SFA model and the conditional mean $e^{-E(u|\epsilon)}$

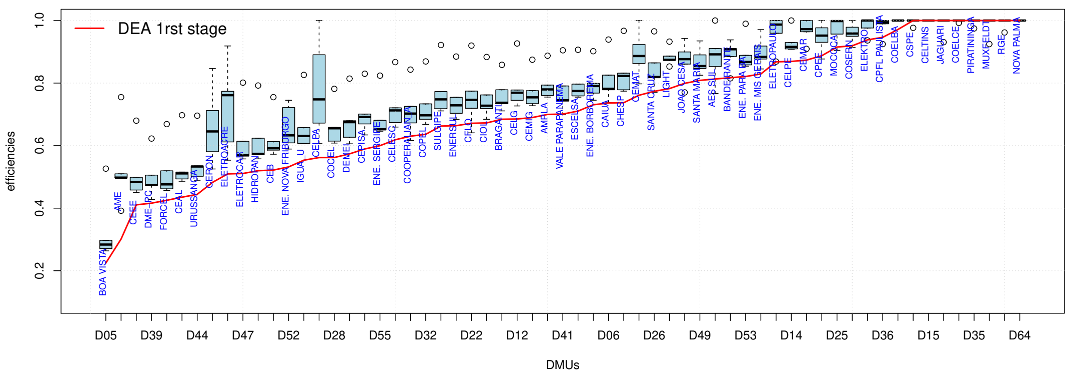


Figure 10 – Corrected scores using the a-SFA model and the conditional mode $e^{-M(u|\epsilon)}$.

because their operational costs were the largest. On average, these utilities achieved an efficiency change of +10%. Therefore, their efficient costs could potentially be increased by 10% due to corrected efficiencies using environmental information, on average. For example, efficient costs for CEMIG could be increased by R$ 170,438,713.07 or U$ 64 Million (considering an average exchange rate of R$ 2.65 per U$ 1.00 in year 2014) using environmental information and a-SFA model with conditional mode. Efficient costs for CELPA could potentially be increased by U$

48 Million and efficient costs for ELETROPAULO could potentially be increased by U$ 44.8 Million. Overall, using conditional mode and a-SFA compound error model, efficient costs could be increased by U$ 575.25 Million due to environmental heterogeneity.

2.4 Discussion and conclusion

Second stage analysis is the most common approach in evaluating the impact of environmental contexts if DEA modeling is used to estimate the efficiencies of DSOs. In brief, it applies a regression model in which the dependent variable is a function of the estimated efficiency scores and the independent variables are related to the environment. The simplest approach is ordinary least squares. Intuitively, input-oriented scores are within the range 0 to 1, output-oriented scores are within the range 1 to $+\infty$, and DEA modeling generates multiple DSOs with efficiencies of 100%. Thus, based on the range of the dependent variable, one alternative is to use the censored Tobit regression model. Furthermore, sophisticated data generating processes are proposed. These models are built under strict assumptions and they propose a correlation structure among inputs, outputs and environmental variables. Nonetheless, most second stage models assume a linear structure among the functions of the efficiency scores and the environmental variables, i.e., a linear regression model.

Second stage regression models try to separate the component of the dependent variable that is correlated to the environment, from the component of the dependent variable that is not correlated to the environment. This last component comprises the residuals of the regression model and, therefore, is used to estimate the final corrected efficiencies. If OLS regression is applied, then final corrected scores may be larger than 100%. If the Tobit regression is applied, then corrected scores are within the range 0 to 1 and multiple DSOs may reach corrected efficiencies of 100%. If compound error models are applied, then corrected scores may be lower than 100% or may reach corrected efficiencies of 100%, depending on the probabilistic equation used to estimate the corrected efficiencies. Therefore, the range of the corrected efficiencies is a user choice for compound error models.

In addition, compound error models are estimated using likelihood maximization. These models assume that the error of the regression model is composed of noise and technical inefficiency. Different probability density distributions for error and technical inefficiency lead to different compound error probability densities and, consequently, different likelihood functions. Approximations are proposed in the literature for specific cases, but lead to major estimation problems as shown in this work. The simplest approach is to assume a truncated normal distribution for the technical inefficiency and a normal distribution for the noise. However, this model may reach an infinite estimate of the shape parameter with positive probability, which was observed in our case study. The literature presents penalized maximum likelihood [Azzalini and Arellano-Valle, 2013], a modified maximum likelihood estimator [Sartori, 2006], among other solutions to generate finite estimate of the shape parameter. We propose to use the OLS determination coefficient (R^2) to estimate the shape parameter, as shown in Equation 27.

In practice, average values of corrected efficiencies using Tobit models are closer to first stage efficiencies. Therefore, only a few DSOs will have their corrected efficiencies larger than first stage efficiencies, and the remaining DSOs will have their corrected efficiencies slightly lower than first stage efficiencies. On the contrary, using compound error models most of the DSOs may reach corrected efficiencies larger than first stage efficiencies. Nonetheless, our case study shows that the DSOs most affected by the environment will have their efficiencies similarly changed using Tobit or compound error models. Therefore, even though different second stage models are applied it is expected that final results are consistent regardless of the applied model. In conclusion, we suggest using the Tobit model as an exploratory tool to evaluate the impact of environmental information on corrected efficiencies. Then, an a-SFA model with conditional mode and varying shape parameter can be used to estimate final corrected efficiencies.

The analysis of the corrected efficiency scores may also raise other issues about the benchmarking modeling, not addressed in this study. A high degree of correction in the efficiency scores may suggest missing variables in the first-stage modeling. Besides, the bias generated by a first-stage misspecified model cannot be corrected by a second-stage procedure. Thus, the second-stage procedure may also be a valuable tool used to identify gaps in the DEA modeling, even if the efficiency scores correction is not the main analyst's aim.

Finally, it is worth mentioning that Tobit and compound error models rely on a strong assumption of *separability*, i.e., models in which the environmental factors do not influence the shape of the production set [Bădin et al., 2012, 2014]. Daraio et al. [2015] provides a statistical procedure to test whether the separability assumption holds. In our case study, we assumed that the separability assumption is true. This is an important limitation that needs to be addressed in the future. Furthermore, alternative DGPs are presented in the literature, such as the model proposed by Simar and Wilson [2007], which is currently being investigated. We did not find in the literature a detailed analysis of the compound error models and the Tobit regression model for DEA second stage analysis, such as we are proposing in this work.

Acknowledgements

The authors thank CNPq, FAPEMIG and CEMIG for financial support, project number APQ-03165-11.

Table 4 – First stage DEA efficiencies, corrected efficiencies using environmental variables, average corrected efficiencies and differences between first stage and corrected average efficiencies using Tobit models.

DSO	DEA	*e-variable*	*e-factor*	precip.	high veg.	net density	Average	Diff.
BOA VISTA	0.2246	0.3866	0.2155	0.2725	0.2242	0.2158	0.2629	0.0383
AME	0.3012	0.6831	0.5590	0.4400	0.5489	0.6051	0.5672	0.2660
CEEE	0.4107	0.4332	0.3828	0.4147	0.4051	0.3995	0.4071	-0.0036
DME-PC	0.4160	0.3220	0.3411	0.4320	0.3846	0.4243	0.3808	-0.0352
FORCEL	0.4252	0.4020	0.3852	0.4767	0.3835	0.3940	0.4083	-0.0170
CEAL	0.4351	0.4454	0.4661	0.3574	0.3933	0.4423	0.4209	-0.0142
URUSSANGA	0.4443	0.4364	0.4280	0.4563	0.4593	0.4495	0.4459	0.0016
CERON	0.4824	0.6521	0.6218	0.5394	0.6629	0.4617	0.5876	0.1052
ELETROACRE	0.5096	0.7375	0.7380	0.5877	0.7160	0.4901	0.6539	0.1442
ELETROCAR	0.5109	0.5706	0.5147	0.5943	0.4795	0.4958	0.5310	0.0201
HIDROPAN	0.5198	0.5525	0.4978	0.6070	0.4832	0.5111	0.5303	0.0105
CEB	0.5219	0.4932	0.5172	0.5108	0.5059	0.5320	0.5118	-0.0101
EN. NOVA FRIBURGO	0.5319	0.4728	0.5612	0.5931	0.6555	0.5322	0.5630	0.0311
IGUAÇU	0.5535	0.5904	0.5832	0.6321	0.5169	0.5473	0.5740	0.0205
CELPA	0.5619	0.8279	0.8442	0.6802	0.6752	0.5436	0.7142	0.1523
COCEL	0.5620	0.5201	0.5536	0.5628	0.5771	0.5551	0.5537	-0.0083
DEMEI	0.5737	0.5663	0.5484	0.6587	0.5371	0.6308	0.5883	0.0146
CEPISA	0.5894	0.5849	0.6572	0.4947	0.6097	0.5720	0.5837	-0.0057
EN. SERGIPE	0.5999	0.5732	0.5937	0.5124	0.5633	0.5908	0.5667	-0.0332
CELESC	0.6188	0.6314	0.6073	0.6712	0.6287	0.6149	0.6307	0.0119
COOPERALIANÇA	0.6302	0.5948	0.5551	0.6375	0.5833	0.6475	0.6036	-0.0266
COPEL	0.6362	0.6309	0.6159	0.6567	0.6099	0.6237	0.6274	-0.0088
SULGIPE	0.6626	0.6984	0.6701	0.6083	0.6880	0.6507	0.6631	0.0006
ENERSUL	0.6638	0.6485	0.6330	0.6420	0.6427	0.6411	0.6415	-0.0224
CFLO	0.6714	0.6949	0.5834	0.7256	0.6607	0.6592	0.6647	-0.0067
CIOL	0.6727	0.6455	0.6331	0.6447	0.6412	0.6580	0.6445	-0.0282
BRAGANTI	0.6844	0.6094	0.6627	0.6859	0.6478	0.6779	0.6567	-0.0277
CELG	0.6852	0.7024	0.7225	0.6779	0.6589	0.6659	0.6855	0.0003
CEMIG	0.6899	0.6319	0.6802	0.6417	0.6688	0.6737	0.6593	-0.0306
AMPLA	0.6998	0.6487	0.7143	0.7000	0.6942	0.6966	0.6908	-0.0090
VALE PARAPANEMA	0.7009	0.6723	0.6503	0.6781	0.6591	0.6824	0.6684	-0.0325
ESCELSA	0.7105	0.6740	0.7093	0.6669	0.6894	0.6995	0.6878	-0.0227
ENE. BORBOREMA	0.7307	0.6670	0.7008	0.5865	0.6837	0.7324	0.6741	-0.0566
CAIUA	0.7363	0.7161	0.6929	0.7124	0.6945	0.7224	0.7077	-0.0286
CHESP	0.7373	0.7518	0.7767	0.7431	0.6904	0.7188	0.7361	-0.0012
CEMAT	0.7611	0.8715	0.8360	0.8089	0.8279	0.7383	0.8165	0.0554
SANTA CRUZ	0.7737	0.7501	0.7310	0.7641	0.7371	0.7593	0.7483	-0.0254
LIGHT	0.7824	0.7083	0.8094	0.7799	0.7872	0.8279	0.7825	0.0001
JOAO CESA	0.7993	0.7226	0.7341	0.8424	0.7782	0.8186	0.7792	-0.0201
SANTA MARIA	0.8087	0.7129	0.7882	0.7550	0.7669	0.7969	0.7640	-0.0447
AES SUL	0.8131	0.8040	0.7330	0.8435	0.8075	0.7956	0.7967	-0.0164
BANDEIRANTE	0.8173	0.7180	0.7804	0.8225	0.8220	0.8270	0.7940	-0.0233
EN. PARAIBA	0.8210	0.7834	0.8167	0.6980	0.7792	0.8103	0.7775	-0.0435
EN. MIS GERAIS	0.8292	0.7607	0.8102	0.8192	0.8030	0.8200	0.8026	-0.0266
ELETROPAULO	0.8680	0.7856	0.8392	0.8748	0.9244	0.9702	0.8788	0.0109
CELPE	0.8693	0.8226	0.8732	0.7239	0.8327	0.8599	0.8225	-0.0468
CEMAR	0.8735	0.9887	0.9264	0.8783	0.9196	0.8544	0.9135	0.0400
CPEE	0.8876	0.8335	0.8511	0.8880	0.8716	0.8754	0.8639	-0.0236
MOCOCA	0.9152	0.8968	0.8817	0.9095	0.9148	0.9027	0.9011	-0.0141
COSERN	0.9192	0.8731	0.8903	0.7851	0.8774	0.9049	0.8662	-0.0531
ELEKTRO	0.9382	0.9143	0.9143	0.9272	0.9326	0.9234	0.9224	-0.0159
CPFL PAULISTA	0.9463	0.9193	0.9070	0.9320	0.9200	0.9364	0.9229	-0.0233
COELBA	0.9714	0.9290	0.9921	0.8526	0.9709	0.9572	0.9404	-0.0310
CSPE	1	0.9528	0.9653	0.9733	0.9841	0.9885	0.9728	-0.0272
CELTINS	1	1	1	1	1	1	1	0.0000
COELCE	1	1	1	1	1	1	1	0.0000
PIRATININGA	1	1	1	1	1	1	1	0.0000
MUXFELDT	1	1	1	1	1	1	1	0.0000
RGE	1	1	1	1	1	1	1	0.0000
NOVA PALMA	1	1	1	1	1	1	1	0.0000
JAGUARI	1	0.9902	1	1	1	1	0.9980	-0.0020

Table 5 – First stage DEA efficiencies, corrected efficiencies using environmental variables, average corrected efficiencies and differences between first stage and corrected average efficiencies using a-SFA models and $e^{-M(u|e)}$.

DSO	DEA	*e-variable*	*e-factor*	precip.	high veg.	net density	Average	Diff.
BOA VISTA	0.2246	0.5264	0.2707	0.2973	0.2837	0.2635	0.3283	0.1037
AME	0.3012	0.7551	0.4977	0.3917	0.5098	0.4977	0.5304	0.2292
CEEE	0.4107	0.6798	0.4497	0.4988	0.4838	0.4581	0.5140	0.1033
DME-PC	0.4160	0.6226	0.4276	0.5058	0.4732	0.4742	0.5007	0.0847
FORCEL	0.4252	0.6689	0.4563	0.5195	0.4762	0.4620	0.5166	0.0913
CEAL	0.4351	0.6973	0.5111	0.5155	0.4860	0.4936	0.5407	0.1056
URUSSANGA	0.4443	0.6958	0.4893	0.5351	0.5333	0.5020	0.5511	0.1068
CERON	0.4824	0.8468	0.6454	0.5806	0.7122	0.5254	0.6621	0.1797
ELETROACRE	0.5096	0.9187	0.7614	0.6119	0.7737	0.5534	0.7238	0.2142
ELETROCAR	0.5109	0.8014	0.5683	0.6140	0.5688	0.5575	0.6220	0.1111
HIDROPAN	0.5198	0.7922	0.5577	0.6238	0.5738	0.5707	0.6236	0.1038
CEB	0.5219	0.7550	0.5725	0.6129	0.5916	0.5856	0.6235	0.1017
EN. NOVA FRIBURGO	0.5319	0.7450	0.6088	0.6329	0.7218	0.5891	0.6595	0.1276
IGUAÇU	0.5535	0.8261	0.6309	0.6577	0.6070	0.6065	0.6656	0.1122
CELPA	0.5619	1	0.8906	0.6721	0.7479	0.6063	0.7834	0.2215
COCEL	0.5620	0.7816	0.6082	0.6555	0.6582	0.6145	0.6636	0.1016
DEMEI	0.5737	0.8143	0.6058	0.6796	0.6268	0.6751	0.6803	0.1066
CEPISA	0.5894	0.8299	0.7011	0.6695	0.6915	0.6342	0.7052	0.1158
ENE. SERGIPE	0.5999	0.8238	0.6461	0.6809	0.6524	0.6509	0.6908	0.0909
CELESC	0.6188	0.8671	0.6594	0.7209	0.7126	0.6739	0.7268	0.1080
COOPERALIANÇA	0.6302	0.8430	0.6165	0.7255	0.6727	0.7025	0.7120	0.0818
COPEL	0.6362	0.8692	0.6680	0.7336	0.6970	0.6844	0.7304	0.0942
SULGIPE	0.6626	0.9217	0.7181	0.7479	0.7731	0.7111	0.7744	0.1118
ENERSUL	0.6638	0.8848	0.6840	0.7544	0.7289	0.7033	0.7511	0.0872
CFLO	0.6714	0.9199	0.6409	0.7745	0.7464	0.7194	0.7602	0.0888
CIOL	0.6727	0.8834	0.6842	0.7622	0.7277	0.7186	0.7552	0.0825
BRAGANTI	0.6844	0.8584	0.7111	0.7786	0.7341	0.7372	0.7639	0.0795
CELG	0.6852	0.9266	0.7692	0.7780	0.7448	0.7270	0.7891	0.1039
CEMIG	0.6899	0.8748	0.7276	0.7758	0.7545	0.7342	0.7734	0.0835
AMPLA	0.6998	0.8875	0.7605	0.7937	0.7797	0.7553	0.7953	0.0956
VALE PARAPANEMA	0.7009	0.9048	0.6991	0.7909	0.7449	0.7430	0.7766	0.0757
ESCELSA	0.7105	0.9065	0.7550	0.7968	0.7746	0.7591	0.7984	0.0879
ENE. BORBOREMA	0.7307	0.9019	0.7452	0.7991	0.7680	0.7905	0.8010	0.0703
CAIUA	0.7363	0.9391	0.7372	0.8255	0.7785	0.7818	0.8124	0.0761
CHESP	0.7373	0.9671	0.8227	0.8317	0.7742	0.7785	0.8349	0.0975
CEMAT	0.7611	1	0.8865	0.8628	0.9238	0.7976	0.8941	0.1330
SANTA CRUZ	0.7737	0.9654	0.7708	0.8646	0.8194	0.8178	0.8476	0.0738
LIGHT	0.7824	0.9325	0.8530	0.8744	0.8734	0.8862	0.8839	0.1015
JOAO CESA	0.7993	0.9428	0.7701	0.8996	0.8607	0.8766	0.8700	0.0707
SANTA MARIA	0.8087	0.9348	0.8251	0.8902	0.8467	0.8544	0.8703	0.0616
AES SUL	0.8131	1	0.7667	0.9107	0.8919	0.8529	0.8844	0.0713
BANDEIRANTE	0.8173	0.9382	0.8151	0.9099	0.9082	0.8847	0.8912	0.0739
EN. PARAIBA	0.8210	0.9897	0.8541	0.8887	0.8583	0.8675	0.8917	0.0706
EN. MIS GERAIS	0.8292	0.9708	0.8452	0.9185	0.8836	0.8770	0.8990	0.0698
ELETROPAULO	0.8680	0.9871	0.8687	0.9593	1	1	0.9630	0.0950
CELPE	0.8693	1	0.9080	0.9297	0.9094	0.9157	0.9326	0.0633
CEMAR	0.8735	1	0.9725	0.9642	1	0.9094	0.9692	0.0957
CPEE	0.8876	1	0.8770	0.9768	0.9518	0.9304	0.9472	0.0597
MOCOCA	0.9152	1	0.9047	1	0.9983	0.9567	0.9719	0.0567
COSERN	0.9192	1	0.9136	0.9785	0.9496	0.9585	0.9601	0.0408
ELEKTRO	0.9382	1	0.9363	1	1	0.9762	0.9825	0.0443
CPFL PAULISTA	0.9463	1	0.9246	1	0.9945	0.9896	0.9817	0.0355
COELBA	0.9714	1	1	1	1	1	1	0.0286
CSPE	1	1	0.9766	1	1	1	0.9953	-0.0047
CELTINS	1	1	1	1	1	1	1	0.0000
NOVA PALMA	1	1	1	1	1	1	1	0.0000
COELCE	1	1	0.9924	1	1	1	0.9985	-0.0015
PIRATININGA	1	1	0.9746	1	1	1	0.9949	-0.0051
RGE	1	1	0.9618	1	1	1	0.9924	-0.0076
JAGUARI	1	1	0.9308	1	1	1	0.9862	-0.0138
MUXFELDT	1	1	0.9248	1	1	1	0.9850	-0.0150

Table 6 – OPEX, Efficient OPEX and changes due to second stage analysis using Tobit and a-SFA models.

DSO	DEA	OPEX	Efficient OPEX	Tobit change	a-SFA change
BOA VISTA	0.2246	R$ 82,104,840.00	R$ 18,440,273.91	+R$ 3,145,668.67	+R$ 8,516,293.31
AME	0.3012	R$ 374,980,226.70	R$ 112,939,446.57	+R$ 99,759,865.69	+R$ 85,952,612.67
CEEE	0.4107	R$ 597,813,956.70	R$ 245,519,242.15	-R$ 2,170,784.46	+R$ 61,778,027.97
DME-PC	0.4160	R$ 30,082,166.67	R$ 12,515,269.58	-R$ 1,059,610.64	+R$ 2,546,850.68
FORCEL	0.4252	R$ 3,741,156.67	R$ 1,590,885.94	-R$ 63,509.52	+R$ 341,665.09
CEAL	0.4351	R$ 312,737,580.00	R$ 136,074,961.96	-R$ 4,446,591.21	+R$ 33,023,437.16
URUSSANGA	0.4443	R$ 4,996,156.67	R$ 2,219,557.61	+R$ 8,175.78	+R$ 533,783.75
CERON	0.4824	R$ 239,274,793.30	R$ 115,425,863.29	+R$ 25,170,469.57	+R$ 42,994,742.95
ELETROACRE	0.5096	R$ 89,155,566.67	R$ 45,436,299.85	+R$ 12,859,669.42	+R$ 19,095,755.64
ELETROCAR	0.5109	R$ 13,944,003.33	R$ 7,124,433.13	+R$ 279,666.13	+R$ 1,548,753.25
HIDROPAN	0.5198	R$ 6,030,620.00	R$ 3,134,762.21	+R$ 63,410.55	+R$ 626,154.40
CEB	0.5219	R$ 333,767,260.00	R$ 174,185,875.74	-R$ 3,355,073.56	+R$ 33,928,669.82
EN. NOVA FRIBURGO	0.5319	R$ 28,054,820.00	R$ 14,922,747.12	+R$ 871,430.97	+R$ 3,580,336.55
IGUAÇU	0.5535	R$ 13,072,183.33	R$ 7,235,216.34	+R$ 267,808.34	+R$ 1,466,070.20
CELPA	0.5619	R$ 577,061,083.30	R$ 324,230,317.40	+R$ 87,906,513.09	+R$ 127,830,685.68
COCEL	0.5620	R$ 15,634,566.67	R$ 8,786,303.90	-R$ 129,355.12	+R$ 1,588,759.62
DEMEI	0.5737	R$ 8,913,560.00	R$ 5,113,963.53	+R$ 129,802.69	+R$ 950,191.47
CEPISA	0.5894	R$ 334,005,756.70	R$ 196,863,979.19	-R$ 1,908,176.21	+R$ 38,689,742.11
EN. SERGIPE	0.5999	R$ 164,595,263.30	R$ 98,741,667.52	-R$ 5,468,363.86	+R$ 14,965,894.34
CELESC	0.6188	R$ 842,382,040.00	R$ 521,230,906.70	+R$ 10,054,939.03	+R$ 91,010,833.71
COOPERALIANÇA	0.6302	R$ 9,767,343.33	R$ 6,155,574.46	-R$ 259,617.76	+R$ 799,151.46
COPEL	0.6362	R$ 1,225,581,910.00	R$ 779,729,537.34	-R$ 10,772,123.91	+R$ 115,444,893.67
SULGIPE	0.6626	R$ 36,088,133.33	R$ 23,910,659.84	+R$ 19,934.82	+R$ 4,035,567.54
ENERSUL	0.6638	R$ 331,261,320.00	R$ 219,904,359.22	-R$ 7,410,120.23	+R$ 28,896,639.68
CFLO	0.6714	R$ 14,326,320.00	R$ 9,619,227.84	-R$ 95,974.54	+R$ 1,271,647.27
CIOL	0.6727	R$ 29,008,853.33	R$ 19,513,898.41	-R$ 816,850.25	+R$ 2,394,157.64
BRAGANTI	0.6844	R$ 38,394,170.00	R$ 26,276,123.02	-R$ 1,061,888.03	+R$ 3,052,162.73
CELG	0.6852	R$ 762,130,693.30	R$ 522,186,551.46	+R$ 265,606.32	+R$ 79,211,972.85
CEMIG	0.6899	R$ 2,041,586,440.00	R$ 1,408,445,836.91	-R$ 62,486,919.25	+R$ 170,438,713.07
AMPLA	0.6998	R$ 479,317,470.00	R$ 335,421,016.78	-R$ 4,327,873.13	+R$ 45,800,554.60
VALE PARAPANEMA	0.7009	R$ 45,450,040.00	R$ 31,855,721.48	-R$ 1,475,501.35	+R$ 3,438,934.10
ESCELSA	0.7105	R$ 302,786,963.30	R$ 215,129,705.67	-R$ 6,869,774.22	+R$ 26,614,155.11
EN. BORBOREMA	0.7307	R$ 35,458,666.67	R$ 25,909,136.34	-R$ 2,006,836.66	+R$ 2,491,956.94
CAIUA	0.7363	R$ 56,770,493.33	R$ 41,800,179.38	-R$ 1,624,772.01	+R$ 4,320,504.00
CHESP	0.7373	R$ 12,527,823.33	R$ 9,236,866.11	-R$ 14,515.82	+R$ 1,222,057.15
CEMAT	0.7611	R$ 423,266,803.30	R$ 322,143,661.97	+R$ 23,453,907.71	+R$ 56,312,592.24
SANTA CRUZ	0.7737	R$ 44,712,816.67	R$ 34,596,027.01	-R$ 1,135,749.73	+R$ 3,302,001.63
LIGHT	0.7824	R$ 722,222,026.70	R$ 565,076,736.33	+R$ 96,651.57	+R$ 73,307,550.20
JOAO CESA	0.7993	R$ 1,848,053.33	R$ 1,477,096.42	-R$ 37,126.67	+R$ 130,667.98
SANTA MARIA	0.8087	R$ 28,950,813.33	R$ 23,412,171.25	-R$ 1,293,664.35	+R$ 1,782,480.87
AES SUL	0.8131	R$ 270,415,596.70	R$ 219,871,519.93	-R$ 4,430,380.66	+R$ 19,293,515.57
BANDEIRANTE	0.8173	R$ 327,364,556.70	R$ 267,543,430.54	-R$ 7,620,247.79	+R$ 24,206,704.64
EN. PARAIBA	0.8210	R$ 249,989,183.30	R$ 205,245,859.18	-R$ 10,874,814.29	+R$ 17,658,421.00
EN. MINAS GERAIS	0.8292	R$ 95,472,570.00	R$ 79,168,161.82	-R$ 2,539,295.00	+R$ 6,663,184.36
ELETROPAULO	0.8680	R$ 1,255,830,567.00	R$ 1,090,014,424.63	+R$ 13,635,928.43	+R$ 119,365,967.45
CELPE	0.8693	R$ 549,361,833.30	R$ 477,560,937.25	-R$ 25,736,108.73	+R$ 34,754,674.32
CEMAR	0.8735	R$ 394,983,213.30	R$ 345,002,378.22	+R$ 15,798,494.26	+R$ 37,818,286.42
CPEE	0.8876	R$ 13,787,390.00	R$ 12,237,101.72	-R$ 325,845.75	+R$ 822,542.39
MOCOCA	0.9152	R$ 9,542,343.33	R$ 8,733,270.15	-R$ 134,755.02	+R$ 541,193.72
COSERN	0.9192	R$ 196,500,780.00	R$ 180,628,322.94	-R$ 10,425,531.55	+R$ 8,022,496.95
ELEKTRO	0.9382	R$ 463,617,950.00	R$ 434,980,748.00	-R$ 7,360,897.77	+R$ 20,523,368.13
CPFL PAULISTA	0.9463	R$ 720,481,060.00	R$ 681,771,543.54	-R$ 16,811,976.99	+R$ 25,558,992.16
COELBA	0.9714	R$ 835,616,980.00	R$ 811,694,357.55	-R$ 25,905,492.15	+R$ 23,922,622.45
CSPE	1	R$ 15,405,500.00	R$ 15,405,500.00	-R$ 419,112.86	-R$ 72,111.65
CELTINS	1	R$ 158,705,426.70	R$ 158,705,426.70	R$ 0.00	R$ 0.00
NOVA PALMA	1	R$ 4,967,863.33	R$ 4,967,863.33	R$ 0.00	R$ 0.00
MUXFELDT	1	R$ 1,781,550.00	R$ 1,781,550.00	R$ 0.00	-R$ 26,803.87
JAGUARI	1	R$ 10,427,793.33	R$ 10,427,793.33	-R$ 20,496.96	-R$ 144,372.60
COELCE	1	R$ 459,836,866.70	R$ 459,836,866.70	R$ 0.00	-R$ 697,999.18
PIRATININGA	1	R$ 273,902,093.30	R$ 273,902,093.30	R$ 0.00	-R$ 1,393,946.61
RGE	1	R$ 244,263,520.00	R$ 244,263,520.00	R$ 0.00	-R$ 1,867,785.60

3 An empirical analysis of the Brazilian Transmission utilities incentive regulation for costs

Abstract

Brazil started to reform its electricity market in the final years of the 1990s. Gradual changes in regulatory policy were implemented in order to strengthen the incentives. In the energy transmission segment, mild results regarding cost reductions were achieved. Major changes in this segment occurred after arbitrary interventions by the government in 2012. Such interventions raised the risk perceived by investors. The negative impacts of this event on the transmission market notwithstanding, the regulatory framework finally improved its incentive power. The results of incentive regulation for Brazilian transmission companies, regarding operational costs, are analyzed in this paper and the effectiveness of the regulatory signals is discussed. It is shown that, despite the immediate losses that the arbitrary changes imposed upon the system, the long-term impact has tended to be positive.

Keywords: emerging markets, regulation, electricity transmission, restructuring.

3.1 Introduction

Electricity markets have been subject to reforms in many countries since the 1980s. Except for Chile, most of the emerging economies followed this trend into the 1990s. In Brazil, incentive regulation tools were implemented after 1997. Brazilian energy companies were vertically segregated and privatization occurred in all segments. An integrated system was created, connecting generators and consumers in a unique network. In this context, transmission system operators (TSOs) emerged as important players in ensuring system reliability.

After its creation, the Brazilian electricity energy regulator (ANEEL) had the challenge to create incentive mechanisms for companies that owned assets in the existing transmission park, and to attract investors to expand the electricity system. The first incentive rules for the existing companies were implemented in 2000, and were gradually improved in subsequent years.

Nevertheless, the Ministry of Mines and Energy (MME) introduced profound changes in the regulatory framework, through a Provisional Act, in 2012. This event affected all segments of the electricity industry, especially transmission and generation. Such interference caused disturbances in the market, raising the risk perceived by investors. Facing the negative repercussion of these interventions, governments installed after 2015 assumed a different attitude in order to ensure technical independence of the regulator, thereby reducing the perception of risk by investors.

An analysis of the incentive-based regulation of Brazilian TSOs is presented in this paper. The analysis focuses on the cost reduction incentives. Specific themes, such as quality, are not addressed. The objective is to provide an overview of the results of the economic incentives, and point out important issues that can be improved.

The paper is organized as follows. Section 3.2 presents an overview of incentive regulation concerning energy markets. Section 3.3 presents details about the electricity energy market in Brazil, focusing on the rules regarding TSOs. Section 3.4 presents the incentive regulation mechanisms for costs, and their results. Section 3.5 presents conclusions and final remarks.

3.2 Natural monopolies in energy markets and regulation

An industry is a natural monopoly if the provision of a particular good or service by a single firm minimizes system costs [Cabral, 2000]. Moreover, in this industry framework, there are considerable fixed cost and relatively low marginal costs [Bogetoft and Otto, 2010]. Alternatively, according to Cabral [2000], legal constraints may lead some firms to monopoly status.

According to Hirschey [2009], monopoly firms are **price makers**. This is in contrast to firms in competitive markets, who are price takers. In addition, to this author, monopoly firms enjoy an informational advantage, thus creating competitive benefits. Monopolies also tend to underproduce and overcharge the services provided [Bogetoft and Otto, 2010], as they are not subject to market forces. Furthermore, monopolies have limited incentives to reduce costs. Regulation emerges, in this context, to correct these distortions.

Hirschey [2009] and Cabral [2000] classify electricity distribution and transmission as classic cases of natural monopolies, since these services do not have close substitutes. Moreover, Bogetoft and Otto [2010] claim that, in the case of energy distribution, the demand is relatively inelastic, which makes a regulatory framework necessary to avoid overpricing. According to these authors, regulators have been empowered to act as *proxy* purchasers of the services, thus imposing constraints on the prices and the modes of production. According to Hirschey [2009], regulation helps constrain the cost advantage that monopolies may have.

According to Laffont and Tirole [1990] and Liston [1993], regulation is subject to three basic constraints. The first constraint refers to the information asymmetry between the consumer and the producer, i.e., the regulator should be able to consider information regarding the relevant service costs and the demand. The second constraint is that regulators must ensure that firms reach the break-even point, preventing them from failing in the long term. Finally, the regulator must deal with political and administrative constraints, ensuring that subsidies and incentives are allocated correctly.

From a historic perspective, regulation has been used broadly as tools in the electric energy sectors of many countries, especially from the 1990s on. According to Sioshansi and Pfaffenberger [2006], in general, electricity industries worldwide started as vertically integrated geographic monopolies, either state-owned or privately-owned, and have evolved to industries that are subject to price and entry regulation. The authors claim that regulation is part of restructuring programs that emerged in electric energy sectors worldwide since the 1990s (or earlier, in the case of United Kingdom and Chile).

The main goal of restructuring electricity power sectors was to improve sector performance, which frequently provided poor service quality, high system losses and low labor productivity. Frequently, prices were too low to cover costs and support new investments [Sioshansi and

Pfaffenberger, 2006]. Thus, for these authors, a common restructuring agenda addressed some key issues, such as:

i. **Privatization of stated-owned utilities**, to create higher incentives for performance improvements, and to make it more difficult for the state to use these companies to pursue costly political agendas.

ii. **Vertical separation of utilities**, to lead potentially competitive segments such as generation and retail supply into market behavior.

iii. **Creation of a public wholesale spot energy.**

iv. **Horizontal integration of transmission and networking operations**, to designate a single independent system operator to manage the operation of the network, to schedule generation to meet demand and to maintain the physical parameters of the network.

According to these authors, significant portions of the total costs of electricity supply, distribution and transmission would continue to be regulated, despite the sector's restructuring. The efficiency of competitive wholesale retail markets depends on a well-functioning network infrastructure supporting transmission and distribution.

From the first frameworks, the regulatory toolbox evolved to contain numerous, more or less ingenious, solutions to the regulator's problems. Bogetoft and Otto [2010] list four main approaches: cost-recovery, fixed-price (revenue, revenue-cap, price-cap), yardstick and franchise auction. The first two approaches are discussed below. We refrain from explaining further models since they are not subject of the present case study. The interested reader may find details in the book of Bogetoft and Otto [2010].

The cost-recovery approach makes use of the cost information supplied by agents. According to Bogetoft and Otto [2010], the regulator may choose to reimburse the reported costs fully, often adding some fixed markup factor. According to Braeutigam and Panzar [1993], the cost-plus approach has the advantage of being simple to apply, but is limited in several situations. It may lead to a distorted capex incentive, encouraging the raising of costs instead of the use of new technologies. In practice, as the firm's price is defined based on its costs, regulated companies tend to raise costs in order to have higher prices. Nevertheless, Pollitt [2004] highlights that the cost recovery approach needs to be defined based on solid accountancy information.

Gradually, the cost-recovery approach has been replaced by regulatory frameworks with greater incentive power. Joskow [2014] points that the development of incentive regulation theory reflects a wide range of assumptions about the nature of the information possessed by the regulator and the firm about: costs, cost-reducing managerial effort, demand and product quality. Designed at the beginning of 1990s, price-cap regulation was broadly adopted by countries to regulate energy and gas utilities. Liston [1993] explains that, in this framework, a cap is defined for the prices and the firms are free to set prices below that. Firms are allowed to retain the efficiency gains they have. Bogetoft and Otto [2010] explain that, in the case of regulation of Distribution Operator Systems (DSOs), regulators usually fix revenues or prices for a regulatory period (typically 4 or 5 years). Efficiency gains in this period may be retained by firms. As stated by Braeutigam and Panzar [1993], price-cap regulation breaks the direct relation between cost and revenue/price.

Price-cap regulation also presents limitations. According to Filippini and Wild [2001], the imperfect information available to the regulator leads to some problems that may be difficult to address. If price caps are set too high, there is the possibility of dead-weight loss. The opposite may also be true, and the regulating authority might have a credibility or commitment problem if the regulated firms are not viable due to price-caps that are set too low. External shocks that may influence costs are also ignored. Moreover, Joskow [2014] explains that, in practice, the freedom to define prices above the cap is limited. Price caps are used primarily as mechanisms to provide incentives for cost reduction by giving the regulated firms exogenous budget constraints.

Joskow [2014] presents an overview of the results of incentive regulation frameworks for the electricity market in the United Kingdom. A similar analysis is done by Pollitt [2004] for the Chilean case. Both countries were pioneers in reforming the electricity sector, providing a critical basis for performance analysis. In both cases, the authors concluded that the incentive regulation approach was successful in terms of reducing costs. The reform in the electricity sector was important to achieve these results and both cases share some common features, such as the privatization of utility companies and vertical segregation of segments. The market stability, guaranteed by the law, is a remarkable attribute of the Chilean as well as the British system.

Brazilian reform of the electricity sector started at the end of the 1990s, within a context of restructuring policies in the emerging markets. Since then, gradual changes in regulation have been made to improve its incentive power. In recent years, heavy state intervention in the electricity sector has changed important rules for revenues and pricing, especially for generation and transmission companies. In the next sections, these changes and their impacts as regulatory signals concerning the TSOs are evaluated.

3.3 Electricity energy market in Brazil

The Brazilian electricity reform started in the mid 1990s, after the economy had stabilized. According to Sanches [2011], political changes occurring at that time resulted in a new energy model aligned with international practices. This new model was based on three pillars: (*i*) privatization, (*ii*) vertical segregation and (*iii*) efficiency.

Between 1996 and 1998, the government led a project to redesign the energy industry. The project, named RE-SEB (*Projeto de Reestruturação do Setor Elétrico Brasileiro*, Restructuring Project of the Brazilian Electric Sector), brought suggestions from stakeholders to modernize the sector. These suggestions included the creation of free energy markets and the creation of a regulatory framework to support private investments in the sector [Brazilian Ministry of Mines and Energy, 2001].

In this context, the National Agency of Electric Energy (*Agência Nacional de Energia Elétrica* – ANEEL) was created in December, 1996. ANEEL is an autarchy responsible for regulating energy companies and overseeing their activities. At about the same period, the

National System Operator (*Operador Nacional do Sistema* – ONS) was also created. The latter is an independent body that manages the supply and dispatch of energy, considering the National Integrated System (*Sistema Integrado Nacional* – SIN). In this centralized model, ONS decides which generation plants should dispatch energy, to ensure the stability of the system and optimize the total cost.

Upon recommendation from RE-SEB, the activities of energy generation, transmission and distribution were segregated. The central idea in the RE-SEB model was to increase competitiveness in the sector. Thus, the generation segment could now follow market rules. As stated previously, energy transmission and distribution are classic natural monopolies and should be regulated. Sanches [2011] states that the regulation of monopolies was not a new issue for the Brazilian government when these changes were proposed. Nevertheless, incentive regulation tools started to be applied to energy companies only after the creation of ANEEL and the passing of laws that enabled private companies to enter the market.

Further reforms, regarding the creation of a free energy market, were introduced after 2004. Since then, the Brazilian energy market has comprised both regulated and free consumers. The first group (also called captive consumers) includes those for which the regional distributor is the compulsory supplier, with a regulated energy rate. The second group includes consumer units which fill some voltage level or demand requirements, and may ask not to be supplied by the DSO. These consumers are free to negotiate directly with generators. Their energy rates follow market rules. Both types of consumers are connected in the National Integrated System (SIN).

In 2012, additional changes were made that affected the electricity market. Governmental interventions, through a Provisional Act, altered the rules for remuneration of regulated companies in all segments and had a strong impact on the generation and transmission companies. This event caused instability in the sector, increasing judicial intervention.

ANEEL defines energy distribution as the segment dedicated to delivering electrical energy to the final consumer. In general, these companies operate at voltage levels under 230 kV. Transmission companies, on the other hand, are responsible for connecting the generators to the distribution companies, operating mostly at voltage levels above 230 kV. Regulation of the latter group is detailed in the next session.

3.3.1 Business models for energy transmission

The expansion of the energy network in Brazil is a centralized decision shared among ONS, ANEEL, the Ministry of Mines and Energy and the Energy Research Office (EPE). Since 2000, investment in new concession areas of transmission networks can be allocated to existing concession contracts, or may be defined through auctions. As a result, there are two business models for TSOs in Brazil, classified as follows:

i. **Existing TSOs:** are the nine TSOs that resulted from the vertical segregation in the 2000s. Some of these TSOs ran auctions after 2000 and, together with their existing concession contracts, also manage bid concession contracts. These companies were responsible for 71% of the operating network circuits of the system in 2016 [ANEEL, 2018b].

ii. **Bid TSOs:** are TSOs whose concession areas are the result of bids in auctions after 2000. There are about 68 Bid TSOs but, at present, some of them are pre-operational, constructing new networks and substations, They are not currently operational.

Both types of companies are subject to the same rules regarding the expansion of their segments. Nevertheless, there are differences concerning their tariff reviews, explained in the following session.

3.3.2 Remuneration of transmission utilities

In the Brazilian electricity market, generation plants and DSOs are interconnected in the SIN. Thus, transmission utilities must be always available in order to allow full integration among generation plants and distributors, and to ensure system reliability. Therefore, transmission system operators (TSOs) are remunerated by the availability of their assets, regardless of the amount of transmitted energy.

The regulated revenues (RAP) of Existing TSOs is defined in chapter 9.1 of the tariff review procedures, Proret [ANEEL, 2018b]. The formula for remuneration is reproduced in Equation 28. The final value includes two main portions: (a) assets amortization and remuneration and (b) efficient operational costs. Assets amortization comprises both a reference guide for the asset purchase value and standardized depreciation rates. The remuneration of the assets is calculated using a regulatory WACC (Weighted Average Cost of Capital). Efficient operational costs are defined using a benchmarking methodology. A third portion, regarding taxes and sectorial charges, is included in the final summation. The total revenues are reviewed each five years, and calculated in annual parcels.

$$RAP = CAA + CAOM + ET \tag{28}$$

where RAP is the annual allowed revenue (*Receita Anual Permitida*), CAA is the annual cost of assets (amortization and remuneration, *Custo Anual dos Ativos*), $CAOM$ is the efficient operational cost (*Custos de Administração, Operação e Manutenção*) and ET are the taxes and sectoral charges (*Encargos setoriais e Tributos*).

The regulated revenues of Bid TSOs are defined in the auctions. Eventual incremental assets or reinforcements, not foreseen in the contracts, are remunerated according to the same rules applied to Existing TSOs. The total revenues are also reviewed each five years, counting from each contract signature date. Therefore, the tariff review for each Bid TSO occurs on a different date.

The original concession contracts of the Existing TSOs are subject to five-year tariff review cycles (TRCs), regarding operational costs and the regulatory remuneration of assets (WACC and asset values). However, the TRCs that occurred between 2000 and 2012 affected only the revenues regarding assets installed after 2000 (the incremental assets), which were less than 14% of the total revenues of the sector. In practice, the revenues related to assets existing when the vertical segregation occurred were not affected by the TRCs, and were protected. This was known in the sector as “shielded revenue”.

The bid contracts are also subjected to TRCs, but within a limited scope. There are revenues, fixed in the bid, that are not reduced. They may be reduced only if the segment X-Factor implies efficiency change in the sector. The WACC of the Bid companies is partially reviewed, making changes just in the debit cost. The regulated revenues of both types of TSOs are divided between consumers and generators regarding a node tariff calculation. It is worth mentioning that the difference in the tariff review between both types of TSO makes the Existing TSOs much riskier. A greater portion of the revenues are subject to periodic reviews, with a greater risk of change.

Furthermore, Existing TSOs were deeply affected by governmental intervention in the regulation of 2012. In September of that year, Provisional Act number 579/2012, converted into Law number 12,783/2013 from the Ministry of Mines and Energy (MME), changed the rules for all electricity segments, including the remuneration of the Existing TSOs. In 2015, their concession contracts were expected to expire, at which time the existing companies would have to compete with new players, for their concession areas, in auctions. However, the government invited these companies to move their concession contract renewals to 2012, i.e., not to go through the auctions. In exchange, the TSOs should accept new remuneration rules.

The new rules required non-amortized assets to be reimbursed, and no longer used to compound the revenue basis. Therefore, the new revenues should cover only efficient operational costs. Authorized reinforcements installed after 2012 would be paid and remunerated according to their depreciation index and the regulatory WACC. In practice, this Law removed the shielded revenue. As a result, in the second half of 2012, the revenues of the Existing TSOs dropped 60%. This value became the baseline for revenues in the subsequent five years. Reimbursement for assets installed between 2000 and 2012 was paid approximately 36 months after contract renewals, but the values for assets installed before 2000 were the target of extensive evaluation and were only paid by the government as an increment to the energy tariff starting in the second half of 2017. This caused a great amount of damage to the companies’ cash flow for the subsequent years.

It is worth highlighting that Provisional Act 579/2012 caused a great disturbance in the electricity market. Beyond the revenues from transmission companies, the generation and commercialization segments suffered from abrupt changes to their rules. Consequently, a large upsurge in the number of lawsuits started to influence these segments.

3.4 Cost incentive regulation for Brazilian TSOs

The Existing TSOs were responsible for the major portion of the revenues transferred to the energy tariff. In addition, these companies are the most affected by incentive regulation tools. Thus, they are the focus of this study. This group comprises 9 companies, 8 of which are state-owned. CTEEP is the only private TSO of this group, privatized in 2006. CEEE, COPEL and CELG are managed by the governments of the states where they operate. CEMIG has its shares listed in the Brazilian stock market, but the state government is its main shareholder. The remaining TSOs of the group, ELETROSUL, CHESF, ELETRONORTE and FURNAS are part of the Federal government's holding ELETROBRAS. This is the greatest electricity company in Brazil, which owns assets on generation, transmission and distribution assets. CTEEP is also the only company in the group that operates exclusively transmission assets. As ELETROBRAS, other companies operate distribution assets as well.

The main incentive for the cost reduction defined by ANEEL for Existing TSOs concerns the tariff review. Through this procedure, the regulator defines the efficient operational cost score θ_i for the i-TSO, which will constitute the baseline for next five years of revenue. The efficient operational cost is defined according to Equation 29 [ANEEL, 2018b]. In this equation, $CAOM_iEf$ is the efficient operational cost of the i-th TSO; PMS_i is the reference operational cost of the i-th TSO regarding personnel, materials and services; and, O_c is the reference operational cost accounting for other expenses.

$$CAOM_iEf = PMS_i \times \theta_i + O_c \tag{29}$$

Usually, the methodology applied in a TRC results from discussions held between the sector stakeholders and the regulator in a formal process called a Public Hearing (*Audiência Pública* — AP). In this process, the regulator first presents a Technical Note (*Nota Técnica* — NT) to show the initial methodological proposal. Subsequently, sector agents submit contributions intended to improve the methodology. Based on these contributions, the regulator decides on the final benchmarking model. The discussion in the Public Hearing may occur in more than one step, i.e., the regulator may present a revised proposal and resubmit it to the sector agents for further contributions. Only the 3$^{\text{rd}}$ TRC did not follow those steps. Instead, the regulator defined the benchmarking model in Technical Note 383/2012-SRE/ANEEL [ANEEL, 2012], approximately one month after Provisional Act 579/2012 was launched, outside of a formal Public Hearing process and without discussion with the agents.

The entire revenues regarding efficient operational costs are defined according to Equation 29. According to Haney and Pollitt [2013], the use of benchmarking techniques is a common feature among regulators in many countries. The authors also claim that regulators commonly use the efficiency scores as one part of the revenue estimation process. In the Brazilian case, the result of the ANEEL procedure is a theoretical total revenue, defined in Equation 29, with an almost null profit margin. From that equation, it can be concluded that the only source of profit for a fully efficient TSO is the remuneration of the assets.

In the definition of the efficient operational cost, ANEEL applied ex-post adjustments in the efficiency scores of all TRCs. Final results have estimated efficiency scores greater than 100% in the last two cycles, which is an unusual characteristic in benchmarking procedures. In the 3$^{\text{rd}}$ TRC (the renewal of the concessions), NT 383/2012-SRE/ANEEL applied a quality adjustment to the DEA efficiency scores, adding percentage points to the companies that were proportional to their performance in the quality indicator. These results are shown in Table 7. Although the regulator shows the quality indicators, the criteria used to group companies into the sub-groups that gained from 10 to 39 extra points are not made explicit in the document. In addition to this adjustment, the final document in which the revenues were published (Ordinance 579 of MME) added an extra 10% margin to the efficiency scores. Later documents from EPE explain that this was a profit margin granted to TSOs, since the renewal of the concessions contemplated just the efficient operational cost.

Table 7 – Final Efficiency Scores from 3rd Tariff Review Cycle

Transmission Company	DEA Scores 2011	Quality Adjustment	Final Scores TN 383/2012	Ordinance 579 of 10/31/2012
ELETROSUL	47%	49%	96%	106%
CTEEP	96%	39%	135%	145%
COPEL	46%	39%	85%	95%
CEMIG	62%	29%	91%	101%
CEEE	58%	19%	77%	87%
CHESF	37%	19%	56%	66%
ELETRONORTE	27%	19%	46%	56%
FURNAS	39%	10%	49%	59%

The *ex-post* adjustment applied to the efficiency scored in the 4th TRC was simpler: ANEEL normalized the DEA efficiency scores by the median of the score samples. The regulator claims that the normalization procedure "tries to improve the incentive in the search of the best practices for maintenance and operation" [ANEEL, 2018b]. The final results are shown in Table 8. As in the previous TRC, some TSOs have efficiency scores greater than 100%. According to Equation 29, this condition implies a revenue regarding the operational costs greater than the current reference cost. In this cycle, there was no mention to the extra 10% margin as granted in the previous one.

Table 8 – Final Efficiency Scores from 4th Tariff Review Cycle

Transmission Company	DEA Scores	Normalized Scores
CTEEP	100.0%	134.07%
CEMIG-GT	99.97%	134.03%
CEEE-GT	92.97%	124.65%
CELG G&T	89.6%	120.13%
COPEL-GT	57.00%	76.42%
CHESF	55.51%	74.42%
FURNAS	53.65%	71.93%
ELETROSUL	38.26%	51.3%
ELETRONORTE	36.21%	48.55%

Source – NT 012/2019-SRM/ANEEL [ANEEL, 2019]

3.4.1 Results of incentive regulation for costs

Since 2000, four tariff reviews cycles were conducted by ANEEL. The last one was concluded in December, 2018. In all of them, benchmarking models were used to define the efficient operational cost. The regulator applied the non-parametric Data Envelopment Analysis (DEA) method to estimate the efficiency scores. Nevertheless, the first and second TRCs, which occurred in 2007 and 2009, covered just a small portion of the TSOs' operational costs related to the incremental assets. In the third and fourth TRCs (2012 and 2018), the total operational cost

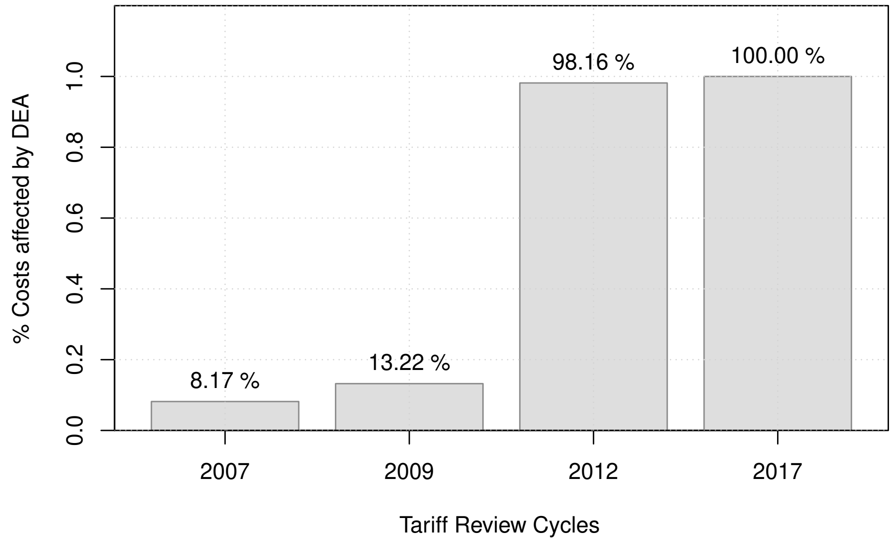


Figure 11 – Percentage of Operational Costs affected by DEA

Source – ANEEL [2007, 2009, 2012, 2017b]

was considered as the reference cost in Equation 29. The portion of the operational costs and, consequently, the regulated revenues affected by the TRC, is shown in Figure 11.

The temporal evolution of the operational costs of the Existing TSOs is shown in Figure 12. Costs are corrected according to the inflation index IPCA[1], in 2016 database, in billions of Brazilian reais (BRL). The TSO CELG is not considered in the graphs since it was vertically segregated after 2006 and is not part of the costs dataset. The information regarding operational costs is taken from technical notes regarding benchmarking models of the 1st, 3rd and 4th TRCs. Operational costs for the years between 2007 and 2017 exclude some lines of the accounting group “other expenses”. Figure 13 shows the evolution of relative indicators regarding operational costs: Brazilian reais (BRL) divided by the network extension (km) and the installed power (MVA).

As can be observed, there is no evident cost reduction until 2012. Indeed, the abrupt decrease of the regulated revenues in 2012 forced the companies to reduce their operational costs, following Provisional Act 579/2012. Between 2003 and 2012, the average variation of the operational costs had a yearly increase of 5%. On the other hand, from 2013 on, there has been a reduction in the costs. Although there is an increase in the final years of the cycle, the total costs are still lower as compared to the costs in beginning of the cycle. The installed power also increases yearly, indicating that there are more assets to be maintained, as shown in Figure 13 using relative indicators.

A close look at the operational costs from 2012 to 2016 shows that the decrease in operational costs was not linear among the regulated companies. Table 9 shows the yearly

[1] IPCA: Índice Nacional de Preços ao Consumidor Amplo, calculated by the Brazilian Institute of Geography and Statistics (IBGE)

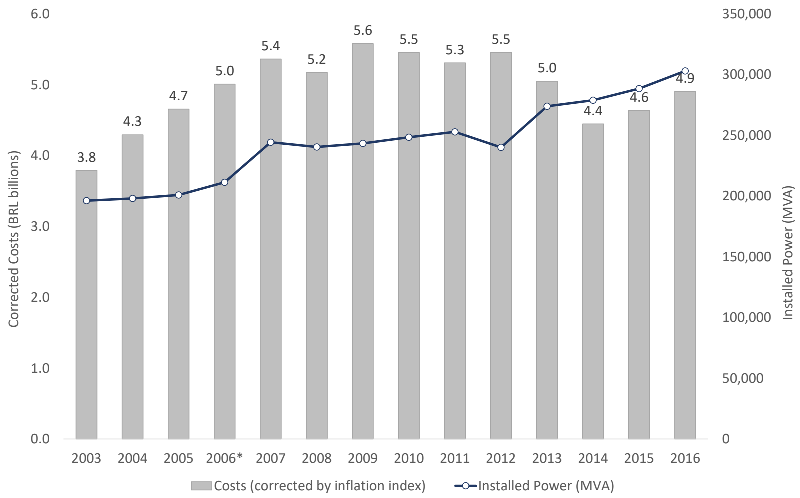


Figure 12 – Evolution of operational costs and installed power

Source – ANEEL [2007, 2012, 2017b]

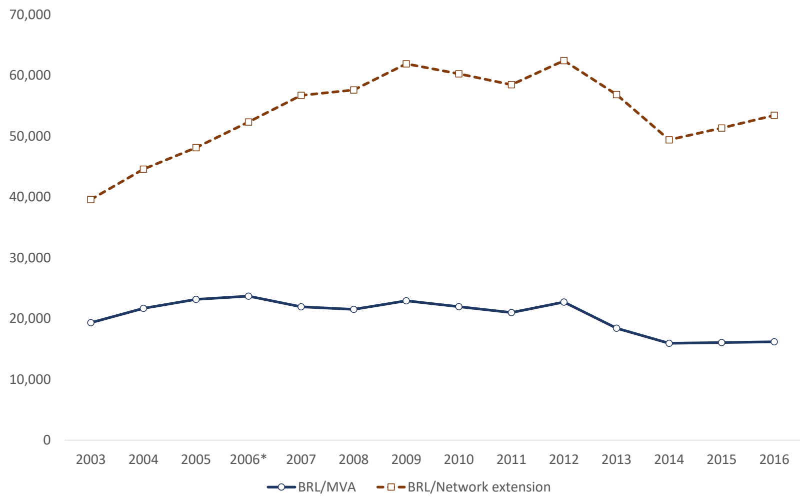


Figure 13 – Evolution of relative indicators, Brazilian Reais (BRL) per installed power (in MVA) and Brazilian Reais (BRL) per network extension (in km)

Source – ANEEL [2007, 2012, 2017b]

variation in operational costs, discounting the inflation rate, for each company. The baseline is the 2012 cost, and each column shows the variation in comparison with the previous year. Two TSOs present final costs in 2016 greater than the initial cost in 2012: ELETRONORTE and CHESF.

The allowed revenues, regarding the operational costs, are shown in Figure 14. The graph

Table 9 – Variation in the operational costs by TSO (discounting inflation rate)

Company	**Yearly variation in operational costs**				
	2013	**2014**	**2015**	**2016**	**2016-2012**
ELETRONORTE	84%	95%	101%	143%	115%
CHESF	94%	93%	115%	101%	102%
ELETROSUL	112%	79%	109%	103%	100%
CTEEP	91%	94%	98%	115%	96%
COPEL-GT	83%	82%	107%	121%	89%
CEMIG-GT	100%	95%	91%	89%	77%
FURNAS	90%	84%	101%	96%	73%
CEEE-GT	94%	82%	102%	83%	66%

Source – ANEEL [2007, 2017b]

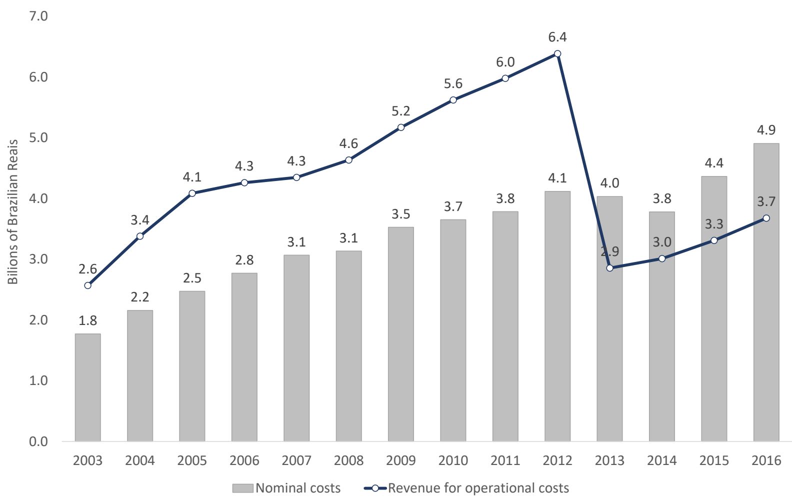


Figure 14 – Evolution of costs and revenues, in nominal values

Source – ANEEL [2007, 2012, 2017b]

also shows a comparison with the nominal costs (not corrected by any inflation index) in the same period. The revenues regarding asset amortization and remuneration are not included in the graph. It is important to mention that the revenues are defined yearly by ANEEL in specific Resolutions. In these documents, revenues are defined in one-year cycles, from July to June of the following year. The cycle revenues are adapted in the graph to match the costs database.

The efficiency scores from the 3rd TRC (Table 7) resulted in total revenues that were lower than the total operational costs of the system. As stated, the cost reduction in the following years was not linear among companies. Nonetheless, the total costs were reduced.

From the energy rate perspective, there is a mild advance. The transmission tariff represents about 8% of the final rate for the consumer, varying among free and captive consumers. As mentioned, the allowed revenues of the TSOs are divided between generators and consumers through a node tariff (TUST). The reduction of the allowed revenues due to Provisional Act

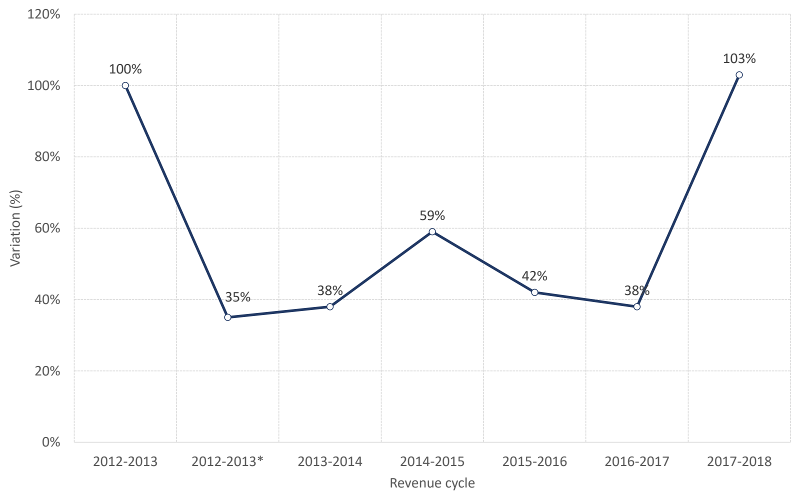


Figure 15 – Variation of the transmission tariff (TUST) to the segment "consumers" (baseline 2012).
(*) Cycle 2012-2013 after the Provisional Act.

Source – ANEEL [2017b]

579/2012 caused an immediate reduction in the consumer's TUST, as shown in Figure 15. After the event (highlighted in the figure with an asterisk), the value of TUST was 35% of the original tariff.

Nevertheless, the provisional act defined the reimbursement of the non-amortized assets to the companies that renewed their concession contracts. The evaluation of the assets was a long process, which ended in 2014. The rules for the payment of the amount and its inclusion in the TUST were defined by Ordinance 120/2016 from the Ministry of Mines and Energy: the payment of the reimbursement should be completed in eight years from 2017, and should comprise a financial portion concerning the interest rate for the years of delay in the payment (2012-2017).

As a result, the reimbursement value was incorporated in the allowed revenues of the Existing TSOs beginning in 2017. The interest rate, added to the asset values, resulted in the consumer's TUST having a final value 3% higher than the original tariff in 2017 (see in Figure 15). In summary, consumers enjoyed a five-year period of low transmission rates but, as soon the payment rules defined in the contracts were accomplished, transmission tariffs returned to the same baseline.

The immediate consequence of government intervention, such as Provisional Act 579/2012 or Ordinance 120/2016, is major disturbance in the market. In addition to the failure of the auctioning of transmission networks, intervention caused a great variation in the investors' perception of risk. The quarterly stock prices of three companies directly affected by those events is shown in Figure 16. These stocks are traded in the Brazilian stock market (Bovespa) and their prices are shown in Brazilian reais (BRL). CEMIG and ELETROBRAS are state companies

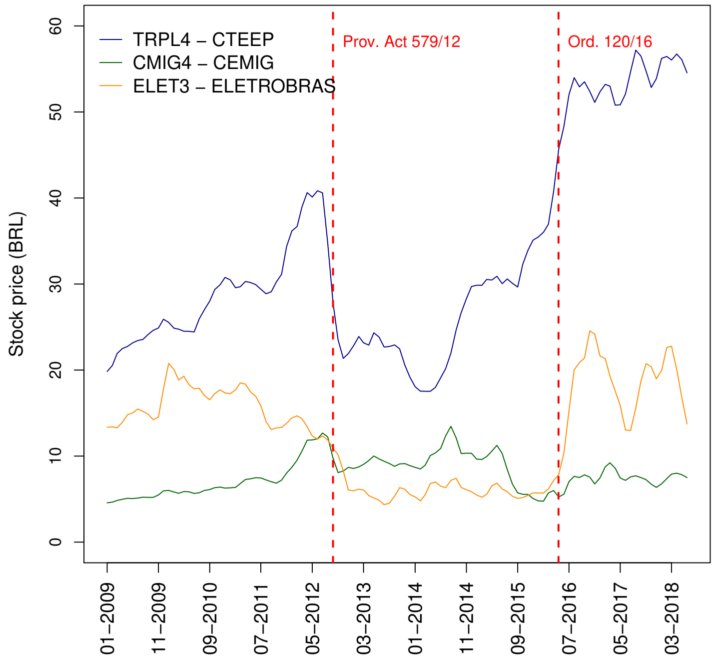


Figure 16 – Quarterly stock prices of Brazilian energy companies (in BRL)

that also hold assets in the generation and distribution segments. Therefore, their results are not defined exclusively by the transmission segment. Nevertheless, Figure 16 shows clearly the variation caused by the governmental actions.

Some issues regarding the effectiveness of regulatory economic signs are discussed in next session.

3.4.2 Effectiveness of the regulatory economic signs

From the perspective of cost reduction, ANEEL's incentives show modest results until 2012. After that, an effective cost reduction is observed. Nevertheless, considering the total 17-year period of the analysis, results could be more consistent. In comparison, Pollitt [2004] and Joskow [2014] present much greater changes in companies from countries such as Chile, United Kingdom and New Zealand.

From the evolution of the total costs shown in Figure 12, it can be argued that the incentive for cost reduction was not effective until the expiration of the shielded revenue in 2012. As just a small portion of the revenues regarding the efficient cost could be affected, companies actually made little effort to reduce their costs. In spite of the sudden change in the revenue rules and its consequences for the market, the expiration of the shielded revenue was an important step for incentive-based regulation.

The immediate, promising results due the Provisional Act 579/2012 notwithstanding, the final results of this event are questionable considering the effects of the cost reduction and the tariff. In the first year, most companies made some effort to reduce their costs (Table 9). However, some of them continued on a rising trajectory in their costs. Even companies whose revenues were not enough to cover their operational costs did not cut them in a consistent way: ELETROSUL was 56% efficient in the 3rd TRC (Table 7), but increased its costs yearly in the following cycle (Table 9). The same occurred with CHESF.

Both TSOs, ELETROSUL and CHESF, have two features in common: they are part of holdings that also operate generation and distribution assets; and, they are state-owned companies. Eight of the nine Existing TSOs actually share such features. Thus, a deficit in the transmission segment may be compensated by other business of the company. Or, in the worst-case scenario, the state may simply share the poor results of its own TSOs.

From the perspective of the transmission tariff, the effects of the Provisional Act 579/2012 were clearly temporary. The reduction of the tariff for consumers was possible in the five-year period between the Act and the payment of the reimbursement to the TSOs. Nevertheless, most companies changed their dynamics of cost management due the expiration of the shielded revenue, which may lead to a sustainable tariff drop in the long term. This effect may be noticed when the payment of the reimbursement is concluded (around 2025).

One important characteristic from ANEEL's regulation model that is worth analyzing is the definition of the efficient operational cost above the current cost, with efficiency scores higher than 100%. This is not a common practice among regulators, and could lead to a misunderstanding of the regulatory signs. Companies whose efficiency scores were higher than 100% in the 3rd TRC according to Table 7 (CEMIG and CTEEP) actually reduced their operational costs in the following cycle (Table 9). Even if their allowed revenues were greater than their operational costs, these revenues were much lower than the previous ones. To maintain the profitability required by shareholders, companies needed to cut costs.

It can be argued that the aim of the regulator, in setting the efficiency score greater than 100%, is to compensate the lack of a profit margin, not foreseen in Equation 28 and Equation 29. According to those equations, a fully efficient TSO starts the cycle with an almost null profit margin and, necessarily, has to cut costs in order to be profitable. However, if the TSO is not fully efficient, reaching the break-even point may be a tough task. Moreover, if the efficiency score is too low, years of negative results are imposed on a non-efficient TSO and harm the regulator's objective of attaining balance among agents.

In practice, the surplus revenue granted by the regulator, using upgraded efficiency scores, did not work as a negative sign to raise costs. However, if the expected profit margin was explicit, a much clearer regulatory economic sign could be supported by the regulator. Moreover, a clearer process could allow companies to negotiate viable cost reductions.

Another issue that must be addressed is the consistency among tariff review cycles. In the Brazilian case, the 3rd TRC, which followed Provisional Act 579/2012, is clearly a sudden change in the regulatory model. With the abrupt drop in revenues, some misleading regulatory signs were produced. The expected effect of successive tariff review cycles within a regulatory framework is the systematic reduction of the revenues of all companies: in each cycle, efficiency scores (equal to or less than 100%) are multiplied by the reference costs. If the costs are in a descending trajectory, each successive cycle will grant regulatory revenues equal to or less than the previous cycle. However, the efficiency scores of the 3rd TRC were very low for some TSOs, and cost reductions closer to 40% were imposed from one year to the next (for instance, see the efficiency scores for CHESF, FURNAS and ELETRONORTE in Table 7). These companies were not able to reach such difficult targets. In fact, CHESF and ELETRONORTE raised their costs. However, as shown in Equation 29, the regulated revenues comprise the efficiency score and a reference cost. Consequently, even though reference costs had risen, those companies had an increase in their allowed revenues in the 4th TRC. In contrast, fully efficient TSOs in the 4th TRC, which followed a decreasing trajectory of costs (CEMIG and CTEEP), were "penalized" with inferior revenues in comparison with the preceding cycle.

Such distortions were caused by two faults in the regulatory model. First, some companies had little incentive to achieve positive results, either because they are state companies or because they may have compensated bad results in other business. Furthermore, the drop in revenues was not enough to make these companies engage in a descending trajectory regarding their costs. Second, the allowed revenues from the previous cycle were difficult to achieve: it is not reasonable to expect that a company will be able to cut 40% of their costs from one year to the next. In the case of FURNAS, a cost reduction was observed, but was nevertheless above the target. In addition, the allowed revenues in the next cycle were greater than in the previous one, in contrast to the reduction imposed on fully efficient TSOs. Haney and Pollitt [2013] show that other regulators impose yearly reductions, no greater than 5%, on the TSOs. In fact, from the 4th TRC on, ANEEL staggered the expected reduction in the following tariff cycle. They did not define a limit for the reduction, and the result is that the total inefficiency must be addressed by the final year of the cycle.

3.5 Conclusions

The regulatory framework used by ANEEL to encourage cost reduction among TSOs is still recent, and it needs to be validated and continuously revised. As stated by Joskow [2014], the regulatory practice requires the observation of the reaction to each act. In this young process, the government intervention that occurred caused deep changes in the regulatory framework.

Current results with Brazilian TSOs provide evidence that, although large intervention in the formalized regulatory process may lead to immediate cost reductions, they might not necessarily be sustainable in the long term. These events cause disturbances in the market, may eventually harm TSO cash flow and their effects are not necessarily sustainable by the end of the cycle. Moreover, the existence of state companies (which are not necessarily concerned about profitability) and companies that operate in more than one market (and may compensate losses in other segments) distorts the average response to incentives.

However, it is worth mentioning that the regulatory model that existed prior to intervention had weak incentive power. This scenario changed with the new rules. Currently, TSOs have more incentives to reduce costs and, currently, most of them are engaged in cost reduction, as previously shown. The new dynamic to manage costs assumed by TSOs will most likely impact positively on the transmission tariff in the long term, when the financial effects of Provisional Act 579/2012 end.

One may claim that the improvement in the regulatory incentive rules could have followed gradual steps and could have been discussed intensively with stakeholders. The cost of such an abrupt change was the increased perception of risk by investors. Moreover, TSOs were subject to cash flow constraints that affected their results and their capacity to renew the transmission assets. According to the regulator [ANEEL, 2016], a great part of the installed assets is at the end of its life cycle. TSOs have not been able to invest in the renewal of the assets for five years, except by marginal or emergency changes, resulting in partial obsolescence. Furthermore, as most of the Existing TSOs are state owned, their deficit results are charged to the taxpayers. In the short term, the damage resulting from such intervention is deep and overlaps possible gains.

Despite the arbitrary way that it was introduced, the new regulatory framework presents strong incentive power for cost reduction. Nevertheless, some issues need to be addressed to improve it. Consistency among tariff review cycles is needed in order to motivate TSOs to maintain a decreasing trajectory of costs. The definition of realistic efficiency scores, to be achieved in the next tariff review cycle, should also prohibit TSOs that raise their costs from receiving larger regulatory revenues in the following cycle.

A clearer sign regarding the profit margin is still required. Ex-post adjustments in the benchmarking results, to increase efficiency scores, may lead to equivocated regulatory signs. This would indicate, to the market and to investors, very high profit margins allowed for some companies, and negative profit margins for others.

Finally, a broad discussion concerning the influence of state companies in the transmission market is needed. Large interventions may be made by governments, without severe consequences, when a large part of the players is state owned. In addition, state companies seem to have a weaker response to incentives. This issue is not a responsibility of the regulator, but of all involved agents.

4 Performance benchmarking models for electricity transmission regulation: caveats concerning the Brazilian case

Abstract

Regulation plays an important role under natural monopoly markets, such as energy electricity distribution and transmission. In recent years, abrupt changes in the regulation of the Brazilian Transmission System Operators (TSOs) has increased the risk perceived by investors, harming the economic stability of the sector. In this paper, we present a review of the benchmarking model used to regulate Brazilian TSOs' operational costs. The objective of the paper is to suggest improvements in the Data Envelopment Analysis (DEA) model proposed by the regulator in 2018. The suggested changes would help to ensure a robust and reliable regulatory process.

Keywords Energy Transmission. Regulation. Data Envelopment Analysis.

4.1 Introduction

Energy distribution and transmission are classical examples of natural monopolies in which economic regulation plays a decisive role. Regulation can encourage investors to improve supply, reduce costs, or simply leave the market. In this context, Bogetoft and Otto [2010] claim that regulators have been empowered to act as *proxy* purchasers of the services, thus imposing constraints on prices and production methods.

Regulatory schemes for electricity monopolies have been further developed into incentive-based regimes in recent years. In many countries, regulators use benchmarking approaches in order to indirectly compare companies that do not face real competition [Bogetoft and Otto, 2010, Haney and Pollitt, 2013, Jamasb and Pollitt, 2003]. Techniques such as the non-parametric Data Envelopment Analysis (DEA) are applied to regulate price or revenue of electricity generation, distribution and transmission companies. DEA uses a linear programming approach to define relative efficiency scores of comparable units, which requires a coherent modeling process able to capture particularities of the analyzed industry.

In accordance with the international trend, the Brazilian energy regulator, ANEEL (*Agência Nacional de Energia Elétrica*), has been applying modern regulation methods for electricity generation, transmission and distribution. These techniques are part of the restructuring context the Brazilian electricity sector was confronted with since 1993 [Mendonça and Dahl, 1999, Sanches, 2011]. Sioshansi and Pfaffenberger [2006] argue that such reforms generally impose hard requirements for cost reduction and service quality improvement on distribution and transmission agents. In addition to these efficiency aims, Araújo [2006] states that Brazilian regulatory reforms also seek to attract and retain investors, which is a common objective of emerging markets. Araújo [2006] also argues that the expansion and maintenance of the transmission system is strategically important to support the adopted energy supply model that is integrated across the territory.

Despite ANEEL's remarkable effort to improve its regulatory model, some government interventions in the electricity market have plunged the Brazilian energy sector into a major crisis, especially after 2012. The Provisional Act 579/2012, later converted into Law 12,783/2013, imposed severe changes for generation, transmission and distribution companies. The effects on the transmission companies, hereinafter referred to as Transmission System Operators (TSOs), were enormous: the total annual revenue of the major TSOs dropped by 60% in 2013. As a result, most of these companies faced cash flow problems in the following years. Moreover, the perceived risk increased, and investors lost interest in the transmission sector. It was not until 2016, after the government announced new guidelines, that this trend was reversed.

These events in the Brazilian electricity industry indicate how regulation affects the energy sector. Moreover, the 131,000 km of transmission networks[1] spread across its continental territory make the Brazilian electricity transmission system a complex structure to regulate. There are approximately 85 transmission companies responsible for managing this system. About 71% of these networks and most of the strategic substations are managed by nine major TSOs, which are subject to specific incentive regulation. Such a structure makes the Brazilian transmission system a singular case to be analyzed, in which a large number of companies must be compared in a heterogeneous environment. In contrast, countries that use non-parametric and parametric benchmarking approaches to regulate TSOs usually compare from one to three companies, using panel data [Haney and Pollitt, 2013]. Larger systems are otherwise dissimilar to the Brazilian case; Australia, for example, applies a unit-cost approach.

The objective of this study is to provide an evaluation of the Brazilian benchmarking model for TSOs, highlighting the main issues that should be addressed to ensure a reliable and relatively predictable regulatory process. Despite relevant changes that have also affected the generation and distribution segments, our analysis focuses on the transmission sector, which is strategically important to the Brazilian electricity system and is heavily affected by a complex system of incentive regulation. Moreover, we also expect to extend the study on benchmarking models for transmission, as this has been highlighted as a gap in the literature by Haney and Pollitt [2013], Agrell and Bogetoft [2014] and Llorca et al. [2016]. The analysis is centered on the DEA model implemented by the regulator in 2018. This study contributes to the DEA modeling in the regulatory context, as we suggest specific improvements regarding the comparability of companies, the adjustment for contextual variables, and the weight restrictions.

The paper is organized as follows: in section 4.2, we review the main benchmarking concepts important to the regulation of electricity transmission. In this section we also describe the regulation of Brazilian transmission companies, focusing on the benchmarking model used to define efficient operational cost. In section 4.3 we discuss the critical issues regarding the Brazilian benchmarking model, providing suggestions for improvements. In 4.4, final conclusions are presented.

[1] Referring to 2016 data provided in Technical Note 204/2018-SRM/ANEEL [ANEEL, 2018b]

4.2 Benchmarking in regulation of electricity transmission

The use of benchmarking models is a popular approach to comparing companies that operate under a monopoly framework, i.e., which do not face competitors in their market. The non-parametric Data Envelopment Analysis (DEA) and the parametric Stochastic Frontier Analysis are the most common models used for this purpose. They are applied in the incentive-based regulatory context, defining maximum regulatory values of tariffs (price cap) or maximum regulatory values of revenues (revenue cap). According to classical regulatory theory, these approaches allow the separate management of costs, revenues, and prices [Braeutigam and Panzar, 1993]. Furthermore, they are useful for dealing with the asymmetry of information between the regulator and the regulated companies.

While these approaches are widely studied in the scope of energy distribution (see, e.g., Jamasb and Pollitt [2003], Arcos-Vargas et al. [2017], Costa et al. [2015]), Haney and Pollitt [2013] state that the benchmarking of TSOs is rarely explored, since it is a challenging topic. Moreover, Agrell and Bogetoft [2014] indicate that the low number of TSOs in each country makes transmission benchmarking analysis a difficult task. Even large transmission systems as the Brazilian are hard to be benchmarked and require technical accuracy, especially considering the financial impact of the efficiency scores.

4.2.1 Data Envelopment Analysis

DEA is a non-parametric benchmarking method that does not require previous assumptions about the production function form. As a starting point in the development of a vast number of specific DEA models, Charnes et al. [1978] proposed a linear programming problem to calculate the efficiency scores of comparable Decision Making Units (DMUs), defined as follows: let the production set T be composed of sets $\mathbf{y} = [y_1, ..., y_s]$ having s output variables and $\mathbf{x} = [x_1, ..., x_m]$ having m input variables. The input-oriented efficiency of DMU under analysis, known as DMU_0, is calculated using the linear programming problem shown in (30), where u_r and v_i are the weight parameters associated with the outputs and inputs, respectively.

$$
\begin{aligned}
& \max \sum_{r=1}^{s} u_r y_{r0} \\
& \text{s. t.:} \qquad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad j = 1, ..., n \\
& \qquad\qquad \sum_{i=1}^{m} v_i x_{i0} = 1 \\
& \qquad\qquad u_r, v_i \geq 0
\end{aligned}
\tag{30}
$$

The linear problem (30) assumes a *constant return to scale* (CRS) production set. A less restrictive function, with *variable returns to scale* (VRS) was proposed by Banker et al. [1984]. The CRS efficiency score, θ_{DEA}, is also denominated Farrell efficiency [Bogetoft and Otto, 2010]. It is a reference to the *distance function* which measures the radial distance of the evaluated DMU to the efficiency frontier, introduced by Farrell [1957]. The inverse of this measure, $1/\theta_{DEA}$, is known as Shephard distance function (see, e.g., Bogetoft and Otto [2010]). In both CRS- and VRS-DEA approaches, the efficiency measure assumes that all inputs are reduced or all outputs are expanded by the same factor, since they represent the radial distance from the frontier [Bogetoft and Otto, 2010]. Further details about DEA benchmarking modeling are described by Cooper et al. [2011] and Cook and Zhu [2008], where *non-decreasing returns to scale* (NDRS) and *non-increasing returns to scale* (NIRS) input or output-oriented models are also presented. Thanassoulis [2001] and Bogetoft [2013] also present details about DEA fundamentals, nevertheless, we briefly introduce below some concepts that are important to our study.

The relative weights u_r and v_i calculated in the linear programming (30) are defined uniquely to each DMU. These values maximize the relation that defines the contraction factor by which the inputs are re-scaled to achieve the efficiency frontier. According to classical linear programming theory, they may be interpreted as the shadow prices of $\mathbf{x}$ and $\mathbf{y}$ [Taha, 2008]. Nevertheless, Bogetoft and Otto [2010] highlight that in some cases we have partial value or price information that may be added in the problem as *weight restrictions.* These extra constraints improve the discriminatory power of the analysis (see, e.g., Podinovski [2004]).

There are two main approaches used to include weight restrictions in the DEA model. The "Type I" weight restrictions represent trade-offs between outputs or between inputs [Thanassoulis, 2001]. In this approach, a restriction is defined as shown in inequality 31, where we assume that relative worth of output h to output t is at least $\alpha_{h,t}$ and at most $\beta_{h,t}$ [Bogetoft and Otto, 2010].

$$\alpha_{h,t} \leq \frac{u_h}{u_t} \leq \beta_{h,t} \tag{31}$$

The "Type II" weight restrictions are defined as ratios between one input and one output. In this case, there is an assumption regarding upper and lower limits of the marginal costs of an output variable, as shown in inequality 32. Bogetoft and Otto [2010] argue that these restrictions are in general more difficult to interpret and justify. Podinovski [2004] claims that the inclusion of such restrictions prejudices the interpretation of the radial contraction expected in a DEA model: the efficient radial target of an inefficient DMU could be not technologically feasible.

$$\gamma_{h,z} \leq \frac{u_h}{v_z} \leq \tau_{h,z} \tag{32}$$

Podinovski [2004] adds an interpretation to the trade-offs stated in weight restrictions, claiming that the trade-offs naturally exist and are based on realistic production characteristics. Even inequalities involving monetary values should hold this exchange interpretation. Further discussions about DEA weight restrictions are provided by Thanassoulis [2001] and Førsund [2013].

Other extensions of the classical DEA analysis regards to the inclusion of environmental variables in the model. The vectors $\mathbf{x}$ and $\mathbf{y}$ of the linear problem (30) are typically composed of controllable variables, which may be managed in order to achieve the efficiency frontier. The effects of non-controllable variables are frequently measured in a second-stage procedure, using econometric approaches. A basic framework is shown in Equation 33. In this equation, the DEA efficiency score θ_i is the dependent variable in a regression model in which the environmental variable z_i is the independent variable, δ_0 and δ_1 are the unknown parameters to be estimated and ϵ_i is the random noise, normally distributed.

$$\theta_i = \delta_0 + \delta_1 z_i + \epsilon_i \tag{33}$$

McDonald [2009] argues that Ordinary Least Squares (OLS) regression provides good estimation of the parameters. Tobit regression is also a frequent approach used in second-stage analyses. In the latter case, there is an assumption of an underlying data-generating process (DGP) that relates the DEA efficiency scores θ_i and the environmental variable z_i. The parameters estimation is done through Maximum Likelihood procedure, regarding assumptions of the DGP, as the normality of the residuals. In both cases, the corrected efficiency scores are estimated considering fundamental of analysis-of-variance identity, explained in details by da Silva et al. [2019b].

Another class of regression-based second-stage procedure are the compound error models, with a more complex underlying DGP. In these models there is an assumption that the disturbance term which distances the production function of the efficiency frontier is decomposed in three portions: the effect of the environmental variable, the random noise (a random variable p), and the inefficiency term (a random variable q). Simar and Wilson [2007] and Banker and Natarajan [2008] present examples of output-oriented compound error models. da Silva et al. [2019b] adapted the latter to an input-oriented problem, according to Equation 34:

$$-\ln(\theta) = \mathbf{z}\delta + \varepsilon \tag{34}$$

where $\varepsilon = p + q$ is the observed compound error, previously explained. The term $\mathbf{z}\delta$ is the linear component that relates the efficiency scores and the environmental variable. According to da Silva et al. [2019b], the observed error component ε must be expressed in terms of the joint distribution of the random variables p and q. Thus, the inefficiency corrected by the environmental effect is estimated as a conditional variable, $q|\varepsilon$. The corrected efficiency scores may be accessed by three procedures: (i) by the expected value of the conditional distribution, $\hat{\hat{\theta}}|\varepsilon = E(e^{-q|\varepsilon})$, ($ii$) by the conditional mean $\ln \hat{\hat{\theta}} = -E(q|\varepsilon)$ and (iii) by the conditional mode $\ln \hat{\hat{\theta}} = -M(q|\varepsilon)$.

4.2.2 Transmission Regulation in Brazil

Electricity generation in Brazil has mostly been based on hydrological exploration. According to IEA [2018], 65% of the electrical energy generated in Brazil in 2016 was produced by hydroelectric power plants. To make use of this hydropower, large power plants have been constructed in locations away from consumers. These power plants are interconnected in a centralized system. The National System Operator (*Operador Nacional do Sistema — ONS*) decides which power plants should dispatch energy. In this context, producers and consumers are interconnected in the Integrated National System (*Sistema Integrado Nacional* — SIN). Therefore, energy transmission is strategic for full integration of generation plants and distributors as well as for ensuring the system reliability.

The Brazilian centralized energy model was introduced in 1998, in the context of the energy sector restructuring. In the following two years, most of the energy companies were vertically segregated (the last energy utility was segregated in 2006). The newly created transmission companies inherited the 20-year concession contracts previously signed by the vertically integrated utilities. Such contracts were expected to expire in 2015. The vertical segregation resulted in nine transmission companies, all state-owned. Until 2019, just one of them was privatized. Hereafter, we will refer to these nine TSOs as *Existing Companies*. Their concession contracts foresaw incentive-based cost regulation and classified the revenue of the TSOs into two portions:(*i*) assets amortization and remuneration and (*ii*) efficient operational costs. The total revenue is calculated in annual parcels (Annual Allowed Revenue — *Receita Anual Permitida*, RAP).

In practice, when the vertical segregation occurred, the regulator initially did not evaluate the assets of all utilities in order to accurately determine the revenue necessary to cover the assets investment and its remuneration. Most of the assets were old, possibly already depreciated and paid via the cost plus scheme in force at that time. The initial revenue regarding assets installed before 2000 was an estimated value that should have been sufficient to cover the companies' operational costs, as well as their capital costs. This revenue was known in the sector as *shielded revenue*, because the value could not be reduced, but was corrected annually using the inflation rate (in practice, the revenue increased annually). Thus, the regulatory rules for TSOs' revenue defined in 2000 [ANEEL, 2000b,a], stated that the *shielded revenue*, which was related to assets installed before 2000, could not be changed. Nevertheless, these resolutions likewise, defined an incentive-based scheme regarding assets installed after 2000. To those assets, the revenue regarding operational cost, as the capital cost, was determined to be the target of tariff reviews. The *shielded revenue* accounted for the greater portion of the TSOs' revenue.

As mentioned above, a substantial change in the sector was imposed by the Provisional Act 579/2012, later converted into Law 12,783/2013. This Act anticipated to 2012 the renewal date of the concession contracts of the nine major TSOs. In this moment, in practice, the *shielded revenue* was eliminated: the non-amortized assets installed before 2012 would be indemnified, and the transmission revenues in their entirety would be related to the efficient operational cost. New assets, installed after 2012, would be incrementally remunerated. As a result, in 2013 the revenue of the transmission companies dropped 60%. This value became the baseline for the revenue in the upcoming five years. The indemnity regarding assets installed between 2000 and 2012 was paid in approximately 36 months, but the values regarding assets installed before 2000 were the target of extensive evaluation, and were only paid by the government as an increment in the energy tariff starting in the second half of 2017. This caused a great amount of damage to the companies' cash flow for the subsequent years.

In addition to TSOs' cashflow problem, the perceived risk increased, moving away investors. Figure 17 shows the respective decline of interest in transmission auctions between 2012 and 2015. This trend was only reversed in 2016, after the government announced new guidelines. In the auctions, transmission assets are grouped in lots. Companies bid lots that are financially interesting.

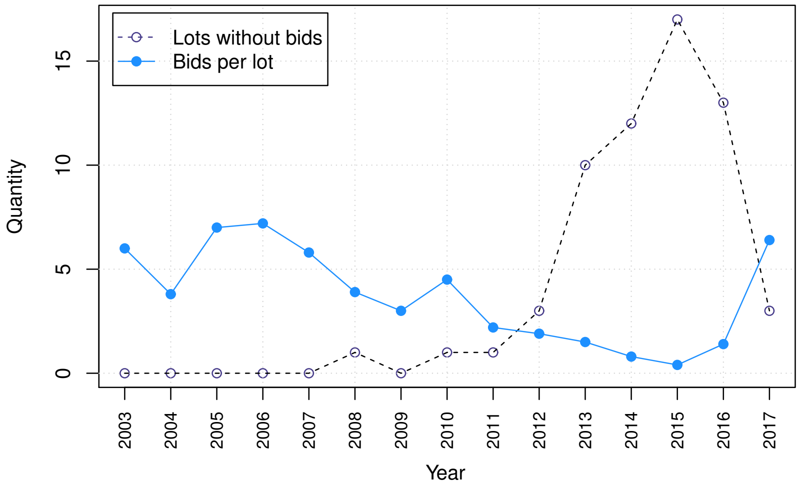


Figure 17 – Energy Transmission Auctions in Brazil

Source: Instituto Acende Brasil [2018]

It is important to highlight that transmission companies which owned concession areas acquired after 2000 were subject to different revenue rules. Therefore, they were not affected by Law 12,783/2013. We will refer to these utilities as *Bid TSOs* henceforth. For the Bid TSOs, there is a revenue regarding operational costs pre-defined in the bid process that must be reduced if there is a technological change in the sector. This is evaluated using the X-factor regulatory method (see, for instance, Bogetoft and Otto [2010]). Furthermore, the Weighted Average Cost of Capital (WACC) of the Bid TSOs is partially reviewed, making changes just in the debit cost, in contrast with the overall review of the WACC of the Existing TSOs.

Between 2012 and 2018, the revenues of the Existing Companies were increased using the inflation rate and an incremental remuneration as well as amortization of any newly installed assets. The process of specifying the conditions for the 4^{th} tariff review cycle started in 2017. In December 2018, the regulator determined the valid conditions regarding efficient operational costs for the period from July 2018 to July 2023.

4.2.3 Benchmarking models for Transmission regulation in Brazil

Existing TSOs were subject to four tariff review cycles (TRCs) in 2007, 2009, 2012[2] and 2018. In these occasions, the regulator reviewed the parameters that comprise the allowed revenue. In all TRCs, ANEEL applied benchmarking models to calculate the efficient operational costs. However, as previously mentioned, in the first and second TRCs, only the portion of the revenues proportional to the newly installed assets was affected. Hence, about 8% and 14% of

[2] The renewal of the concessions is considered by ANEEL the third TRC

the revenues regarding operational costs were in the first and second TRCs. From 2012, the full revenues regarding to operational costs were evaluated.

Usually, the methodology applied in a TRC is the result of discussions among the sector stakeholders and the regulator in a formal process called Public Hearing (*Audiência Pública* — AP). In this process, the regulator first presents a Technical Note (*Nota Técnica* — NT) with the initial methodological proposal. Sector agents submit contributions to improve the methodology. Based on these contributions, the regulator decides about the final benchmarking model. The discussion process within a Public Hearing may occur in more than one iteration. The 3^{rd} TRC did not follow those steps. Instead, the regulator presented the benchmarking model in Technical Note 383/2012-SRE/ANEEL [ANEEL, 2012] about one month after Provisional Act 579/2012, outside a formal Public Hearing process.

This study focuses on the 4^{th} TRC, which defines the Existing TSOs' revenues for the period between 2018 and 2023. However, a brief summary of the previous benchmarking models is presented in Table 10 in order to provide an evolutionary perspective. Details about the first TRC are provided by Pessanha et al. [2010]. The ANEEL benchmarking models are all similar among them. The basic method is DEA, either in its one-stage or two-stage version. In the next sections, the model of the 4^{th} TRC is detailed.

4.2.3.1 Model specification and dataset

The DEA model of the 4^{th} TRC was defined in NT 204/2018-SRM/ANEEL [ANEEL, 2018b]. Its results were later corrected by NT 012/2019-SRM/ANEEL [ANEEL, 2019], with no changes in the methodology. This model shows major differences if compared to previous TRCs. Although ANEEL still applies an NDRS-DEA weighted restricted model, new TSOs were included in the sample. The 14 evaluated TSOs are classified in two groups. Nine of them are the Existing TSOs that resulted from vertical segregation in the 2000s. The remaining five companies that compose the sample are the Bid TSOs, whose concession areas resulted of bids in auctions after 2000. These TSOs comprise "virtual holdings" aggregated by the regulator, considering the concession areas of different contracts, but under the same controller. As mentioned, Bid TSOs are not affected by the methodology defined in the TRC and were included in the model in order to enlarge the comparison basis.

The DEA model of the 4^{th} TRC uses a 4-year panel data (2013 to 2016). ANEEL uses the efficiency score of the last year of the panel data (2016) to define the efficient operational costs for the upcoming cycle (2018 to 2023). The final dataset is comprised of 74 observations: 56 from the panel data and 18 extra information added referent to the year 2016. In summary, these extra observations were included to deal with the Existing TSOs that manage concession areas from bid contracts (see NT 160/2017-SRM/ANEEL for further details).

Regarding the input variable, in the 4^{th} TRC the regulator adjusted the Operational Expenditures (OPEX), also called operational costs, on the groups "wages and benefits" and "services", to tackle the regional differences in the wage levels. In its approach, ANEEL crossed information from TSOs with regional data from Ministry of Labour. A detailed description of the adjustment procedure is provided by the regulator in the Appendix of Technical Note

Modeling	1^{st} **Tariff Review**	2^{nd} **Tariff Review**	3^{rd} **Tariff Review**	4^{th} **Tariff Review**
Reference document	NT 182/2007-SRE/ANEEL [ANEEL, 2007]	NT 396/2009-SRE/ANEEL [ANEEL, 2009]	NT 383/2012-SRE/ANEEL [ANEEL, 2012]	NT 204/2018-SRM/ANEEL [ANEEL, 2018b]
Benchmarking method	One stage DEA	Two stage DEA	One stage DEA with weight restrictions	Two stage DEA with weight restrictions
Number of benchmarking models	One DEA model	One DEA model	Two DEA models	One DEA model
Orientation	Input-oriented	Input-oriented	Input-oriented	Input-oriented
Returns to Scale	NDRS	NDRS	NDRS and CRS	NDRS
Data	Panel data (2003—2005)	Panel data (2002—2008)	Panel data (2007—2011)	Panel data (2013—2016)
Compared companies	8 Existing TSOs	8 Existing TSOs	8 Existing TSOs (the 9^{th} one was considered outlier)	9 Existing TSOs and 5 Bid TSOs
Number of observations	24	56	40	74
Input	Operational costs	Operational costs	Operational costs with adjustment in the "wages and benefits" account	Operational costs with adjustment in the "wages and benefits" and "services" accounts
Outputs	Number of switch modules, number of power transformers, installed power (MVA), network extension (km).	Number of switch modules, number of power transformers, installed power (MVA), network extension (km).	Number of switch modules, number of power transformers, installed power (MVA), network extension divided into 6 voltage levels: 69-88 kV, 138 kV, 230 kV, 325 kV, 440-525 kV, 600-765 kV	No. of switch modules, no. of substation equipment and network extension divided into two voltage levles: $<$ 230 kV and $\geq$ 230 kV, installed power (MVA), reactive power (Mvar), average time under outage
Environmental variables		Voltage level, concession area, wage per region		Precipitation, age of assets, network density
Ex-post adjustment	Efficiency scores normalization between 80% and 100%	Second-stage ("Tobit")	Adjustment regarding quality (outage)	Normalization concerning the scores median
Range of efficiency scores (1^{st} stage before ex-post adjustment)	35%—100%	16%—100%	CRS model: 24%—100% NDRS model: 29%—100%	24%—100%
Mean of efficiency scores (1^{st} stage before ex-post adjustment)	70%	58%	CRS model: 53% NDRS model: 66%	63%

Table 10 – Summary of ANEEL benchmarking models for TSOs

160/2017-SRM/ANEEL [ANEEL, 2017a].

The DEA model of NT 204/2018-SRM/ANEEL [ANEEL, 2018b] comprises nine output variables, whose descriptive statistics are shown in Table 11. One of them is a quality variable defined as the average time of outage for the years 2013 to 2016. This variable is considered an undesirable output in the model, implemented as a non-discretionary variable and represented with a negative sign.

Variable	**Unit**	**Mean**	**Min.**	**Max.**	**Std Dev**
Network extension with voltage $<$ 230 kV	km	879.74	0.00	6.533.28	1,689.00
Network extension with voltage $\geq$ 230 kV	km	6,387.65	686.50	17,758.50	5,022.11
Transformation capacity	MVA	24,375.81	1,407.17	93,030.54	24,706.73
Reactive power	Mvar	7,610.10	0.00	37,733.88	9,761.33
Substation equipment[3] with voltage $<$ 230 kV	units	97.45	0.00	376.00	117.80
Substation equipment with voltage $\geq$ 230 kV	units	262.58	24.00	661.00	212.16
Switch modules with voltage $<$ 230 kV	units	424.93	6.00	1,676.00	491.70
Switch modules with voltage $\geq$ 230 kV	units	343.76	20.00	982.00	253.65
Average time of outage	min/ year	35,354.35	70.99	212,779.09	57,255.50

Table 11 – Outputs of the DEA model of the 4^{th} TRC and their descriptive statistics
Source: ANEEL [2018b]

4.2.3.2 Weight restrictions

Table 12 presents the relations between variable weights used in the restrictions applied in the DEA model of NT 204/2018-SRM/ANEEL [ANEEL, 2018b]. Eight relations result in 16 restrictions. Six of them relate one output variable with one monetary unit (represented by the OPEX variable). Their limits represent the marginal cost of each evaluated asset. For example, the seventh line of Table 12 shows that the variable network extension below 230 kV costs between 2500 and 8500 monetary units.

The ten remaining restrictions represent trade-offs between outputs. For example, $0.2 \leq u_{NE<230}/u_{NE\geq 230} \leq 0.75$ comprises the limits of the relative weights of network extension under 230 kV, and above and equal to 230 kV. The regulator states in NT 160/2018-SRM/ANEEL [ANEEL, 2017a] that these latter restrictions aim at comparing the cost of maintenance and operation of the two respective outputs. In the example, it is argued that the cost of those networks under 230 kV should be between 20% and 75% of the cost of networks above and equal 230 kV.

The final efficiency scores resulting from this DEA model present a high dispersion, with the lowest value of 24.49% and the largest value of 100.0%. The average efficiency is 63.54%. These results indicate missing variables in the model. Consequently, a second-stage analysis was applied by the regulator.

[3] Power transformers, power reactors, banks of capacitors, synchronous condensers, series condensers, static condensers and frequency converters.

#	Relation	Limits	Value
1	Reactive power *vs* Transformation capacity	Minimum	0.5
		Maximum	2.0
2	Substation equipment $\geq$ 230 kV *vs* Switch modules $\geq$ 230	Minimum	1.0
		Maximum	10.0
3	Network extension < 230 kV *vs* Network extension $\geq$ 230 kV	Minimum	0.20
		Maximum	0.75
4	Switch modules < 230 kV *vs* Switch modules $\geq$ 230 kV	Minimum	0.20
		Maximum	0.75
5	Substation equipment < 230 kV *vs* Substation equipment $\geq$ 230 kV	Minimum	0.20
		Maximum	0.75
6	Opex *vs* Transformation capacity	Minimum	800.00
		Maximum	2,000.00
7	Opex *vs* Network extension $\geq$ 230 kV	Minimum	2,500.00
		Maximum	8,500.00
8	Opex *vs* Switch modules $\geq$ 230 kV	Minimum	15,000.00
		Maximum	75,000.00

Table 12 – Weight Restrictions of the DEA model of the 4^{th} TRC
Source: ANEEL [2018b]

4.2.3.3 *Second-stage analysis and ex-post adjustment*

ANEEL evaluated the following twelve contextual variables: average precipitation index, average declivity, average age of the assets, area of intersection with indigenous areas, average height of vegetation, proportion of high vegetation, network density, fire incidence, number of intersections with roads, network overlap, lightning density and number of entrances to roads.

To select the variables to be used in the second-stage, ANEEL evaluated all possible combinations of multivariate Tobit regressions. In these evaluations, the dependent variable was the Shephard distance (inverse of efficiency scores, $1/\theta_{DEA}$), while contextual factors were the independent variables. Only models having a maximum of three contextual variables were evaluated. The contextual variables were selected according to three criteria: the fitness of the corresponding OLS model, the statistical significance of the variables in the models and the coherence of the coefficient signs. Thus, ANEEL selected three contextual variables: average age of the assets, average precipitation index and network density. ANEEL used the Tobit regression outcome to calculate a *severity index*: the Tobit regression fitted value minus the intercept coefficient, normalized between 0 and 1.

The severity index was used to define n different sub-samples of the n evaluated DMUs, as in a dynamic clustering procedure. Then, the first stage DEA model was applied to each sub-sample, defining the final efficiency score. To deal with the loss of the discretionary power caused by the reduction of the sample, the ANEEL model fixes 2/3 of the original sample as the minimum size for the subgroups. Consequently, if the *i-th* DMU cluster is smaller than 2/3 of the original sample, companies with lower severity indexes are included. As a result, the second-stage DEA efficiencies are at least equal to or larger than those of the first stage, mainly due to the smaller number of DMUs in the sub-samples. The resultant final efficiency scores were still high dispersed. The minimum value was 35.85% and largest value of 100.00%. The average efficiency is 73.37%.

ANEEL states in NT 204/2018-SRM/ANEEL [ANEEL, 2018b] that this proposed approach was adapted from Coelli et al. [2005]. In fact, these authors show a similar alternative for adjusting contextual variables. However, the proposal presented by Coelli et al. [2005] consists in ordering DMUs, based on contextual variables, into a few clusters and applying DEA to each cluster. Nonetheless, the Brazilian regulator created additional steps such as the Tobit regression and the dynamic clustering.

As in previous TRCs, an *ex-post* adjustment is applied to the final scores. The NT 204/2018-SRM/ANEEL [ANEEL, 2018b] proposes the normalization of the efficiencies by the median value, i.e., the final efficiency comprises the three-stage efficiency divided by the median value of 74.59% [4]. Consequently, some TSOs achieved a final efficiency larger than 100%. The regulator claims that the normalization procedure "tries to improve the incentive in the search of the best practices for maintenance and operation" [ANEEL, 2017a].

4.3 Critical issues concerning the Brazilian TSOs' regulatory benchmarking models

The benchmarking modelling process is an important step in a revenue cap regulation scheme. The resulting model has to be able to provide correct economic signs to regulated companies, as well to the whole market, showing scores which are coherent with the companies' production context. In this sense, the Brazilian benchmarking models proposed by the regulator for TSOs have clearly evolved from the 1^{st} to the 4^{th} tariff review cycles, despite some arbitrary government intervention. For instance, the recent changes implemented in order to consider environmental variables and different voltage levels are noteworthy. However, even with these modelling advances, the benchmarking model still requires some adjustments, in order to provide coherent and reliable efficiency scores.

The final results of the 4^{th} TRC's DEA model lead us to infer that there are still some gaps in the modelling process. The concentration of efficient DMUs in a particular group of TSOs, for example, is a warning signal: in the DEA first stage, Bid TSOs achieved the larger efficiency scores. In addition, 75% of the fully efficient TSOs are part of this group. Moreover, some full efficient DMUs are the reference for a great number of non-efficient TSOs. In one case, one unique DMU defines the efficiency frontier for 68 out of 74 observations. It is worth noticing that Bogetoft and Lopes [2014] argue that in such cases, an outlier analysis is required to assure that the efficiency frontier is not define by outliers.

As a consequence of these results, in the first step of the Public Hearing of the 4^{th} TRC, six out of ten agents submitted contributions arguing that Bid TSOs are not comparable to Existing TSOs. Thus, the first issue to be addressed in the benchmarking modeling rises beyond the outlier detection, regarding the comparability of the companies. In the following sections, we also discuss the weight restrictions that were used and the second-stage approach.

[4] Sample median without extra observations

4.3.1 Comparability of the companies

A simple assumption for DMUs to be benchmarked is that they must operate under the same technology. However, the DEA model presented in NT 204/2018-SRM/ANEEL [ANEEL, 2018b] compares two different groups of transmission companies, the Existing TSOs and the Bid TSOs.

Both groups of TSOs obviously have the same core activity, the service of electricity transmission. However, there are some remarkable differences regarding its operation. Firstly, Bid TSOs are not subject to the same regulatory rules with regard to their revenues. Incentives for cost reduction require specific approaches. Contracts result from auction processes that started in 2000, regarding specific transmission networks or substations of the integrated system. Thus, the Bid TSOs are not geographically spread across the Brazilian territory as the Existing TSOs. Furthermore, most of the companies in this latter group were founded in the 1960s, within a context of state intervention. Thus, the main difference between the two groups is the embedded technology of their installed assets. The contextual variable "average age of the assets", illustrated in Figure 18, reveals this. While Bid TSOs have assets with an average of 7.6 years of operation, assets of the Existing TSOs have an average of 19.3 years of operation.

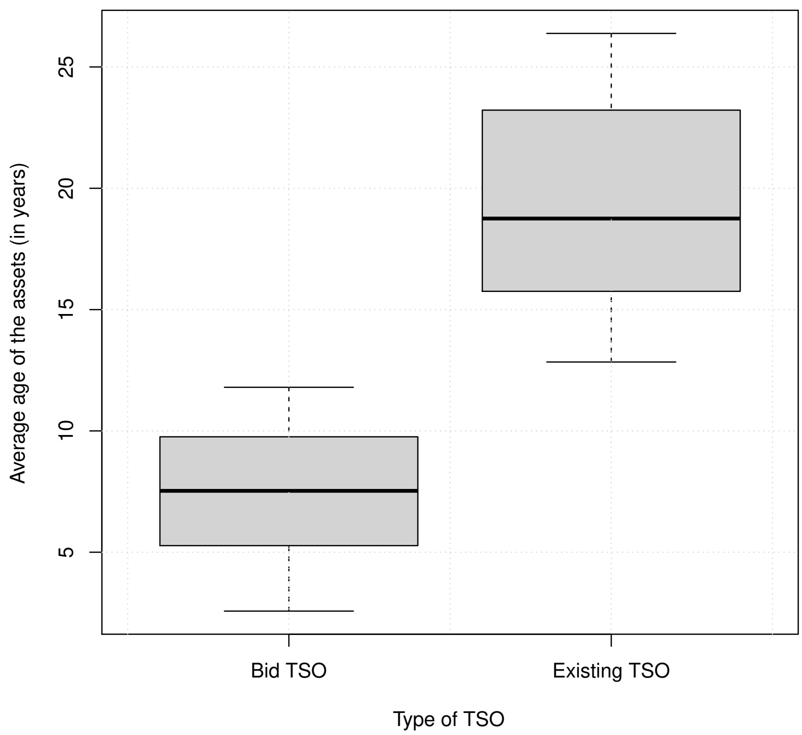


Figure 18 – Average age of assets by TSO type

Source: ANEEL [2018b]

It is important to mention that the age of the assets installed before 2000, which compose the sample, is estimated considering their accounting lifetime, and it is saturated at the maximum of this theoretical age [ANEEL, 2018a]. It means that the average age of the assets is an underestimated measure for the Existing TSOs. These companies operate assets installed since the 1960s and have limited power to decide about their replacement. Actually, when the accounting lifetime of equipment is reached, a TSO may ask permission to replace it [ANEEL, 2014a]. But, in practice, if the operational lifetime is greater than the accounting lifetime, TSOs keep the equipment operating. This practice contributes to the tariff modicity, but increases the risk to which the TSO is exposed. According to Wang et al. [2002] and Brown [2004], the yearly failure rate of the assets increases with their age. Thus, although the technology of transformers and switch modules have been roughly the same for the last forty years, inspections and interventions are more often required, raising the operational costs.

Another basic DEA assumption, likewise claimed by Charnes et al. [1978], is that compared DMUs must use the same inputs to produce the same outputs. In the ANEEL model, outputs are *proxies* of the installed assets that were chosen to represent the transmission functions performed by the TSOs. As mentioned, Bid TSOs manage specific transmission networks or substations, according to each auction process. Thus, their operational infrastructure is not as complex as that of the Existing TSOs. As a consequence, Bid TSOs own less equipment than Existing TSOs. Figure 19 shows the distribution of the DEA outputs among the TSOs in 2016. It is worth noticing that none of the Bid TSOs owns transmission networks and substation equipment under 230 kV. From the nine output variables, three present zero values for Bid TSOs. Rather than a scale problem, which is addressed by DEA modeling, these features imply that Bid TSOs and Existing TSOs do not operate the same transmission functions, and then do not own the same outputs.

It is worth mentioning that the initial assumption of Charnes et al. [1978], for equality of inputs and outputs when using DEA, is equivalent to claim that all input variables $\mathbf{x} \in \mathbb{R}_{+}^{*}$ and all output variables $\mathbf{y} \in \mathbb{R}_{+}^{*}$ must be nonzero. That is, all companies must use non-zero inputs to produce non-zero outputs. This assumption was later relaxed with respect to negative variables (see, e.g., Pastor and Ruiz [2007]), but the non-zero condition is still an assumption to DEA modeling.

The weak comparability of the TSOs may be also inferred by analyzing the voltage level of their assets. The Brazilian transmission system has assets operating in nine different voltage levels, from 34.5 kV to 750 kV. As expected, not all TSOs operate in all voltage levels. The distribution of the network extension by TSO is shown in Figure 20. ANEEL has aggregated the asset variables used in NT 204/2018-SRM/ANEEL [ANEEL, 2018b] in two voltage levels (under 230 kV and above or equal 230 kV), not distinguishing how each voltage level impacts the operational cost. Obviously, a DEA model is not expected to comprise one variable to each voltage level. Therefore, the input and output variables should be selected or transformed accordingly, before applying DEA.

Agrell and Bogetoft [2014], for instance, present a similar problem in an international benchmarking study. They describe the implementation of a benchmarking model used to compare 22 TSOs from 19 countries in 2012, in a study made on behalf of the Council of European Energy Regulators (CEER). In order to consider a number of different assets and voltage levels,

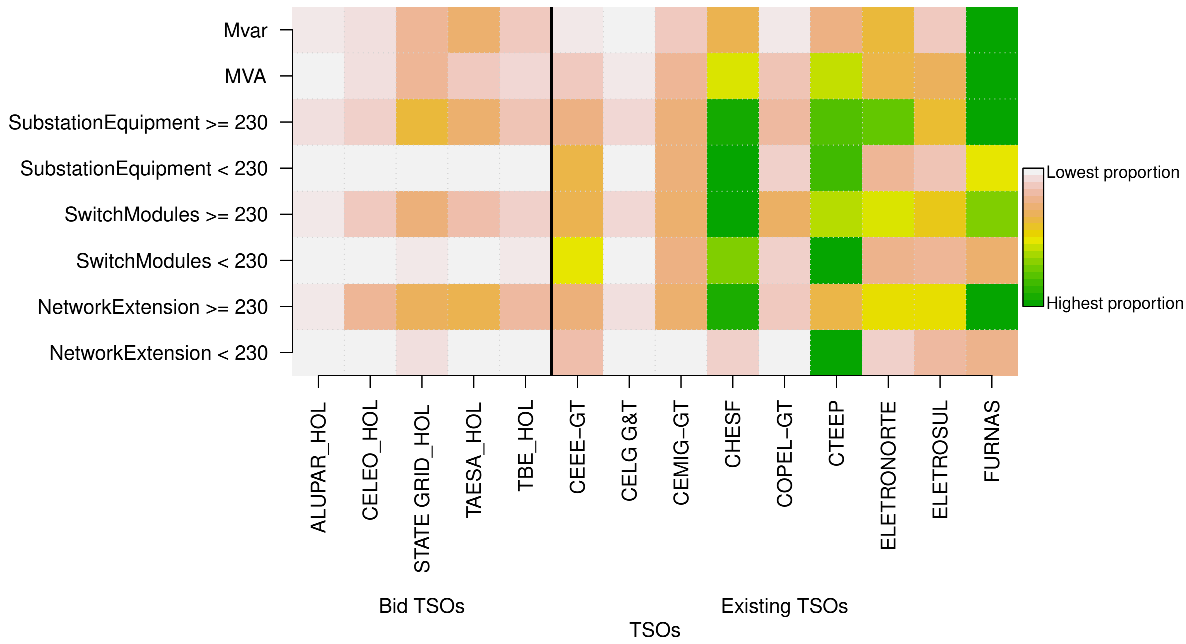


Figure 19 – Distribution of ownership of the outputs among TSOs (2016)

Source: ANEEL [2018b]

they proposed an equivalent grid as the output variable. The authors state that power system engineers estimated a system of 2196 relative weights for operational costs and capital investments, spanning over assets organized in nine groups and four categories (power, voltage, short-circuit current, cross-section).

As we pointed out, the Brazilian model needs to address two issues in order to improve the comparability of the TSOs: (*i*) the differences between the embedded technology of Existing and Bid TSOs and (*ii*) differences regarding voltage levels. The Brazilian model considers adjustments of the main differences among TSOs in a second-stage analysis. The inclusion of the variable "average age of the assets" represents an important improvement in the model, since this variable carries the implicit information about the embedded technology of the companies. This improvement holds if the second-stage procedure accurately computes the differences regarding the variable in the efficiency scores. As we discuss later in Section 4.3.3, the second-stage procedure adopted by ANEEL smooths the evaluation of the effects of the contextual variables on the efficiency scores. Thus, this approach is not enough to deal with the differences between Bid and Existing TSOs. Moreover, the second-stage proposal ignores other important issues concerning the comparability of the TSOs, such as the differences among the output variables. Further adjustments to the data are still required.

We suggest the construction of an equivalent grid, as seen in the European model approach implemented by Agrell and Bogetoft [2014]. The implementation of such solution requires the engagement of all compared TSOs in the long term. To do so, the regulator needs to ensure

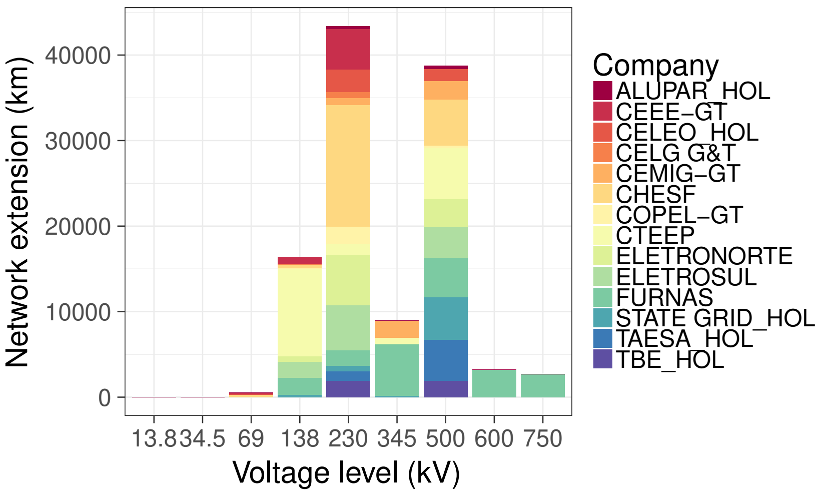


Figure 20 – Network extension by voltage level and TSO (2016)

Source: ANEEL [2018b]

that costs are standard treated among companies. An alternative approach is to construct an equivalent grid based on engineering assumptions. Kirschen and Strbac [2004] provide some evidence on how transmission assets may be aggregated, considering their operational features. In addition, in order to deal with the differences between Bid an Existing TSOs, we suggest keeping the two-stage procedure, whereas it is able to properly capture the differences. A broader discussion concerning the second-stage is presented in subsection 4.3.3.

Besides the differences between Bid and Existing TSOs, the regulator included both types of TSOs in the sample in order to raise the efficiency of the system, searching for the best practices of the transmission sector. Thus, to achieve this goal, it is important that the benchmarks may be emulated by less efficient companies. From the regulatory point of view, the fact that a company is new, small or private does not necessarily make it less comparable to others. In this way, the maintenance of the Bid TSOs in the sample may represent a good practice, as long as technological differences can be addressed properly. Otherwise, results will not represent a reliable reference for the sector.

4.3.2 Weight restrictions

The Brazilian regulator claims in NT 160/2017-SRM/ANEEL [ANEEL, 2017a] that the applied weight restrictions are based on the interpretation proposed by Podinovski [2004]. As previously stated, Podinovski [2004] interprets the weight restrictions under a feasible trade-off perspective. However, the DEA model presented in NT 204/2018-SRM/ANEEL [ANEEL, 2018b] has 16 weight restrictions: six of them are Type I constraints, and the remaining ten are characterized as Type II weight restrictions. To hold the interpretation proposed by Podinovski [2004], even the latter group of restrictions should assume a trade-off perspective.

The use of weight restrictions is justified in most cases as a means to improve the discriminatory power of the model. In other cases, the analyst may include known information in the modelling process to improve the practicability of the efficiency scores. Subsequently, both weight restriction types can be justified in the model if their values are consistent with engineering practices [Dyson et al., 2001].

Therefore, the weight restrictions proposed ANEEL must be consistent with the physical and real relations. To analyze this condition, we have verified if the definition of each weight restriction type is compatible with the physical features of the problem. A second discussion regards the feasibility of the weight restriction limits. However, this latter issue was not investigated due to the lack of suitable data.

The restrictions that relate one output with the input variable (OPEX) imply a trade-off relation between one unit of the analyzed output and one unit of the monetary input. Thus, the analysis of the feasibility of such restrictions is connected with the chosen limits. Nevertheless, the interpretation of the weight restrictions that relate differents outputs requires a closer look. The idea of the trade-off restrictions described by Podinovski [2004, 2007] and Atici and Podinovski [2015] is to evaluate resources that could, in fact, be replaced. As an example, consider the relation described in line 2 of Table 12: $1 \leq u_{SE\geq230}/u_{SM\geq230} \leq 10$, where $u_{SE\geq230}$ is the relative weight of the substation equipment above 230 kV and $u_{SM\geq230}$ is the relative weight of switch modules above 230 kV. Acording to Podinovski [2004], the interpretation of this relation is that one substation equipment compensates the loss of one switch module within the stated limits. From a technical perspective, this assumption does not hold. To operate a transmission substation, companies need substation equipment (e.g., a transformer) as well as switch modules (e.g., the connection module). Therefore, the trade-off between these assets is not feasible. The lack of coherence between the weight restrictions and physical features is also observed in the relation between high- and low-voltage assets. The TSO cannot decide by itself to change the voltage level of a group of assets, such as the network extension.

Since the trade-off restrictions are not feasible from an operational perspective, they should not be used in the DEA modeling. Nevertheless, simply removing these restrictions would reduce the discriminatory power of the model. There is a large number of outputs and a small number of compared DMUs. Without the weight restrictions, the number of fully efficient TSOs would increase. Alternatively, we suggest converting the trade-off restrictions that relate outputs into restrictions linking the output variables with the input variable. This approach was detailed in a proposal of the TSO Eletrobras within the Public Hearing of the 4^{th} TRC [Eletrobras, 2018].

The conversion of the restrictions that relate outputs into restrictions related with the OPEX may be achieved through some algebraic manipulation of the information provided in Table 12. Six relations are constructed between the input variable (OPEX) and the output variables (installed power in MVA, network extension above 230 kV and switch modules above 230 kV). These three output variables are related to four other output variables in the trade-off restrictions (reactive power in Mvar, network extension under 230 kV, substation equipment above 230 kV and substation equipment under 230 kV). Therefore, there is an indirect relation between these last four variables and the input variable (OPEX). The relation among these variables is shown in Figure 21. Thus, it might be possible to convert the weight restrictions which relate outputs into constraints related just with the OPEX, complying with the limits required by the regulator.

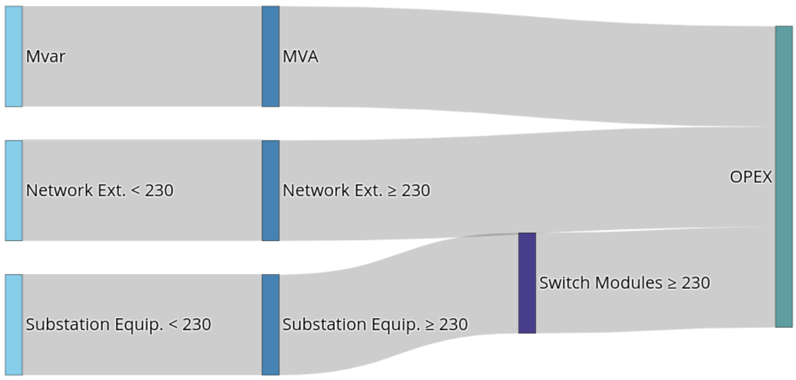


Figure 21 – Relation among variables in ANEEL's weight restrictions

It is worth mentioning that the proposed conversion generates weight restrictions which are feasible from the engineering perspective. Thus, the interpretation intended by ANEEL, according to the trade-off perspective proposed by Podinovski [2004], holds. That is, the new trade-offs are based on the exchange of one output with one monetary unit.

The evaluation of the weight restriction limits requires technical knowledge of the industry and/or the use of cost data of the compared DMUs. In NT 160/2017-SRM/ANEEL [ANEEL, 2017a], the regulator claims that the limits of the weight restrictions are based on data from regulated contracts among TSOs. This information was not published, so the assumptions that support the model had to be accepted. Some of these assumptions are strong; for instance, six trade-off weight restrictions are based on the argument that the operational costs of all low voltage networks and equipment are lower than the costs of equipment with voltage levels above 230 kV. Detailed data required to validate the definition of limits are not provided by the regulator. Despite the relevant impact of these limits in the DEA scores, a technical evaluation is not within the scope of this study.

4.3.3 Second Stage

Second-stage analysis is a frequent approach used to deal with the environmental heterogeneity of compared DMUs. In the 4^{th} TRC, ANEEL introduced a second-stage procedure using a dynamic clustering method to correct the efficiency scores. The regulator calculated a severity index using three contextual variables and applied it to define sub-samples for each TSO. The inclusion of environmental variables in the TSOs' benchmarking analysis represents an important improvement in the DEA modelling in Brazil. Nevertheless, this second-stage approach still requires further improvements in order to properly address the environment's impact on each TSO.

The second-stage procedure proposed by Coelli et al. [2005], and referenced by ANEEL [ANEEL, 2018b], proposes ranking the DMUs according to one environmental variable. Subsequently, "the efficiency of the *i-th* firm is compared with those firms in the sample which have a value of the environmental variable which is less than or equal to that of the *i-th* firm" (Coelli et al. [2005], page 167). In contrast, the analysis proposed by the regulator in NT 204/2018-SRM/ANEEL [ANEEL, 2018b] employs an adapted ranking based on a severity index. ANEEL uses the fitted values of a Tobit multivariate regression model to calculate this severity index. Thus, the estimated severity represents a smooth version of the environmental components. Furthermore, Coelli et al. [2005] do not mention how to deal with the loss of the discretionary power caused by the reduction of the sample. The ANEEL model fixes 2/3 of the original sample as the minimum size for the subgroups, generating corrected scores equal or superior to the original efficiencies, mostly due to the smaller number of DMUs in the sub-samples. This result, which is shown in Figure 22, differs significantly from classical second-stage approaches, especially those based on linear regression models such as Ordinary Least Squares (OLS) or Tobit. These methods tend to result in an average adjustment close to the mean of the original scores [da Silva et al., 2019b].

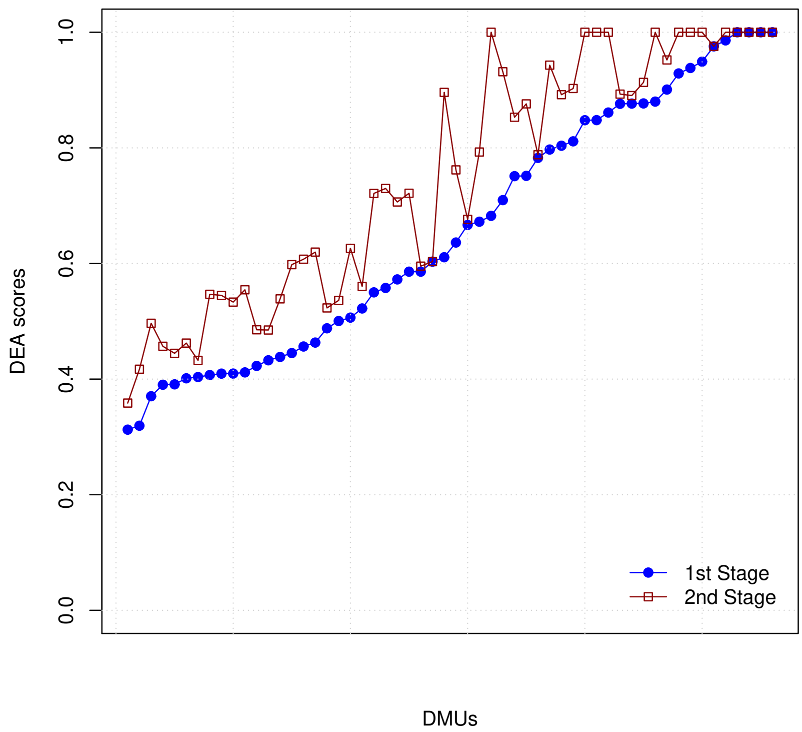


Figure 22 – Efficiency scores of NT 012/2019

Source: ANEEL [2019]

The major problem with the ANEEL second-stage approach is the low discriminatory power of the estimated severity index. Despite the effort to collect twelve environmental variables, only three of them were chosen to correct the DEA efficiency scores. In addition, their effects on the DEA scores were smoothed out by the Tobit regression. Furthermore, the criteria used to select the environmental variables were based on multivariate linear regressions of auto-correlated variables which can generate biased results. As a consequence, some important information could be not considered in the evaluation. Moreover, even if the severity index were a good alternative to represent the environment, the procedure to determine the sample sizes of the dynamic clusters allows the DMUs with larger severity index to be compared with companies in better environments. Thus, the resulting adjustments were not even proportional to the calculated severity index, as shown in Figure 23. The figure shows that DMUs with the greatest severity indexes, above 0.83, have their efficiency scores adjusted by an average of 3.0%. Meanwhile, DMUs with severity indexes around 0.25 have their efficiency scores adjusted by 15% or 30%.

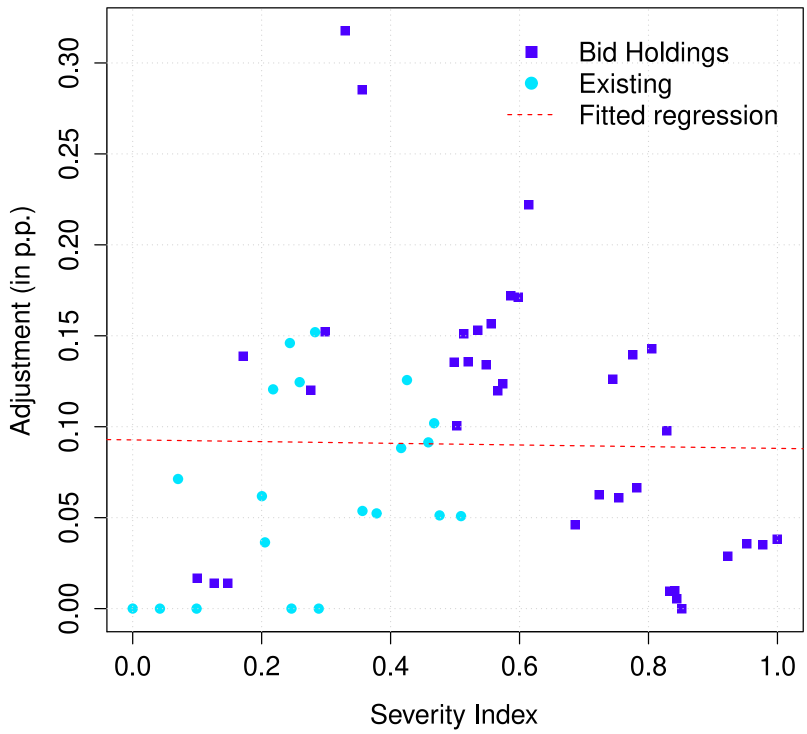


Figure 23 – Adjustment of DEA scores x Severity Index

The use of a smooth version of the contextual variables proved not being effective in isolating the effects of the contextual variables. Then, we suggest the use of second-stage procedures which evaluate directly the effects of the contextual variables on the efficiency scores. As previously explained, regression-based models are the most intuitive and easy to interpret.

OLS and Tobit adjustments generate a final result quite different of the ANEEL's "upper bound". These classical procedures adjust the efficiency scores considering a liner relation between contextual variables and the efficiency scores. Some DMUs have their scores positively adjusted, while other DMUs have their scores negatively adjusted.

An alternative that could provide an "upper bound" to the DEA scores is a second-stage approach using a compound error model, as the one described by Banker and Natarajan [2008] and the one applied by da Silva et al. [2019b]. In this latter approach, the authors considered the expected mode of the conditional inefficiency to calculate the corrected efficiency scores. This adjustment provides a similar upper bound to DEA 1^{st} stage scores. Nevertheless, the application of compound error approaches is a difficult task. The parameters estimation tends to present convergence problems, especially with small samples as the TSOs' dataset.

Actually, the Brazilian dataset has complex issues to be treated in a multivariate regression model. First, contextual variables are highly correlated among them. Moreover, there is a great number of contextual variables (12), compared with the sample size (14 DMUs). The panel data also requires attention.

Considering the difficulties that must be overcome to build a multivariate regression model, we suggest a simpler approach, based upon univariate regression models. In such a procedure, each m environmental variable is the independent variable in a univariate OLS regression with the efficiency scores. Then, we run m DEA scores adjustments. The final adjusted efficiency may be defined according to an aggregation function such as the percentile. In this case, the aim to create the "upper bound" on the first stage scores may be maintained.

In summary, numerous second-stage procedures could be used in order to relate efficiency scores directly to the environmental variables. Nevertheless, the difficult handle of the dataset imposes some constraints on the analysis. Therefore, we propose to use a simple and intuitive approach that is able to overcome the environmental disparities.

4.4 Conclusions

Regulatory modeling practice is close to what McDonald [2009] classifies as the aim of "instrumentalist" analysts, who are not interested in defining theoretical properties, but rather in the success of the procedures. However, the "freedom" inherent in creating benchmarking models is limited in the regulatory context. Regulators of natural monopolies are responsible for sending appropriate signs to the market and creating a stable and balanced environment for both consumers and investors. The experiences with sudden changes in the Brazilian regulatory history prove that a predictable and reliable benchmarking approach is essential.

In this context, this paper analyzed the Brazilian benchmarking model used to regulate Transmission System Operators, focusing on the 2018 DEA model. Despite the methodological advances introduced in the last tariff review cycle, there are still some issues to be solved in the model. Slight changes to some specific topics of the model could provide a benchmarking approach that better represents the reality faced by the companies. Notably, we discussed the improvement of three subjects of the modeling: the comparability of the companies, the weight restrictions and the second-stage procedure.

First, we analyzed the comparability of the companies and showed that Existing and Bid TSOs face different operational conditions that should be properly addressed in the DEA model. The inclusion of the variable average age of the assets, which carries information about the TSOs' embedded technology, helps to deal with the problem. However, this inclusion only works if the variable is properly used in the model, in a way that its relation with the efficiency scores can be isolated. In addition, asymmetry in the type of assets and voltage levels between TSOs may be treated with the construction of an equivalent grid of outputs. To do that, we suggest an engineering-based approach, considering technical features of the equipment.

With respect to the weight restrictions, we assert that the trade-off weight restrictions used by the regulator are not representative from the operational perspective. Their suppression would damage the discriminatory power of the model. Thus, we suggest converting trade-off to value-based weight restrictions, which compare the output variables and the input variable.

Finally, the second-stage procedure used by the regulator is ineffective in isolating the impact of the contextual variables. We suggest a simpler and intuitive approach, based on the aggregation of multiple univariate regression-based models. This alternative procedure allows the inclusion of a broad set of variables and is more effective in representing the impact of these variables on the efficiency scores.

Further issues not discussed in this paper suggest interesting topics for future research. The approach to defining the weight restrictions and the arbitrary inclusion of extra information in the DEA modeling should be investigated. The comparison among the DEA models in the different TRCs and their impacts are also worth studying.

Acknowledgements

This work was supported by Deutscher Akademischer Austauschdienst (DAAD) with funds of Bundesministerium für Bildung und Forschung (BMBF) under Grant 57391086. In addition, authors thank CAPES (PROBAL Program 483/2018) and CNPq [Grant numbers: PQ-308361/2014-8 and CNPq 402070/2016-0] for financial support.

5 An evaluation of DEA models with multiple environmental variables for cost regulation of the Brazilian transmission companies

Abstract

The non-parametric benchmarking method Data Envelopment Analysis (DEA) is frequently used by regulators to compare units under natural monopolies. The Brazilian Energy regulator uses such approach to define the efficient operational costs of the transmission companies. In 2018, they applied a second-stage procedure to include the effects of environmental variables in the efficiency scores. The used approach was limited regarding the number of variables to incorporate and a variety of other themes. This study evaluates an alternative to deal with multiple contextual variables that affect DEA scores. We propose to correct the DEA input variable, based on fundamental analysis-of-variance properties. We applied the proposal to the Brazilian transmission case and achieved satisfactory results.

Keywords: Energy Transmission Regulation. Data Envelopment Analysis. Environmental variables. Input variable correction

5.1 Introduction

Second-stage Data Envelopment Analysis (DEA) refers to the family of techniques that incorporate the effect of contextual variables on the DEA scores. The most common approaches are based on linear regression procedures which capture the average behavior of the efficiency scores regarding a set of non-controllable variables.

In such approaches, DEA efficiency scores are defined as the dependent variable of a regression model, and the contextual variables are defined as independent variables. Hoff [2007] and McDonald [2009] advocate that Ordinary Least Squares (OLS) and censored regression models as Tobit are good options to represent the average behavior of the efficiency scores regarding contextual variables. Furthermore, there are some econometric approaches which define the data-generating process (DGP) of the production set. The methods proposed by Simar and Wilson [2007] and Banker and Natarajan [2008] are examples of this group of analyses.

Second stage techniques based on regression models imply some assumptions about the relation among contextual variables and the efficiency scores, such as the format of the error distribution or the independence of residuals. In addition, real applications may impose constraints on the regression analyses that are difficult to overcome. An example is the benchmarking model of Brazilian Transmission System Operators (TSOs). In 2018, the Brazilian Energy Regulator (ANEEL) defined a benchmarking model with a second stage procedure to compare TSOs. The regulator's approach, which was based on the proposal of Coelli et al. [2005], used the outcome of a Tobit regression between efficiency scores and three contextual variables to calculate a severity index to each TSO. This number was then used to define dynamic clusters for each TSO and re-run the DEA model, within each subsample. The second stage procedure created an upper bound to the efficiency scores, i.e., corrected scores were equal to or larger than the first stage scores.

Applying linear regression techniques to the specific problem of benchmarking Brazilian TSOs is itself a challenging topic. The dataset is composed of a reduced number of companies: 14 TSOs replicated in four-year panel data. The twelve contextual variables defined by the regulator are highly correlated among themselves. In addition, the variables do not have a linear effect on the analyzed TSOs. Thus, a robust regression model between DEA efficiency scores and the contextual variables would be required to overcome problems ranging from variable selection to correction of the efficiency scores.

As an alternative, this study proposes an approach for considering the effects of the contextual variables in the DEA **input** variable. The procedure uses the **fundamental analysis-of-variance identity for a regression** to correct the input variable. The whole set of contextual variables is used in univariate regression analyses and generates multiple DEA-corrected efficiency scores, which are summarized in a subsequent procedure.

The paper is organized as follows. In section 5.2 we present the relevant concepts involved in the problem of the inclusion of environmental variables in a DEA model. In this section, we also explain the regulation model for Brazilian TSOs. In section 5.3 we present the case study to which the proposal is applied. Results are presented in section 5.4 and conclusions are shown in section 5.5.

5.2 Methodology

5.2.1 Regulation of Brazilian energy transmission companies

The Brazilian electricity model comprises a centralized and integrated system. Power plants and consumers are integrated across the whole territory in the National Integrated System (*Sistema Integrado Nacional* — SIN) which is managed by the National System Operator (ONS). The energy companies were vertically segregated in the 2000s into generation, transmission, distribution and commercialization segments. Such model is the result of a restructuring process implemented by the Ministry of Mines and Energy (MME) since mid 1990s and described by Araújo [2006] and Sanches [2011].

In this integrated system, ONS decides which power plant should dispatch energy. Because of that, transmission networks play a strategic role in the system and are responsible for ensuring its reliability. Then, Transmission System Operators (TSOs) are paid by the availability of their assets, rather than the amount of transmitted energy. The Brazilian energy regulator, ANEEL (*Agência Nacional de Energia Elétrica*), uses a revenue-cap scheme to regulate TSOs. According to Bogetoft and Otto [2010], under this regime the regulator caps an allowable revenue for each TSO for a pre-determined period, typically 4-5 years. Braeutigam and Panzar [1993] claim that this class of regulatory scheme breaks the direct relation between cost and revenue and increases the incentive for cost reduction.

The expansion of the energy network in Brazil is a centralized decision shared among

ONS, ANEEL, the Ministry of Mines and Energy and the Energy Research Office (EPE). Since 2000, these planners may allocate the investments in new transmission networks and assets to the existing concession contracts or may grant them to new players through auctions. As a result, there are two business models for TSOs in Brazil, classified as follows: (*i*) Existing TSOs are the nine TSOs that resulted from the vertical segregation in the 2000s. Some of these TSOs ran auctions after 2000 and, together with their existing concession contracts, also manage bid concession contracts. These companies were responsible for 71% of the operating network circuits of the system in 2016 [ANEEL, 2018b]. (*ii*) Bid TSOs are those whose concession areas are the result of bids in auctions after 2000. There are about 68 Bid TSOs but, at present, some of them are pre-operational, constructing new networks and substations.

Both types of companies are subject to the same rules regarding the expansion of their networks. Nevertheless, there are differences concerning incentive regulation for costs. Existing TSOs are subjected to periodic Tariff Review Cycles (TRC) each five years. Then, all the parameters used to define the TSOs' revenues for the upcoming cycle are recalculated (e.g., cost efficiency, rate of return on investments, and so on). Otherwise, Bid TSOs face a less comprehensive tariff review. Each five years from the bid, ANEEL reviews two parameters used to calculate each Bid TSOs' revenues, the sector productivity gain and the debit cost (one portion of the the rate of return on investments).

Approximately 70% of the Existing TSOs' revenues refer to a pass-through regarding efficient operational costs. ANEEL applied a benchmarking model in each TRC to define the efficiency score used to calculate the efficient costs and respective revenues for the upcoming years. In the four TRCs concluded until 2019, the regulator used the non-parametric benchmarking model Data Envelopment Analysis (DEA).

ANEEL concluded the 4^{th} TRC of Existing TSOs in 2018, defining the methodology for the efficient operational cost in Technical Note (Nota Técnica — NT) 204/2018-SRM/ANEEL [ANEEL, 2018b] and showing its final results in NT 012/2019-SRM/ANEEL [ANEEL, 2019]. In this cycle, the regulator used a DEA model to calculate efficiency scores and applied a second stage procedure to correct them by three contextual variables. ANEEL adapted its second stage procedure from a proposal of Coelli et al. [2005].

5.2.2 Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a non-parametric benchmarking method which uses linear programming techniques to calculate relative efficiency scores of comparable Decision Making Units (DMUs). Charnes et al. [1978] introduced the seminal model, assuming a constant return to scale (CRS) production set. This condition implies that the variation in the input set causes a proportional variation in the output set. Banker et al. [1984] extended this model to a variable return no scale (VRS) production set. Both models enhance the basic framework of Farrell [1957], which defined an input-based measure of technical efficiency. Such a measure regards the Euclidian distance from a specific point (the DMU location in the production set) to the efficiency frontier in a radial direction orthogonal to the output plan. The technical efficiency defined by Farrell [1957] is known as *Farrell distance* and is reciprocal of the input distance function due to Shephard [1953].

The non-parametric nature of DEA implies that previous knowledge about the efficiency function is not required. Instead, some assumptions need to hold, as the convexity of the function. DEA uses a linear programming problem which relates a set of input and output variables to define the efficiency frontier. Let i Decision Making Units consist of the production set T, where $i = [1, ..., n]$. The production set comprises an output vector $\mathbf{y} = [y_{1i}, ..., y_{sn}]$ of s output variables and a vector $x = [x_{1i}, ..., x_{kn}]$ of k input variables. To each analyzed DMU (DMU_0), the linear problem (LP) 35 defines the optimal weight parameters related to outputs, υ, and to the inputs, ν. The efficiency score θ_i results from the objective function.

$$
\begin{aligned}
&\max \sum_{r=1}^{s} \upsilon_r y_{r0} \\
&\text{s. t.:} \qquad \sum_{r=1}^{s} \upsilon_r y_{ri} - \sum_{j=1}^{k} \nu_j x_{ji} \leq 0, \quad i = 1, ..., n \\
&\qquad\qquad \sum_{j=1}^{k} \nu_j x_{j0} = 1 \\
&\qquad\qquad \upsilon_r, \nu_j \geq 0
\end{aligned}
\tag{35}
$$

The linear problem 35 refers to an input-oriented problem with a constant return to scale (CRS) production set. The linear problem 35 may also comprise weight restrictions. Cook and Zhu [2008] and Thanassoulis [2001] provide further models considering non-decreasing return to scale (NDRS), output orientation and dual formulations, for instance.

Charnes et al. [1978] define the inputs $\mathbf{x}$ and outputs $\mathbf{y}$ of a DEA model as controllable variables. In this context, the decision-maker may manage them in order to improve its efficiency score. However, there is another important set of variables which comprises non-controllable factors, $\mathbf{z} = [z_{1i}, ..., z_{mn}]$. Banker and Morey [1986] adapted the DEA model to include such variables. Nevertheless, the most popular procedures to consider the contextual variables in the DEA model are the second stage approaches, which relate DEA scores with the contextual variables through regression-based techniques. The most usual treatments of contextual variables are detailed in the next subsection.

5.2.3 Usual treatments of contextual variables in DEA

The effects of contextual variables are frequently included in the DEA scores through second stage approaches. Regression-based techniques require an econometric definition of the DEA problem. Simar and Wilson [2007] state that DEA measures the efficiency of comparable DMUs relative to a non-parametric *estimate* of an unobserved *true* frontier, conditional on observed data resulting from an underlying data-generating process (DGP). That is, the Production Possibility Set (PPS), ψ, can be seen as a joint function f_{XYZ} depending on the random variables X, Y and Z which comprise the mentioned vectors $\mathbf{x}$, $\mathbf{y}$ and $\mathbf{z}$, $f_{XYZ}(x, y, z)$ [Daraio et al., 2015, Simar and Wilson, 2007]. The joint density function $f_{XYZ}(x, y, z)$ may be decomposed as Equation 36.

$$f_{XYZ}(x, y, z) = f_{XY|Z}(x, y|z)f_Z(z) \tag{36}$$

Daraio et al. [2015] state that these conditional equations imply that the relation of inputs and outputs (X, Y) exists conditioned to the presence of the the environmental variables Z. Therefore, the production possibility ψ may be characterized as ψ^z. As previously explained, the efficiency frontier $g(\cdot)$ of such PPS is non-parametric estimated by the LP 35. The typical regression-based second stage procedures makes the parametric estimation of the DGP, considering that the efficiency score $\boldsymbol{\theta}$ may be estimated as the result of Equation 37.

$$\hat{\boldsymbol{\theta}} = g(\mathbf{z}) = \mathbf{z}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{37}$$

where $\boldsymbol{\beta}$ is a set of unkown parameters and $\boldsymbol{\varepsilon}$ is the random noise, normally distributed, with zero mean and variance σ_ε. The parameters estimation is usually done through censored regression (Tobit) or Ordinary Least Squares (OLS). See, e.g., Bogetoft and Otto [2010] and McDonald [2009] for further details about such approaches.

Most of DEA studies which use these econometric approaches are concerned about evaluating the impact of the contextual variables $\mathbf{z}$ on the efficiency scores. See, for instance, the studies of Wolszczak-Derlacz [2017], Haug and Blackburn [2017] and Banker et al. [2010]. Their analyses are focused on the estimation procedures and the evaluation of the statistical significance of the regression coefficients. Nevertheless, da Silva et al. [2019b] specify the procedure to correct DEA scores by the environmental variables in Tobit and OLS approaches. The correction is based on the analysis-of-variance identity of a regression model.

Other class of regression-based second stage procedures are the compound error models, which comprise a more complex DGP. In these models, there is an assumption that the production function is distanced from the efficiency frontier by a disturbance term δ. Such disturbance term may be decomposed in three portions: the effect of the environmental variables, $\mathbf{z}\boldsymbol{\beta}$, the random noise (a random variable v) and the managerial inefficiency (a random variable u).

The DGPs presented by Simar and Wilson [2007] and Banker and Natarajan [2008] are examples of output-oriented compound error models. An adaptation of the latter was proposed by da Silva et al. [2019b], considering the input-oriented case. This DGP stands that $\mathbf{x} = h(\mathbf{y}) \cdot e^{\delta}$, where δ is the disturbance term, $\delta = \mathbf{z}\boldsymbol{\beta} + \epsilon$ and $h(\cdot)$ is the function which relates the variables. da Silva et al. [2019b] claim that the input-oriented DEA $\hat{\boldsymbol{\theta}}$ may replace the ratio $\mathbf{x}/h(\mathbf{y})$, in the case of one input variable, $\hat{\boldsymbol{\theta}} = \hat{h}(\mathbf{y})/x$, which leads to:

$$-log(\hat{\boldsymbol{\theta}}) = \mathbf{z}\boldsymbol{\beta} + \boldsymbol{\epsilon} \tag{38}$$

where $\boldsymbol{\epsilon}$ is a vector composed by the random variable $\epsilon = u + v$, which is the input-oriented compound error. Thus, in the regression which relates the efficiency score $\hat{\boldsymbol{\theta}}$ with the contextual variables $\mathbf{z}$, the compound error $\boldsymbol{\epsilon}$ fits the observed estimation error. The inefficiency term u is estimated as the conditional random variable $u|\epsilon$. As the random variable ϵ is a convolution of variables u and v, it is important to define its probability distribution functions. Banker and Natarajan [2008] consider that the technical inefficiency assumes a Gamma distribution with parameters 2 and φ, while the noise is normal truncated at parameter V^M, centered in zero. The adaptation of da Silva et al. [2019b] uses a half normal distribution for the inefficiency term and a normal distribution for the noise component.

The corrected efficiency score, $\hat{\hat{\theta}}$, may be accessed through three procedures: (1) by the expected value of the conditional distribution, $\hat{\hat{\theta}}|\epsilon = E(e^{-u|\epsilon})$, (2) by the conditional mean $\ln \hat{\hat{\theta}} = -E(u|\epsilon)$ and (3) by the conditional mode $\ln \hat{\hat{\theta}} = -M(u|\epsilon)$. These three procedures are analogous to those used in the Stochastic Frontier Analysis (SFA) estimation, and result in different corrected scores.

In addition to these econometric approaches, there are also no regression-based alternatives to treat contextual variables in DEA. Coelli et al. [2005], for instance, propose three methods to deal with contextual variables. In the first proposal, the authors suggest to order the contextual variable from the least to the most detrimental effect upon efficiency. Then, the approach of Banker and Morey [1986] may be followed, including an extra restriction in the dual formulation of the LP 35. This restriction assures the comparison of the $i-th$ DMU with others in a better or equal environment, considering one contextual variable z_m, where $m = 1$. In practice, each DMU is compared to a restrict number of DMUs, smaller than the total sample.

The second proposal of Coelli et al. [2005] to deal with contextual variables is appropriate to cases in which there is no natural ordering of the environmental variables. The proposal consists of dividing the sample into sub-samples, according to the categorical variable. Therefore, the DEA model is solved in each sub-sample and all observed data points are projected into their respective frontiers. Finally, a single DEA is solved using the projected points in the previous steps. The third proposal of Coelli et al. [2005] suggests including the contextual variable(s) directly into the DEA LP problem. To do that, the contextual variable may be treated as non-discretionary neutral variable, a discretionary input or a non-discretionary output. Coelli et al. [2005] and Zhu and Cook [2007] describe alternatives to deal with such variables.

Methods 1 and 2 proposed by Coelli et al. [2005] are limited in the treatment of contextual variables. They admit just one contextual variable and have reduced discriminatory power, due to the use of sub-samples. The regression-based second stage approaches are likewise limited in some sense. The compound error models impose the definition of a DGP and may face problems of convergence in the parameters estimation. Moreover, these methods impose strong assumptions regarding the contextual variables as the separability condition stated by Simar and Wilson [2007]. To overcome these problems, we suggest an alternative which considers the effect of the contextual variables in the input variable. This approach is detailed in the following section.

5.2.4 Correction of DEA scores by input adjustment

Second stage DEA procedures use regression analysis to identify the portion of DEA scores that is explained by the contextual variables. From another perspective, the residuals of such a fitted regression correspond to an inefficiency that cannot be explained by other reasons, but by a purely technical/managerial inefficiency.

To correct the input variable regarding the contextual variables, first we identify the portion of the input variable which is explained by the output variables. The relation is established by a regression analysis. Theoretically, the residuals of such a regression are the portion that is not explained by output variables and may be interpreted as a sum of three portions: (*i*) the random noise, (*ii*) the technical/managerial inefficiency, and (*iii*) the effects of the contextual variables. To identify the portion related to the contextual variables, the residuals of this regression analysis are evaluated in a second linear regression procedure. In this analysis, the residuals are the dependent variable and the contextual variables are the independent variables. By the fundamental analysis-of-variance identity of the later regression, the input variable is corrected.

Consider the PPS previously defined, with one input variable, $\mathbf{x}$, s output variables $\mathbf{y}$ and m contextual variables $\mathbf{z}$. Frequently, the s output variables of vector $\mathbf{y}$ are nonorthogonal, and a multivariate regression model, which uses them as independent variables, has multicollinearity problems. Furthermore, if it is likely that the number of predictive variables s is close to the sample size n, the regression model will have poor predictive power, so the use of a regression technique is required to overcome these issues. Ridge Regression is an alternative to deal with nonorthogonal variables, providing the best predictive model [Hoerl and Kennard, 1970]. This technique generates biased estimators. Nevertheless, as we are interested in the model's residuals, statistical inference about estimated parameters is not relevant.

The classic ordinary least squares regression model which relates the input variable $\mathbf{x}$ and the output variables $\mathbf{y}$ is defined as follows. A linear relation between the dependent random variable $\mathbf{x}$ and independent variables $\mathbf{y}$ is assumed, as shown in Equation 39.

$$\mathbf{x} = \mathbf{y}\mathbf{b} + \boldsymbol{\omega} \tag{39}$$

where $\boldsymbol{\omega}$ is the random noise, a variable normally distributed with mean zero and variance σ_ω. In this equation, $\mathbf{b}$ is the matrix of unknown parameters to be estimated by the least-squares minimization. If Equation 39 is heteroscedastic, the dependent variable $\mathbf{x}$ may be evaluated in its logarithm form. Ridge regression is used to define the estimators $\hat{\mathbf{b}}$ by adding a constraint to the classical least squares approach:

$$\begin{aligned} \hat{\mathbf{b}} &= \arg\min_{b} (\mathbf{x} - \mathbf{y}\mathbf{b})^T(\mathbf{x} - \mathbf{y}\mathbf{b}) \\ \text{s. t.:} &\sum_{i=1}^{n} b_i^2 \leq c \end{aligned} \tag{40}$$

The solution of Equation 40 is obtained through Lagrange multipliers. Further details regarding Ridge Regression may be found in Montgomery et al. [2012].

For the sake of simplicity, $\mathbf{x}$ and $\mathbf{y}$ used in Equations 39 and 40 are the same to be applied as input and outputs of the DEA model. The following step is to identify the portion of the estimated residuals ω_i of the best predictive model (Equation 39) that can be explained by the contextual variables $\mathbf{z}$. To do that, residuals $\hat{\omega}_i$ will be estimated through a regression with each z_m contextual variable in univariate models, as shown in Equation 41.

$$\hat{\omega}_{im} = \alpha_0 + \alpha_1 z_{im} + \xi_i \tag{41}$$

where α_0 and α_1 are the intercept and the slope parameters, respectively. In this equation, ξ_i is the random noise, normally distributed, centered in zero with variance σ_ξ. To simplify the notation, let $\hat{\omega}_{im} = a_{im}$.

Notice that Equation 41 identifies the effects of the contextual variable in the residuals of the best predictive model. The residuals of this equation (variable ξ) represent the random noise and the technical/managerial inefficiency that cannot be explained by the contextual variable. We may now estimate a corrected variable a^*_{im} which is not linearly correlated with the contextual variable z_{im}. This can be achieved by using the fundamental analysis-of-variance identity for a regression model, by the sum of squares decomposition [Montgomery et al., 2012, Livingstone, 2009], shown in Equation 42.

$$\sum_{i=1}^{n}(a_i - \bar{a})^2 = \sum_{i=1}^{n}(\hat{a}_i - \bar{a})^2 + \sum_{i=1}^{n}(a_i - \hat{a}_i)^2 \tag{42}$$

where $\hat{a}_i$ is the fitted linear equation in accordance with Equation 41 and $\bar{a}$ is the sample mean, $\bar{a} = \sum_i a_i/n$. As previously stated, we are interested in isolating the portion of the residuals which represents the correlation between the dependent variable a and the independent variable z_m. This portion is known as the *Explained Sum of Squares* (ESS) and is the first term of the right-side of Equation 42. ESS may be written as $ESS = \sum_i reg_i^2$ where $reg_i^2 = (\hat{a}_i - \bar{a})$. This is the component to be excluded from the corrected residuals, according to Equation 43.

$$\begin{aligned} a_i^* &= a_i - reg_i \\ &= a_i - (\hat{a} - \bar{a}) \\ &= \bar{a} - \hat{\xi}_i \\ a_i^* &= \omega^*_{im} \end{aligned} \tag{43}$$

The procedure described in Equation 43 is the same as adopted for the correction of DEA scores in second stage OLS approaches. The adjustment by Tobit regression, which is analogous, is detailed in the study of da Silva et al. [2019b].

The corrected residuals ω^*_{im} now exclude the effect of the contextual variable z_m. The adjusted vector is now replaced in Equation 39, generating the adjusted input variable $\mathbf{x}^*_m$:

$$\mathbf{x}^*_m = \mathbf{yb} + \boldsymbol{\omega}^*_m \tag{44}$$

This procedure is repeated for each environmental variable, resulting in m corrected input variables, $\mathbf{x}^*_m$. The use of univariate regression models is an alternative to deal with nonorthogonal contextual variables. It is worth mentioning that variables which are poorly correlated with the residuals of the best predictive model will result in mild adjustments of the input variable.

However, to some DMUs these mild adjustments may be important and would be ignored by other variable selection procedures.

The final step in the proposed method regards the aggregation of the corrected variables, $\mathbf{x}^*_m$, in order to generate a unique corrected input variable, $\mathbf{x}^*$. The proposal is to preserve the calculated effects of the contextual variables as much as possible. Then, we run m DEA models, generating m corrected efficiency scores, $\Theta^*_i = [\theta^*_{i1}, ..., \theta^*_{im}]$ with each calculated $\mathbf{x}^*_m$. Thus, the final efficiency score is the $p-th$ percentile of the θ^*_{im} corrected scores.

$$\theta^*_i = p \times \Theta^*_i \tag{45}$$

where p corresponds to the chosen percentile of the corrected scores. The $p-th$ percentile may be chosen according to the analysts' objectives. For example, in the case of the Brazilian TSO benchmarking model, the second stage procedure generated an upper bound to the DEA first stage scores. To hold this objective, the analyst may choose the $p-th$ percentile to which the minor correction results in zero. In more generic cases, the 75^{th} percentile is a good choice since it avoids unusual adjustments.

It is worth mentioning that we propose the adjustment of the input variable using two regression analyses due to the problem characteristics. The first regression model (input variable *vs.* output variables) aims to isolate the portion of the input that is not explained by the outputs in the residuals information. Then, the second regression model estimates the portion of the residuals which are explained by the contextual variables. A unique regression model with output and contextual variables may not isolate properly the expected information. Furthermore, the large number of output and contextual variables difficult a unique model, even with the use of Ridge Regression.

5.3 Application

As previously mentioned, this study evaluates alternatives to the second stage procedure used by the Brazilian energy regulator in the 2018 Tariff review of TSOs. Thus, we briefly explain the ANEEL's model and point out its problematic issues. The variables and relevant information regarding the dataset are meanwhile explained.

5.3.1 ANEEL's DEA model

ANEEL proposes in NT 204/2018-SRM/ANEEL [ANEEL, 2018b] an input-oriented NDRS-DEA model with weight restrictions. The dataset is composed by a 4-year panel data (2013-2016) of 14 DMUs: 9 Existing TSOs and 5 Bid TSOs. In addition to these 56 observations, ANEEL run the DEA first stage with 18 extra data. The extra information refers to virtual units created to deal with Existing TSOs which manage bid concession contracts. Nine of these virtual units comprise data of the last year of the panel data (2016), with the same input as to their counterparts, but without the outputs referent to bid concession contracts. The remaining nine observations also have excluded from the output variables the assets to be transferred to distribution companies in the following years. Further details about the virtual units are provided by the regulator in NT 160/2017-SRM/ANEEL [ANEEL, 2017a].

In this DEA model, there is one input variable, the operational cost (also called Operational Expenditures — OPEX) and nine output variables. Two of them refer to capacity features, the transformation capacity in MVA and the reactive power in Mvar. Six output variables express the quantity of operational assets: kilometers of network extension below 230 kV, kilometers of network extension greater than or equal to 230 kV, number of switch modules below 230 kV, number of switch modules greater than or equal to 230 kV, number of substation equipment below 230 kV and number of substation equipment greater than or equal to 230 kV. The latter two variables comprise the quantity of the following equipment: power transformers, power reactors, banks of capacitors, syncrhonous compensator, serial compensator, static compensator and frequency converters.

The last output variable is a quality information, defined as the average time of outage for the years 2013 to 2016. This is an undesired output, included in the model with negative sign. This DEA model resulted in efficiency scores ranged between 24% and 100%, with mean of 63%.

The second stage approach proposed by ANEEL comprises the 56 observations of the panel data and uses three contextual variables to correct the DEA efficiency scores. The regulator selected these variables from a set of twelve environmental factors. The variable selection procedure evaluated all possible combinations of Tobit regression models between the Shephard distance (the inverse of the efficiency score, $1/\theta$) and the contextual variables. Only models with a maximum of three contextual variables were evaluated. The variables were selected according to three criteria: the fitness of the corresponding OLS model, the statistical significance of the contextual variables in the model and the coherence of the coefficient signs. The variables selected from this procedure were the average age of assets, the average precipitation index and the network density.

The regulator's second stage approach is based on the first proposal of Coelli et al. [2005], described in subsection 5.2.3. The regulator adapted the method in order to use more than one contextual variable. Instead of ranking the DMUs according to one variable, ANEEL uses a *severity index* to rank the TSOs. To calculate this index, the regulator fits a Tobit regression between the Shephard distance and the selected contextual variables, $1/\theta_i = \beta_0 + \beta_1 z_{1i} + \beta_2 z_{2i} + \beta_3 z_{3i} + \varepsilon$. The result of this regression is shown in Table 13. The severity index (Φ) consists of the fitted value of the Tobit regression excluding the intercept, $\Phi_i = \beta_1 z_{1i} + \beta_2 z_{2i} + \beta_3 z_{3i}$. The final value of Φ is normalized between 0 and 1.

	Estimated Coefficient (β_m)	**Standard error**	**t-value**	**Pr($> t$)**
Intercept	0.89482	0.24611	3.636	0.000277
Average age of assets	1.43129	0.27245	5.253	1.49×10^{-7}
Average precipitation index	0.57337	0.28281	2.027	0.042619
Network density	-1.06100	0.30789	-3.446	0.000569
logSigma	-0.68775	0.09820	-7.017	2.27×10^{-12}

Table 13 – Tobit regression of the selected model
Source: ANEEL [2019]

ANEEL ranks the DMUs according to the severity index and defines subsamples to each of them. These dynamic clusters consist of DMUs with higher severity indexes than the evaluated DMU, i.e., each TSO is compared with companies within a worst environment. Nevertheless, ANEEL fixes 2/3 of the original sample as the minimum size for the subsamples. Consequently, if the $i - th$ DMU cluster is smaller than 2/3 of the original samples, TSOs with smaller severity indexes are included in the comparison.

The second stage procedure applied by ANEEL generated an "upper bound" to the first stage DEA scores: the corrected efficiencies were equal or higher than the original scores, mostly due to the reduction of the sample size. The final efficiency showed in NT 012/2019-SRM/ANEEL [ANEEL, 2019] ranges from 35% to 100% with average of 73.37%.

5.3.2 Case study

In this study, we use the dataset provided by the Brazilian regulator in NT 012/2019-SRM/ANEEL [ANEEL, 2019]. We apply the method to correct the input variable of the DEA model described in subsection 5.2.4. To do that, we run two regressions analyses. In the first one, we regress the input variable with the output variables. The residuals of this regression represent the portion of the input which is not explained by the outputs. The second analysis regresses the residuals of the first model with the contextual variables. Then, analysis-of-variance properties are used in order to adjust the residuals of the latter regression. The corrected residuals are used to adjust the input variable.

In the first regression model we are concerned in explore the relation between output variables and the input variable. We define the input variable x as the OPEX, as well as the regulator does in NT 012/2019-SRM/ANEEL [ANEEL, 2019]. The output variables must represent the cost drivers of the evaluated TSOs. ANEEL defines the DEA output variables in means of operational features and number of equipment. We keep this central idea, but rearrange the grouping of equipment in order to consider technological differences. Distinct technologies have distinct maintenance and operation requirements and affect dissimilarly the operational cost.

Thus, in our model, we replace the variable "number of substation equipment" by three variables. The first one is the "adjusted number of substation equipment", which comprises only power transformers, power reactors, banks of capacitors and serial compensators. The static compensators are segregeted from this group to compound a second variable, since they are classified as power-electronic equipment. According to Schlabbach and Rofalski [2014], static compensators use thyristors, the first-generation technology of power-electronic equipment. The synchronous compensators and the frequency converters are grouped in a third variable, because they use the second-generation technology of power-electronic equipment, employing inverse gate bipolar transistors (IGBT) as semiconductor devices [Schlabbach and Rofalski, 2014]. As in the ANEEL's model, these three variables are split in low- and high-voltage variables. The remaining output variables from the ANEEL's model are kept in the $\mathbf{y}$ vector of the new model: number of switch modules below 230 kV, number of switch modules equal or higher than 230 kV, network extension below 230 kV, network extension equal or higher than 230 kV, installed power in MVA and reactive power in Mvar. The quality variable is not used, since we want to represent the direct cost drivers. In addition, it is worth mentioning that the quality variable has a very short effect on the model.

This first regression model that relates the input x and the outputs $\mathbf{y}$ is estimated with a penalized OLS procedure, using Ridge Regression. In a second step, we evaluate the residuals of this regression, $\boldsymbol{\omega}$, in univariate regression models in which the contextual variables are the independent variables. We select from the ANEEL's dataset the contextual variables correlated with the residuals as expected. For example, the higher is the average age of the assets, the greater the TSO inefficiency is expected to be. Thus, if the residuals $\boldsymbol{\omega}$ and the variable average age of the assets are positively correlated, the variable is included in the analysis. All the twelve contextual variables provided by ANEEL are evaluated. Their definition and descriptive statistics are presented in Table 14.

5.4 Results

We first evaluate the statistical significance in changing the output variables in comparison with the ANEEL's DEA model. We run an *F test* comparing the variance of the restricted regression model, M_0, with the variance of the unrestricted regression model, M_1. In this case, the output variables from the ANEEL model compound M_0. The quality variable is excluded of the analysis. The $\mathbf{y}$ vector containing the variables segregated from the *substation equipment*, as explained in subsection 5.3.2, compound M_1. The *F test* uses definitions from ANOVA to calculate the critical value. Under the null hypothesis, both variances are equal and the unrestricted model is not defensible. Further details about the *F test* may be found, for instance, in Gujarati and Porter [2011]. The dependent variable in M_0 and M_1 is the logarithm form of the OPEX. The result of the *F test* is shown in Table 15. The null hypothesis may be rejected with statistical significance greater than 99%.

As the unrestricted model better reflects the cost drivers and is statistical significant, it is used in the first regression analysis. However, the use of 12 independent variables in a model with 56 observations generates an overfitted OLS model. Moreover, the independent variables are highly correlated among them. To deal with such problems, we apply a penalized Ridge Regression procedure. Figure 24 shows the penalty factor $c = 6.703$ which maximizes the predictive capacity of the regression model.

The best predictive model achieved by the Ridge Regression procedure is not useful to make a statistical inference of the coefficients. Because of that, we do not present the regression results in detail. We are just concerned in hold the residuals of such a model to the next step.

The second regression analysis uses the residuals of the best predictive model as the dependent variable, compared with each contextual variable. The correlation matrix of the contextual variables and the residuals of the best predictive model is shown in Figure 25.

The contextual variables are correlated with the residuals of the best predictive model in different order of importance and magnitude when compared with the efficiency scores generated by DEA. To illustrate the differences, Figure 26 shows on the left side the correlation coefficients

Variable	Description	Mean	Min.	Max.	Std. Dev.
Average precipitation index	Average of annual accumulated precipitation 1 km around the transmission lines of each company.	1,478.8	976.1	1,851.3	219.0
Average declivity	Average slope of the land under the transmission lines of each TSO.	0.0978	0.0673	0.1425	0.0268
Average age of the assets	Average age of the assets managed by each TSO.	16.01	2.57	26.66	6.61
Area of intersection with indigenous territories	Relation between the area of 1 km around the transmission lines and the area of indigenous territories and conservation units (Federal, State and municipal levels)	0.0627	0.0000	0.1863	0.0527
Average height of vegetation	Average height of vegetation around 1 km of transmission lines of each TSO.	3.42	2.34	3.93	0.44
Proportion of high vegetation	Percentage of areas with vegetation high between 5 m and 50 m within 1 km of the transmission lines.	0.040	0.001	0.077	0.021
Network density	Relation between the extension of the transmission network and the area of the smallest circumference that circumscribes them.	0.0097	0.0022	0.0304	0.0069
Fire incidence	Average fire incidence within the area of 1 km around the transmission lines of each TSO.	0.2161	0.0453	0.5649	0.1346
Number of entrances of roads	Quantity of entries in roads per km^2 of the area of 1 km around the transmission network.	0.0423	0.0200	0.0836	0.0165
Intersections with roads	Relation between the intersection of the area of 1 km around the transmission lines and the area of 1 km around roads.	0.3084	0.1236	0.4499	0.0707
Network overlap	Proportion of transmission network of each TSO that overlaps other transmission lines.	0.4949	0.0187	0.8526	0.2514
Lightning density	Average density of lightning within 1 km around the transmission network of each TSO.	7.49	1.96	9.83	1.83

Table 14 – Contextual variables provided by ANEEL in the 4$^{\text{th}}$ TRC and their descriptive statistics

Source: ANEEL [2018a] for variable description and ANEEL [2018b] for descriptive statistics

among the DEA scores and the contextual variables. Its right side shows the correlation coefficients with the residuals of the best predictive model. In the figure, dots are showing the expected sign of the correlation in both situations. This information is based on a table provided by ANEEL in NT 204/2018-SRM/ANEEL [ANEEL, 2018b].

Only the contextual variables that are correlated as expected with the residuals of the best predictive model were used in the analysis. As an example, the variable average age of the assets is expected to be positively correlated with the the residuals (the greater the average age of the assets, the greater the inefficiency). Thus, as the correlation sign of this variable is positive, we include it in the analysis. As can be seen in Figure 26, the remaining seven contextual variables were: average asset age, average declivity, proportion of high vegetation, average vegetation high,

Model	Residuals Degrees of freedom	Residual Sum of Squares	Degrees of Freedom	Sum of Squares	F	Pr($>F$)
M_0	47	7.3632				
M_1	43	4.0996	4	3.2636	8.558	3.584 $\times 10^{-5}$ ***

Table 15 – F test of the proposed output variables
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

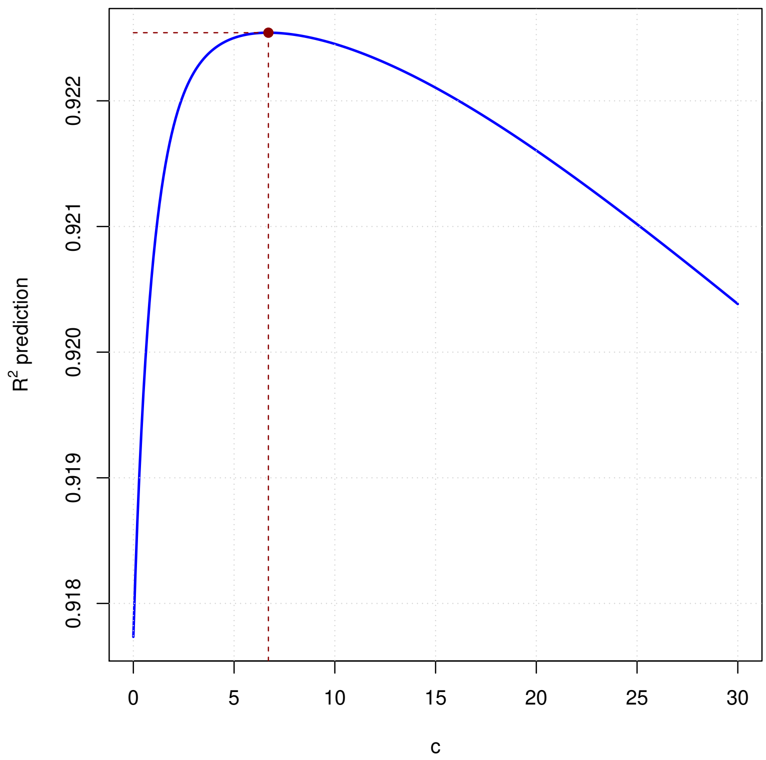


Figure 24 – Ridge Regression penalty *vs* R^2 predictions

network density, intersection with indigenous areas and conservation units, precipitation index and fire incidence index.

The residuals of the best predictive model ω_i were adjusted through m univariate regression analyses with these seven contextual variables. The adjustment was done according to Equation 43. The corrected residuals ω^*_{im} replaced the original residuals of the first regression, according to Equation 44. Then, we finally reached the corrected input variable, x^*_{im}, where $m = 7$. As expected, the input variable OPEX was slightly affected by each contextual variable, with corrections no greater than 9.2%. Figure 27 shows the adjusted variables in the log-scale.

The seven adjusted input variables were used in seven DEA models. As expected, the efficiency scores were corrected to values lower or higher than the original scores, because the procedure used to reach them was OLS-based. The variables average age of assets, proportion of high vegetation and intersection with indigenous areas and conservation units generated the

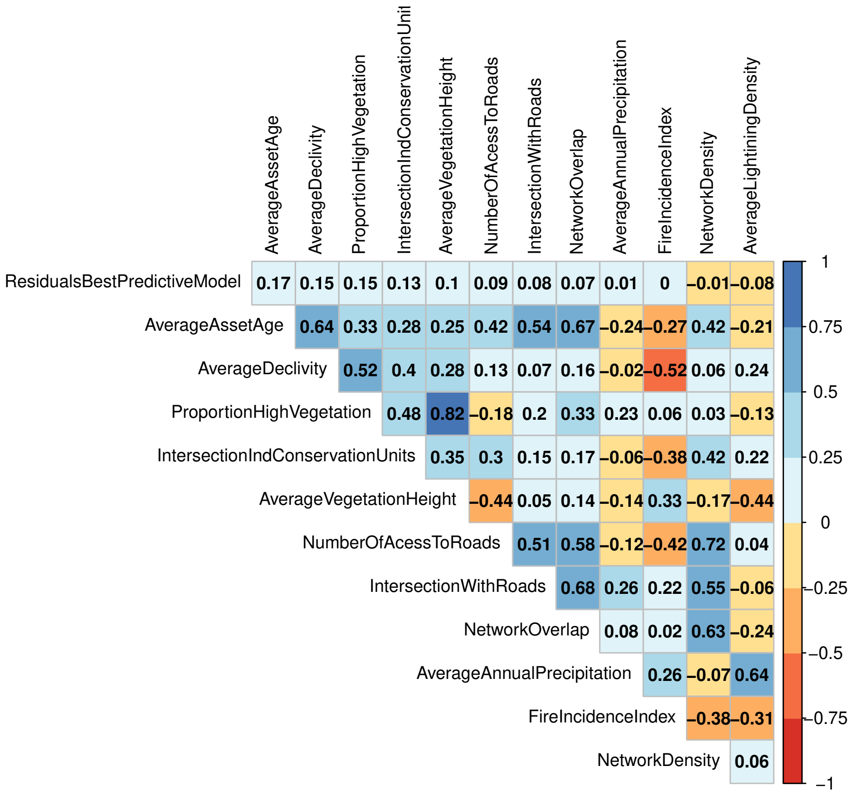


Figure 25 – Correlation matrix of contextual variables and residuals of the best predictive model

higher adjusted scores. The maximum adjustments were of 5.92, 5.90 and 5.4 percentage points, considering these three variables, respectively. In Figure 28 we show boxplots of each DMU comprising the corrected DEA scores. In this graph, we also show the first and second stage DEA scores provided by ANEEL.

As a final step in the procedure, we aggregate the corrected efficiency scores Θ_i^* in one final score, θ_i^*. To do that, we applied Equation 45, considering the 75$^{\text{th}}$ percentile of the corrected scores. The final result is shown on Figure 29.

The conclusions regarding the results are discussed in the following section.

5.5 Discussion and conclusions

In this study, we proposed a procedure to include the effects of the contextual variables in the DEA efficiency scores through the input variable correction. To do that, we used fundamental analysis-of-variance properties. This proposal tried to mitigate some of the limitations of the DEA second stage presented by the Brazilian energy regulator for the TSOs.

The proposed procedure was based on a two-step regression analysis. In the first step,

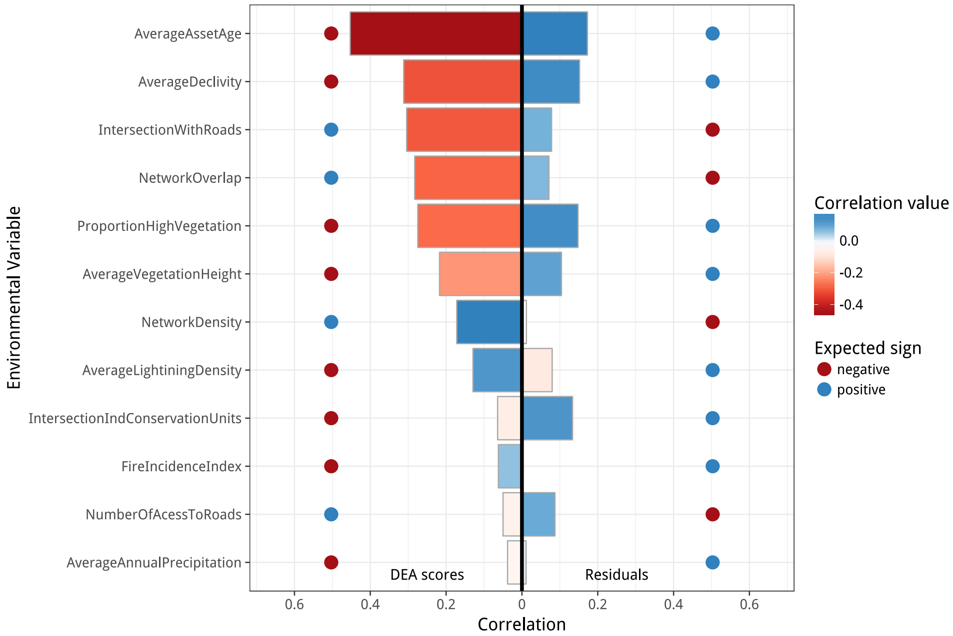


Figure 26 – Comparison among correlation

we estimated through a penalized regression the best predictive model considering the relation between input and output variables. The residuals of this best predictive model were used as the dependent variable in the second step, in a regression with each significant contextual variable. The advantage of doing that is that in the first regression model, we could properly isolate the effects of the output variables, and avoid to assign to contextual variables some effect from the output variables. The residuals of the first regression comprised the portion of the input which was not explained by the output variables. This portion comprised the managerial inefficiency, the effects of the environment and some noise.

Figure 26 shows some interesting features of such segregation. A regular second-stage procedure compares the DEA efficiency scores with the contextual variables (left side of the figure). When we change this relationship and use the residuals of the best predictive model of outputs (right side of the figure), the magnitude of the correlation coefficients reduces. It is a good point considering that our objective is to correct the efficiency scores. In practice, we do not expect that the environment is able to explain a large portion of the DMUs' inefficiency.

Still analyzing Figure 26, some variables that were not relevant when compared with the DEA scores now emerge as important drivers to the inefficiency. The variables proportion of high vegetation and intersection with indigenous areas and conservation units are examples of that. In addition, the use of multiple univariate regression models allows the inclusion in the model of all variables that affect the DMUs, even those which impact few companies.

The proposed procedure resulted in slightly adjustments of the input variable Opex, as shown in Figure 27. None of the contextual variables caused corrections higher than 9.2%. The most relevant adjustments were caused by the variables average asset age, average declivity, percentage of high vegetation and intersection with indigenous areas and conservation units.

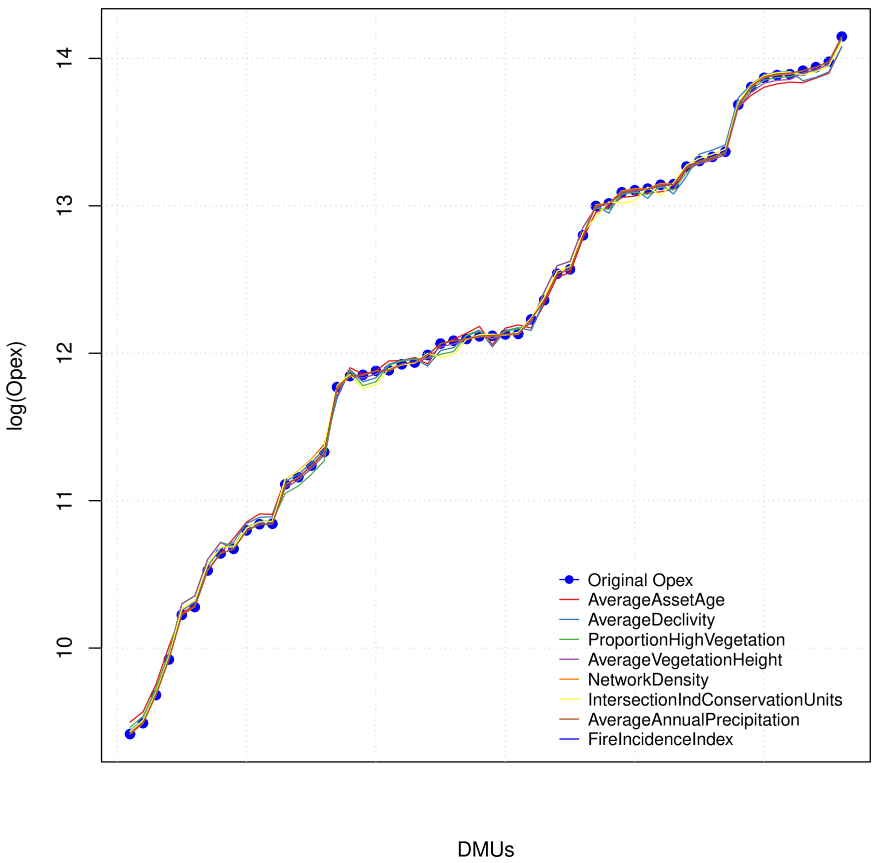


Figure 27 – Adjusted Opex

As a result, the proposed model assigns to the environment a more parsimonious effect than regular second-stage procedures. In Figure 28, we may compare this result with the ANEEL's second stage model, shown in the yellow line. Some DMUs increased their efficiency scores in 30 percentage points, while the proposed approach gives a maximum of 5.92 percentage points. The aggregation rule summarized in Figure 29 is a suggestion on how to use the information of all relevant contextual variables. The analyst may choose a different percentile of the corrected scores, according to the context.

One indirect benefit of correcting the input variable is related to the DEA modeling bias. We used a penalized regression procedure to find the best predictive model for the operational costs. Then, we were able to include as many variables as necessary to represent the cost drivers, with no prejudice to the final result. On the other hand, the DEA modeling limits the number of variables to represent the cost drivers. Furthermore, regular second-stage procedures carry eventual modeling mistakes to the final analysis and may be prejudiced by them. Addressing the effects of the contextual variables before the DEA modeling may avoid sequential errors.

The final results are similar to those that could be achieved applying compound error second-stage approaches. Nevertheless, the benchmarking of the Brazilian TSOs is a problem with inherent features which difficult the application of such approaches. The reduced number

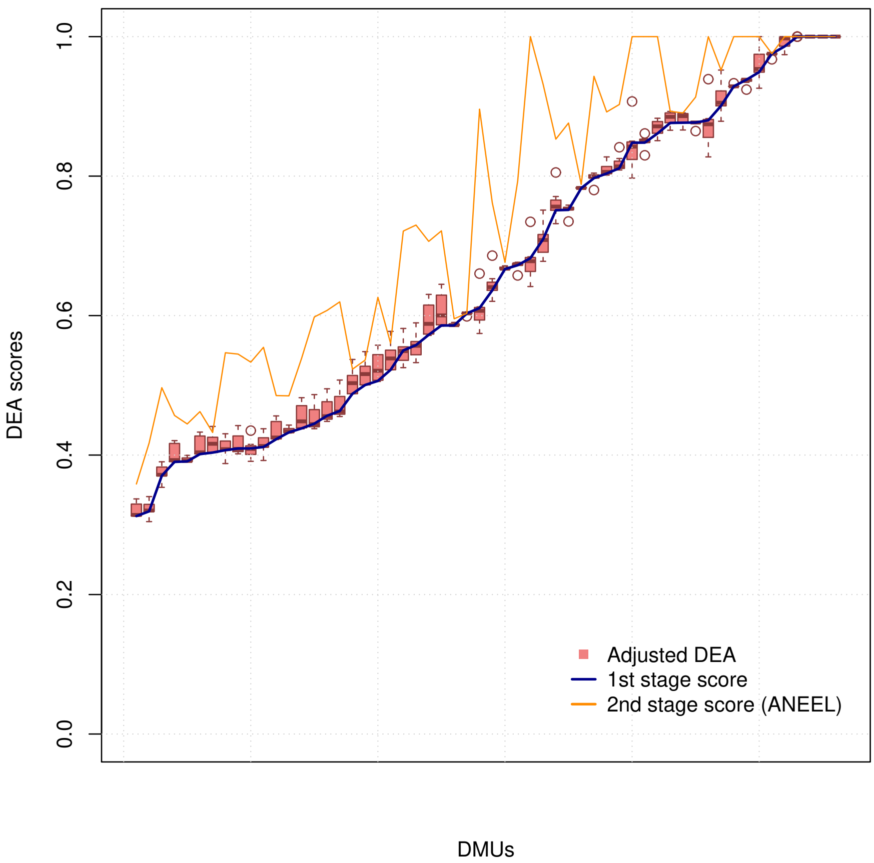


Figure 28 – Adjusted scores

of compared units, the use of panel data and the great number of environmental variables that affect unequally the companies are some of them. In face of that, the proposed approach may be useful to other complex real problems, where the data can not be manipulated.

Further issues not addressed in this paper are worth of future studies. Tests of separability regarding the contextual variables are an example. The comparison with other second-stage procedures is also an important issue.

Acknowledgements

This work was supported by Deutscher Akademischer Austauschdienst (DAAD) with funds of Bundesministerium für Bildung und Forschung (BMBF) under Grant 57391086. In addition, authors thank CAPES (PROBAL Program 483/2018) and CNPq [Grant numbers: PQ-308361/2014-8 and CNPq 402070/2016-0] for financial support.

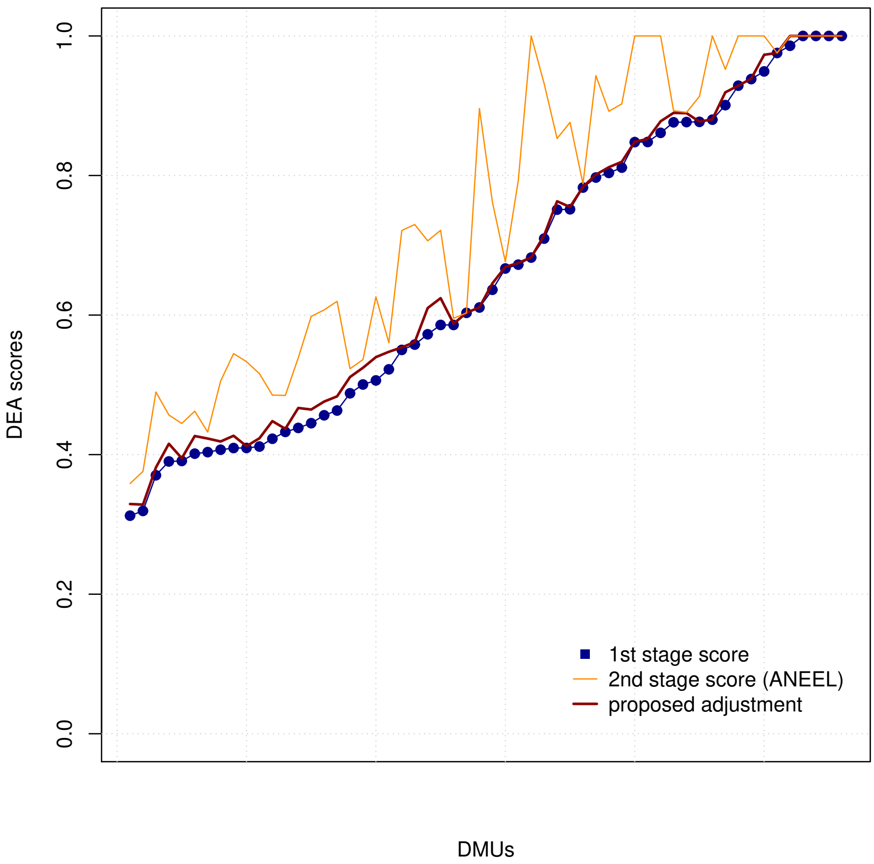


Figure 29 – Final adjusted scores

6 Conclusion

This thesis presented four independent and complementary papers regarding the benchmarking modeling for cost incentive regulation of Brazilian electricity companies. The papers show that the benchmarking modeling for DSOs and TSOs has improved in later years, but still needs some enhancements in order to become more reliable and predictable. The use of benchmarking techniques in such a real problem as regulation is a challenging topic that needs to combine theoretical rigor and practical solutions.

In the first paper, presented in chapter 2, we show that the environmental variables are relevant in the benchmarking modeling of the Brazilian DSOs. Moreover, we also show that the technique used to include them in the efficiency scores may lead to different results. The compound error model proposed in this study fulfills the statistical requirements in terms of econometric relation of the efficiency scores and the DEA results. The final adjusted scores that the model provides is as satisfactory as the Tobit adjustment, which could be an intuitive alternative to consider the environment in the DEA scores.

Concerning the incentive regulation of TSOs, the three remaining papers presented between chapter 3 and chapter 5 are complementary in defining the complex background of the sector and highlight the improvements necessary to become the regulation more predictable and reliable. The cost regulation of transmission companies had suffered abrupt changes in later years, and the benchmarking modeling needs to represent the real problems faced by the companies.

We concluded in chapter 3 that in 17 years, the incentive regulation was able to make TSOs reduce costs, especially after 2012. In this year, an abrupt change in the regulatory scheme reduced in 60% the revenues of the main TSOs. We show that the regulatory framework that existed between 2000 and 2012 had a weak incentive power and was, in fact, the greatest problem. The new regulatory scheme had a better incentive power, but was abruptly implemented, causing injury to the TSOs' cash flow and putting away the investors. In this paper, we discuss that the regulatory process must be predictable in order to attract and retain investors.

Under this complex background, ANEEL proposed a new benchmarking model in the 4$^{\text{th}}$ TRC, described in the paper of chapter 4. In this study, we concluded that the benchcmarking modeling presented some improvements, as the inclusion of environmental variables, but still has gaps to be addressed. There are important caveats regarding the comparability of the companies included in the model. The differences in the business model of the compared TSOs and the type of assets they have may be overcome through the construction of an equivalent grid, for instance. In addition, we showed that the weight restrictions modeling ignores the technical interpretation of the constrains, and should be reviewed. Finally, we show that the second stage procedure proposed by ANEEL is not effective in isolating the effects of the environment.

The last paper, shown in chapter 5, investigates deeply the last issue raised in chapter 4. We propose an alternative to include the effects of the environmental variables in the efficiency scores through the adjustment of the DEA input variable. We concluded that this procedure like is more effective in isolating the effects of the environment, and avoids the propagation of the DEA modeling bias. The proposed approach proved to be a good alternative to deal with multiple environmental variables that affect unequally a small set of compared firms.

In summary, the set of papers show that the benchmarking modeling for cost incentive regulation is a challenging topic, especially in the specific case of Brazil. Although, we show that there are alternatives to deal with such challenges that comprise theoretical requirements and practical solutions. Analysts must find a balance between these two fields, considering simplicity principle that guides the regulation.

Some limitations of this study refer to the availability of data. Further alternatives could be tested to overcome the raised issues regarding benchmarking modeling if more data about the companies were available. As an example, one can mention the proposal of an equivalent grid for the TSOs, presented in chapter 4. The lack of public information about the companies forbids the execution of this suggestion.

For future research we suggest the analysis of the cost incentive regulation within a more complete scenario. The benchmarking modeling could be studied in terms of its interaction with other features of the incentive regulation. For instance, TSOs and DSOs are subject to incentive regulation for investments, which is complementary to the costs management.

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