Journal of Production, Operations and Systems Management

e-ISSN: 1984-2430

Open Access

Editor-in-chief: Paula de Camargo Fiorini

Received:26/05/24 Approved: 11/09/24

# HYBRID METHOD FOR BENCHMARKING THE OPERATING COSTS OF BRAZILIAN ENERGY DISTRIBUTORS

# MÉTODO HÍBRIDO PARA AVALIAÇÃO DOS CUSTOS OPERACIONAIS DE DISTRIBUIORAS BRASILEIRAS DE ENERGIA

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## ABSTRACT

**Purpose:** This study aims to propose a model for benchmarking evaluation, applied to the Brazilian regulatory system in establishing efficient operating costs for electricity distribution concessionaires.
**Theoretical framework:** The application of data envelopment analysis to the regulation of electrical energy distribution is discussed, elucidating how different regulatory models accompany this modality.
**Methodology:** The proposed methodology is based on a benchmarking evaluation model that integrates the associated use of Data Envelopment Analysis and Stochastic Frontier Analysis, through a methodology that establishes the evaluation of efficiency in Three Stages.
**Findings:** The results of the performance assessment were expressed in terms of management efficiency, in which the effects of the operational environment and statistical noise are controlled, resulting in a rigorous measure of efficiency, by introducing manageable and unmanageable variables into the calculation directly from efficiency.
**Originality:** The methodology allows to adjust operational costs, by levelling the operating environment of each electricity distribution concessionaire before repeating the DEA analysis, making the concessionaires' performance more coherent with the characteristics of the Brazilian market.
**Keywords:** Electricity Distribution; Efficient Operating Costs; Benchmarking; Data Envelopment Analysis (DEA); Stochastic Frontier Analysis (SFA).

**RESUMO**

**Objetivo:** O objetivo deste estudo é propor um modelo para avaliação de benchmarking, aplicado ao sistema de regulação brasileiro no estabelecimento dos custos operacionais eficientes das concessionárias de distribuição de energia elétrica.
**Referencial Teórico:** Aborda-se a aplicação de análise envoltória de dados a regulação de distribuição de energia elétrica, elucidando como diferentes modelos regulatórios acompanham esta modalidade.
**Metodologia:** A metodologia proposta baseia-se em um modelo de avaliação benchmarking que integra o uso associado da Análise Envoltória de Dados e Análise de Fronteira Estocástica, por meio de uma metodologia que estabelece a avaliação de eficiência em Três Estágios.
**Resultados:** Os resultados da avaliação do desempenho foram expressos em termos de eficiência de gestão, em que são controlados os efeitos do meio ambiente operacional e do ruído estatístico, resultando em uma medida rigorosa de eficiência, pela introdução de variáveis gerenciáveis e não gerenciáveis no cálculo direto da eficiência.
**Originalidade e valor:** A metodologia permite ajustar os custos operacionais, ao nivelar o ambiente de atuação de cada concessionária de distribuição de energia elétrica antes de repetir a análise DEA, tornando o desempenho das concessionárias mais coerente com as características do mercado brasileiro
**Palavras-chave:** Distribuição de Energia Elétrica; Custos Operacionais Eficientes; Benchmarking; Análise Envoltória de Dados (DEA); Análise de Fronteira Estocástica (SFA).

**DOI:** 10.15675/gepros.3021

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## 1. INTRODUCTION

Since 1990, the liberalization of the global economy has influenced the electricity sector, leading to its segmentation and privatization, which have transformed its structure, operating environment, and governance. The goals of liberalization and restructuring are to enhance efficiency and competitiveness, thereby providing reliable energy at a more affordable cost to society. However, in sectors characterized as natural monopolies, it is essential to develop a regulatory system that ensures companies are aligned with market demands.

An increasing number of regulators have employed benchmarking to set parameters for periodic tariff control and supply quality standards as part of incentive-based monopoly regulation (Blázquez-Gómez & Grifell-Tatjé, 2011; Kuosmanen et al., 2013; Martins et al., 2024). Benchmarking evaluations within a yardstick competition framework encourage greater efficiency by simulating a competitive market environment for companies (Boonlert et al., 2023).

Different approaches have been discussed to benchmarking evaluation in regulatory systems (Jamasb & Pollitt, 2001; Jamasb et al., 2004; Haney & Pollitt, 2009; Kuosmanen et al., 2013; Mullarkey et al., 2015). Each methodology has its advantages and disadvantages, and the selection of an approach remains a contentious issue, given that the State's perspective is shaped by its environment, expertise, and experiences (Saleem, 2007; Omrani et al., 2015). However, Haney and Pollitt (2009) argue that techniques based on the construction of efficiency frontiers are the most suitable for benchmarking evaluation, with Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) being particularly prominent.

Based on linear programming, DEA is a non-parametric technique that estimates a piecewise linear efficiency frontier from a set of similar organizations, which are differentiated by varying combinations of inputs and outputs in their processes (Charnes et al., 1978; Cook & Seiford, 2009; Liu et al., 2013; Cook et al., 2014). The main advantage of the DEA approach is that it does not impose an explicit functional form on the data. However, the estimated frontier may be distorted if the effects of the operating environment, statistical errors, and managerial inefficiency are not accounted for (Cordero et al., 2009).

In the realm of parametric techniques, the SFA econometric model addresses frontier analysis stochastically, imposing an explicit functional form on the data while assuming that uncertainties follow a specific probability distribution, which is introduced as statistical noise in the model (Aigner et al., 1977; Meeusen & van den Broeck, 1977). Additionally, this approach controls for environmental effects and conducts conventional hypothesis testing. However, it requires the specification of parameters in a functional form and the identification of the inefficiency's probability distribution, and it also does not support multiple products (Avkiran & Rowlands, 2008).

To challenge the traditional paradigm of frontier construction, this study proposes benchmarking through an integrated approach combining DEA and SFA. The evaluation of the efficiency of Brazilian distribution companies is conducted in three stages. The proposed model accounts for the impact of external factors on manageable variables, adjusting operating costs to equalize the operating environment of each distribution concessionaire. Consequently, performance is evaluated in terms of management efficiency, where the effects of the operating environment and statistical noise are controlled. This results in a more rigorous efficiency measure by incorporating both manageable and non-manageable variables into the direct calculation of efficiency.

From this perspective, this research contributes to the literature by presenting a model capable of addressing regulated entities that operate in different environments, whether favorable or unfavorable to performance. By adjusting the evaluation data to account for the operating environment, the model offers decision makers a reliable parameter for periodic tariff control and supply quality standards, based on an accurate assessment of the operational efficiency of distribution companies, as demonstrated by Giannakis et al. (2005), Jamasb et al. (2004), Ramos-Real et al. (2009) and Medeiros et al. (2022).

Given the limitations in establishing a universal set of variables for modeling electricity distribution activities, this study proposes an arrangement of inputs and outputs tailored to the performance evaluation of regulated entities, aligned with the three perspectives of the regulatory body's objectives regarding the interests of: (1) investors, (2) consumers, and (3) the government. These three groups are the stakeholders in the sector, each with distinct interests (Pedrosa, 2005). Furthermore, the study acknowledges that exogenous environmental variables contribute to inefficiencies in managing operating costs. Accordingly, these variables are classified into three categories: (a) market factors; (b) geographic factors; and (c) factors related to company structure and size.

The next section provides an overview of benchmarking evaluation in the electric power distribution industry. Section 3 outlines the research method used to assess the efficient operating costs of power distribution companies, employing a technique that integrates both manageable and non-manageable factors in the performance evaluation. Section 4 identifies and discusses the variables deemed relevant to the construction of the mathematical model. Section 5 presents the main results and accompanying discussions. Finally, Section 6 offers a summary and concludes the article.

## 2. LITERATURE REVIEW

The regulation of the electricity sector is a broad topic. Globally, various studies employ different approaches and methodologies to assess the effects that regulation by comparison can have on the energy segment. In this context, studies utilizing DEA and SFA as evaluation methods in regulatory frameworks within the electricity supply sector are particularly noteworthy.

In a survey of 43 regulators across 40 countries in Europe, Australia, and Latin America, Haney and Pollitt (2009) found that 65% of regulators in the electricity sector use frontier-based benchmarking methods, with DEA being the second most utilized technique for evaluating electricity distribution and transmission companies in countries such as Austria, Belgium, Finland, the United Kingdom, the Netherlands, Slovenia, Iceland, Norway, Argentina, Brazil and Colombia. Although SFA is not implemented as extensively as other methods, its use in combination with techniques like DEA enables the incorporation of environmental factors beyond the control of regulated entities, yet still affecting their relative performance. This approach helps to adjust for uncertainties and mitigate penalties for companies that fall significantly below the efficient frontier.

Studies on the use of DEA and SFA in regulatory schemes within the electricity supply sector primarily focus on three key themes: (i) improving the quality and reliability of energy supply by establishing parameters for control within a penalty and incentive-based regulation system; (ii) evaluating the management of operating costs through methodologies that govern tariff reviews; and (iii) analyzing the sector's evolution in terms of productivity and efficiency following the restructuring of the electricity distribution sector in each country.

Service quality became a significant issue in regulatory procedures following the restructuring of the electricity sector, as the trade-off between distribution costs and supply quality necessitates the adoption of economically efficient and market-oriented systems (Pessanha et al., 2007; Omrani et al., 2024). Simab and Haghifam (2012) highlight that, among the aspects of electricity supply quality, continuity indicators stand out, measured by the duration and frequency of supply interruptions, reflecting the service availability provided by the concessionaire. As a result, the objective is to establish targets for supply continuity, defining maximum allowable values for the number and duration of interruptions for each concessionaire.

From the perspective of economies of scale, it is observed that its presence in the sector facilitates market expansion with decreasing incremental costs. Given these productivity gains, regulatory agencies are responsible for periodically reviewing tariffs to ensure coverage of efficient operating costs as well as the remuneration of investments made by distributors (Pereira de Souza et al., 2010a; 2010b; Martis et al., 2024). This strategy aligns with the principles of regulation by comparison (Jamasb et al., 2004), as it encourages energy distribution companies to use their resources efficiently (Blázquez-Gómez & Grifell-Tatjé, 2011; Boonlert et al., 2023).

In an effort to better understand the process of restructuring the energy sector, several studies (Ramos-Real et al., 2009; Blázquez-Gómez & Grifell-Tatjé, 2011; Yadav et al., 2013) use benchmarking techniques to assess whether the reforms have successfully provided affordable, efficient, and reliable electricity over time. These applications evaluate the impact of restructuring in the electric power sector based on both static and dynamic assessments of concessionaire performance (Edvardsen & Førsund, 2003; Estellita Lins et al., 2007; Saurin et al., 2013), while also measuring the evolution of productivity and technological change in the sector over time (Pérez-Reyes & Tovar, 2009; Santos et al., 2011; Altoé et al., 2017; Medeiros et al., 2022).

Table 1 summarizes the information obtained from the theoretical foundation, organizing the variables used in studies evaluating the electricity distribution sector. The input (I), output (O), and environmental (E) variables are grouped into four categories: Process, representing materials or resources used directly in the energy distribution process; Financial, indicated by monetary indicators within this segment; Market, reflecting measures that characterize the market served; and Service, which includes variables that assess the quality of service provided.

The literature on relative efficiency analysis and benchmarking does not reflect a universal consensus on the set of variables for modeling electricity distribution activities. In a benchmarking survey of the electricity transmission and distribution sectors, Jamasb and Pollitt (2001) highlight the disparity in the variables used, which underscores the lack of agreement on how the core functions of electric utilities should be modeled.

The systematization presented aligns with the findings of Jamasb and Pollitt (2001). The most used input resources include operating costs, number of employees, transformer capacity, and the length of the distribution network. Additionally, this review, in line with other studies (Edvardsen and Førsund, 2003; Estellita Lins et al., 2007; Ramos-Real et al., 2009; Growitsch et al., 2010; Blázquez-Gómez & Grifell-Tatjé, 2011), emphasizes the inclusion of the variable 'energy losses,' as it accounts for the discrepancy between total energy distributed and total energy billed.

**Table 1**

Description of the most used variables for benchmarking in the electric distribution segment

| Variable | | Description |
|---|---|---|
| *Inputs* | Operating Costs | used in a more traditional model of regulation by incentive, to express the potential reduction of the operating costs of each concessionaire |
| | Extension of the distribution network | The distribution network is a fundamental resource for the energy distribution activity, and the use of its extension as a variable works as a proxy for the capital invested by the concessionaire |
| | Number of employees | used as a proxy to estimate the human capital needed to perform functions within the system |
| | Energy Losses | refers to the quality of the system and the waste generated, being an undesirable output and sometimes modeled as input , to be eliminated from the energy distribution process |
| | Transformer capacity | Electrical voltage transformers are also a resource used in the energy distribution activity and the use of their capacity in modeling works as a proxy for the capital needed for utilities to perform their functions |
| *Outputs* | Extension of the distribution network | Indicative of the difficulty of operation related to the geography of the land and the dispersion of consumers |
| | Consumer units served | Directly expresses the size of the market served |
| | Distributed electricity | Measures the amount of electricity distributed by each utility |

It is also noted that the most commonly used variables to express outputs are the amount of energy distributed, the number of consumer units served, and the size of the concession area, as previously discussed by Jamasb and Pollitt (2001). The use of the network extension variable as both an input and output has been observed. Moreno et al. (2015) argues that using network extension as an input is plausible, as it represents one of the primary, if not the most significant, resources for distribution companies. However, Ramos Real et al. (2009) and Pereira de Souza et al. (2010a) contend that the size of the concession area is not a manageable factor, given that the region to be served by distributors is determined by the government's concession act. As such, this variable should not be classified as an input, since the service capacity of distributors is constrained by the concession area, an uncontrollable factor.

The use of network length as an output is also justified when aiming to indicate the operational challenges related to geography and consumer dispersion (Edvardsen & Førsund, 2003; Jamasb et al., 2004; Moreno et al., 2015). Given the similarity between the variables network length and operating cost, using both as inputs in a model becomes redundant, as a utility's operating cost is directly dependent on the length of its distribution network. Therefore, it is more appropriate to use network length to characterize the organizational environment as either an output or an exogenous variable (Jamasb et al., 2004; Pessanha et al., 2007). In this study, we opted to treat it as an output.

The other specifications required for using DEA also lack consensus among the authors studied. Some researchers (Edvardsen & Førsund, 2003; Jamasb et al., 2004; Growitsch et al., 2010) support the use of the constant returns to scale (CRS) approach, arguing that grid operators can optimize their scale by addressing inefficiencies that arise from deviations from the optimal scale. On the other hand, other authors (Estellita Lins et al., 2007; Blázquez-Gómez & Grifell-Tatjé, 2011) evaluate power distribution units under the assumption that utilities employ technologies that allow for variable returns to scale (VRS).

With respect to model orientation, input-oriented models are generally considered more suitable for electric power distribution concessionaires, as the demand for their services is derived and must be met (Resende, 2002; Jamasb et al., 2004). Efficiency is thus measured based on the operator's ability to minimize inputs while maintaining a fixed vector of outputs (Edvardsen & Førsund, 2003; Blázquez-Gómez & Grifell-Tatjé, 2011).

## 3. METHODOLOGY

This research aims to develop a model for determining the efficient operating costs of energy supply. To achieve this, a benchmarking evaluation model is proposed, integrating the combined use of DEA and SFA, based on the methodologies of Fried et al. (1999), Fried et al. (2002), Muñiz (2002), and Avkiran and Rowlands (2008). The study adopts an approach that ensures a rigorous efficiency measure for each concessionaire, allowing for the identification and decomposition of the key factors driving their performance through a three-stage efficiency evaluation.

The first stage involves specifying the production technology by determining the characteristics of the DEA model used to estimate the efficient frontier. Only quantitative data on the manageable variables – inputs and outputs of the system – are utilized to evaluate the conversion of resources into outputs (Liu et al., 2013; Cook et al., 2014).

To ensure comparability among concessionaires, the use of a Variable Returns to Scale (VRS) model is proposed. Introduced by Banker et al. (1984), the VRS model incorporates the concept of variable returns to scale into DEA to evaluate the technical efficiency of a Decision-Making Unit (DMU), which generalizes any set of production units analyzed with DEA. This model assumes that the units under analysis can adopt technologies with constant, increasing, or decreasing returns to scale.

The portion of operating costs incurred by an energy supply concessionaire represents a significant challenge in the economic regulation process, as it is the primary focus of incentive mechanisms. These costs are directly influenced by the managerial actions of distribution companies. Therefore, efficiency measures should be aimed at reducing resources and inputs to create incentives for lowering operating costs.

In this context, the benchmarking evaluation used to estimate the production frontier in the first stage employs a linear programming model. This model estimates a piecewise linear production frontier and measures the production efficiency of each organization under analysis. The model is defined by the set of expressions (1), (2), (3), (4), and (5).

$$\text{Min} \quad \theta_0 - \varepsilon\left(\sum_{j=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{1}$$

$$\text{Subject to:} \quad \sum_{j=1}^{n} x_{ij} \cdot \lambda_j + s_i^- = x_{i0} \cdot \theta_0 \qquad i = 1, \ldots, m; \tag{2}$$

$$\sum_{j=1}^{n} y_{rj} \cdot \lambda_j - s_r^+ = y_{r0} \qquad r = 1, \ldots, s; \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad (4)$$

$$\lambda_j \geq 0; s_i^- \geq 0; s_r^+ \geq 0;\ \theta_0 \geq 0 \qquad \forall\, i, r, j \qquad (5)$$

The coefficients yrj and xij are, respectively, the known outputs and inputs of the j organizations under analysis (j = 1, ..., n), constant values, obtained through past observations, in decisions made regarding the i inputs (i = 1, ..., m), resulting in a set r of outputs (r = 1, ..., s). The technical efficiency score of the concessionaire 0, oriented to the input, is represented by θ0; si- and sr+ are the gaps observed in the inputs and outputs and result from the managerial inefficiency of the organization; and λj represents the contribution of DMU j to project 0 on the efficient frontier. The term non-Archimedean, ε > 0, is a positive element, less than any real number and prevents the efficiency of unit 0 from being calculated based on a pareto-inefficient face. More details on the DEA model adopted can be found in Cooper et al. (2006), Cook and Seiford (2009) and Cook et al. (2014).

The objective of the second stage is to adjust the variables of interest based on the factors in the operating environment that impact the efficiency of the concessionaires. To achieve this, an econometric analysis is required to determine the compensatory effects present in each environment where energy supply companies operate, considering the relationship between the manageable variables and the control or exogenous variables.

The gaps identified in the first stage will be decomposed into exogenous effects and statistical noise, allowing for control over the external influence on technical and managerial inefficiency. To achieve this, Avkiran and Rowlands (2008) recommend using a stochastic regression model, SFA. In this approach, a regression of the gaps on exogenous variables is performed, incorporating a compound error term that can distinguish managerial inefficiency from random error. The general function of SFA regressions for input gaps is represented by Expression (6).

$$s_{ij}^- = f_i(z_{ij};\ \beta_i) + v_{ij} + u_{ij} \qquad i = 1, ..., m; \qquad (6)$$

Where are the gaps of $s_{ij}^-$ input i, calculated in the First Stage; zij represent the exogenous variables that have an effect on the performance of input management; βi are the parameters estimated to explain the exogenous variables on the gaps of the inputs. The compound error term is the sum between uij and vij, with uij being an estimate of the effect of managerial inefficiency, following an exponential or positive normal distribution, while vij explains the statistical noise, normally distributed.

The proposed adjustment standardizes the operating environment of each concessionaire before repeating the DEA analysis. Fried et al. (2002) and Avkiran and Rowlands (2008) suggest that DMUs operating in more favorable environments or benefiting from statistical noise should have their input variables adjusted upwards. This ensures that all units are evaluated from a pessimistic perspective, reflecting the worst-case competitive scenario.

To achieve this, the estimates of the βi parameters, obtained from SFA regressions, are used to predict the input gaps attributable to external factors. Consequently, the input variables, based on each organization's historical data, can be adjusted to account for the impact of the external environment and statistical noise, as shown in Expression (7).

$$x_{ij}^A = x_{ij} + [Max_j(z_{ij} \cdot \hat{\beta}_i) - z_{ij} \cdot \hat{\beta}_i] + [Max_j(\hat{v}_{ij}) - \hat{v}_{ij}] \qquad i = 1, ..., m; \qquad (7)$$

Where is the adjusted quantity of $x_{ij}^A$ input i, unit j, xij is the observed value about input i. The product value represents the predicted value of the input clearance $z_{ij} \cdot \hat{\beta}_i$ attributed to the operating environment, while it is the estimate for statistical noise. The first adjustment in Expression 7 levels the operating environment regarding exogenous variables, by positioning all production units in the less favorable operational context of the sample. The second adjustment places all units in an unfavorable situation regarding the measurement of variables. Thus, inputs will obtain upward adjustments when concessionaires participate in a favorable environment. $\hat{v}_{ij}[Max_j(z_{ij} \cdot \hat{\beta}_i) - z_{ij} \cdot \hat{\beta}_i][Max_j(\hat{v}_{ij}) - \hat{v}_{ij}]$.

The third stage involves repeating the first stage, but this time using the variables adjusted in the second stage. In other words, the performance of the concessionaires is reassessed, taking into account the impact of external factors on the manageable variables. As a result, performance is evaluated purely in terms of management efficiency, with the effects of the operating environment and statistical noise controlled.

### 3.1 Data collection and selection of variables

To define the production technology in the first stage, the goal was to measure the efficiency of distributors in relation to the development of the electricity market, in alignment with government policies and for the benefit of society. In this context, variables were selected to evaluate the performance of the concessionaires from the three perspectives of the regulatory agency: Investors, Consumers, and Government.

The model includes a single input – operating costs of the concessionaires (opexj) – following a traditional incentive-based regulation approach that reflects the potential for operating cost reduction for each concessionaire.

From the perspective of the Investor, output variables were selected to reflect the concessionaire owners' objective of maximizing revenue, even though they cannot directly influence the demand for their services. To represent this effect, the billed market indicator (MFj) for each concessionaire j was used. This indicator consists of the algebraic sum of each company's billing results across the low, medium, and high voltage markets.

Another concern for investors is the elimination of non-technical losses, which refer to energy losses caused by theft, fraud, or errors in the commercial processes of reading, measuring, and billing. Non-technical losses (PNTj) are considered an undesirable output from the investor's perspective, as they consume resources to transport the energy but do not generate corresponding revenue. These losses must be minimized in the energy distribution process.

From the Consumer's perspective, the most crucial factor in evaluating a distributor's performance is the quality of the energy supplied. Several studies, including Pessanha et al. (2007), Growitsch et al. (2010), Simab and Haghifam (2012), and Xavier et al. (2015), emphasize the importance of supply continuity as a key aspect of electricity distribution quality. Continuity is typically assessed by the duration of supply interruptions (DECj) and the frequency of supply interruptions (FECj) within the concessionaire's area of operation. These variables represent undesirable outcomes in the electricity distribution process and must be minimized to avoid compromising the continuous supply to consumers.

The Government dimension evaluates the reach and dispersion of electricity supply, as concessionaires are responsible for promoting universal access to electricity, which supports economic and social development. To measure this effect, the number of consumer units (UCj) served within a given concession area j is used. Additionally, to express the dispersion of infrastructure needed to provide electricity services, the total length of the distribution network (netj) for each concessionaire j is considered.

It is important to note that non-technical energy losses (NTPj), the duration of supply interruptions (DECj), and the frequency of supply interruptions (FECj) are undesirable outputs in the energy distribution process and should be minimized (Tschaffon & Meza, 2014). In such cases, Seiford and Zhu (2002) recommend transforming these outputs using the inverse translated additive method, ensuring that the values remain positive and can be incorporated into the linear programming model as outputs.

In the evaluation of companies operating under variable returns to scale, units with the lowest levels of inputs or the highest levels of outputs in at least one variable are classified as efficient. As a result, a concessionaire may be considered efficient due to operating the largest distribution network, which does not necessarily indicate greater overall efficiency.

One method used to address this issue is to limit the number of variables in the model (Wagner & Shimshak, 2007), thereby avoiding potential flaws in DEA models (Dyson et al., 2001). To ensure that the output variables covering the three perspectives of the regulatory agency's performance are not excluded, it was decided to evaluate the concessionaires' performance in each of the three areas separately. This approach involves using three individual models to assess the concessionaires in each area of interest to the regulatory body. The combined efficiency index for each concessionaire j, denoted as $\bar{\theta}_j$, is determined by calculating the arithmetic mean of the efficiency scores obtained in the three evaluated dimensions: Investor, Consumer, and Government.

The exogenous variables used in the second stage to level the environmental effect among concessionaires are considered representative of the external factors that influence operating costs. According to Pessanha et al. (2007), the costs of energy supply depend on the type of distribution network and the characteristics of the market served. In line with this, the exogenous environmental variables used to explain inefficiencies in managing operating costs were classified into three categories: (i) market factors, which relate market composition to costs; (ii) geographic factors, which examine how local characteristics influence operating costs; and (iii) factors related to the structure and size of the company, which help differentiate the contribution of each concessionaire.

The market composition identifies the types of customers served by a given concessionaire and how this composition affects its operating costs (Ramos-Real et al., 2009). To examine the effect of market size and composition on the performance of the concessionaires, three quantitative variables were selected: (i) low voltage billed market (BTj), (ii) medium voltage billed market (MTj), and (iii) high voltage billed market (ATj).

Geographic factors characterize the regions served by each concessionaire. According to Pérez-Reyes and Tovar (2009), the inclusion of exogenous variables to measure the effects of climate, terrain, and the size of the service area helps identify the causes of inefficiency in electricity distribution models. Five quantitative variables were selected to assess the impact of geographic characteristics on concessionaire performance: (i) size of the concession area (areaj), (ii) average slope of the terrain (declj), (iii) lightning discharge density (descj), (iv) extent of remaining vegetative cover (vegj), and (v) precipitation index (rainj).

Although factors related to the size of the concessionaire are not considered exogenous, as they are manageable by the distribution unit, the company is still obligated to provide adequate service to meet the required supply levels (Giannakis et al., 2005). In this context, decisions regarding the technological structure and the productive resources necessary for service provision are considered key factors in shaping the cost structure of electricity distribution concessionaires (Jamasb et al., 2004). To assess the impact of these factors on concessionaire performance, three variables were used: (i) total number of transformers (Vj), (ii) number of distribution substations (subj), and (iii) transformer capacity (MVAj).

In the Brazilian context, the regulatory agency classifies the size of energy concessionaires based on the amount of energy distributed. Large distributors are those operating in concession areas with consumption greater than 1 TW (one terawatt), while companies with demand below this threshold are classified as small. To account for the size classification, a dummy variable (sizej) was included to examine differences in the performance of large companies.

The Brazilian electricity supply market consists of 64 companies, with information about these companies available in the ANEEL (2017) and ABRADEE (2017) databases. Due to limitations in the availability of data required for this research, the sample was restricted to 48 electric power concessionaires across Brazil, covering a 10-year period from 2003 to 2012, resulting in 480 observations. Table 2 presents the descriptive statistics for the variables mentioned above.

**Table 2**

Descriptive Statistics for the Evaluation Variables of Energy Distribution Concessionaires

| Variable | Un. | Average | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Input | | | | | | |
| *Opexj* | R$ | 228456,23 | 139884,46 | 287369,98 | 2731,29 | 1873436,00 |
| *Output* | | | | | | |
| *MFj* | R$ | 7065168,75 | 3376094,47 | 9439397,10 | 64090,37 | 45609295,14 |
| *PNTj* | % | 0,18 | 0,10 | 0,23 | 0 | 1,53 |
| *DECj* | h/*m2* | 18,52 | 14,04 | 14,99 | 2,79 | 102,00 |
| *FECj* | occurrences/*m2* | 15,30 | 10,62 | 12,04 | 2,85 | 64,26 |
| *UCj* | | 1281442,54 | 821713 | 1496652,61 | 12021,00 | 7460089,00 |
| *netj* | km | 57209,04 | 35855,03 | 77164,78 | 0 | 497665,79 |
| *Exogenous* | | | | | | |
| *Vj* | - | 66935,73 | 33887,50 | 110142,14 | 0 | 790777,00 |
| *subj* | - | 81,19 | 51,23 | 95,60 | 0 | 410,00 |
| *MVAj* | In | 2249,69 | 1138,75 | 2853,26 | 0 | 13245,40 |
| *ATj* | R$ | 1622070,02 | 438894,49 | 2971688,92 | 0 | 19923040,77 |
| *MTj* | R$ | 2144617,99 | 923788,17 | 2796047,49 | 11260,99 | 14139562,34 |
| *BTj* | R$ | 3298480,74 | 1803271,18 | 4234774,54 | 35740,58 | 25155421,13 |
| *areaj* | km² | 55454,02 | 17718,99 | 79593,30 | 283,47 | 425628,31 |
| *declj* | % | 6,94 | 5,15 | 4,40 | 1,13 | 23,30 |
| $desc_j$ | downloads/km² | 6,50 | 6,95 | 3,17 | 0,54 | 15,43 |
| $veg_j$ | km² | 15645,05 | 2404,22 | 22589,93 | 8,49 | 92192,39 |
| $rain_j$ | mm | 1409,12 | 1444,90 | 344,61 | 697,45 | 2169,67 |

## 4. RESULTS AND DISCUSSION

The objective of the first stage is to quantitatively assess the level of efficiency from three perspectives: Investors, Consumers, and Government. Performance evaluation in each dimension involved different combinations of input and output variables, with the goal of classifying the energy distribution concessionaires based on their efficiency scores. An average index across the three dimensions was then calculated to compare the measurable parameters of the concessionaires, reflecting the relationship between the conditions provided and the productivity outcomes generated by these operators. The descriptive statistics of efficiency for each dimension are presented in Table 3.

**Table 3**

Descriptive Statistics for the efficiency scores obtained in the First Stage

| | | | | | Investors | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Parameter** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** |
| *Average* | 22,71 | 26,59 | 26,06 | 28,21 | 28,21 | 24,38 | 22,69 | 25,71 | 25,55 | 20,06 |
| *Median* | 6,16 | 6,45 | 7,26 | 6,85 | 6,85 | 4,84 | 4,91 | 4,82 | 4,59 | 4,07 |
| *Standard deviation* | 32,82 | 35,69 | 35,29 | 36,97 | 36,97 | 34,94 | 32,96 | 36,23 | 37,13 | 31,90 |
| *Minimal* | 0,34 | 0,35 | 0,36 | 0,35 | 0,35 | 0,34 | 0,32 | 0,33 | 0,34 | 0,35 |
| *Maximum* | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| *Efficient* | 6 | 7 | 7 | 8 | 8 | 7 | 6 | 7 | 8 | 5 |
| | | | | | **Consumers** | | | | | |
| **Parameter** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** |
| *Average* | 32,07 | 24,03 | 32,40 | 32,40 | 26,06 | 31,38 | 22,46 | 28,47 | 23,88 | 27,97 |
| *Median* | 10,74 | 6,53 | 9,88 | 9,88 | 8,54 | 8,35 | 7,73 | 10,87 | 6,57 | 8,28 |
| *Standard deviation* | 38,67 | 34,14 | 39,38 | 39,38 | 33,59 | 38,70 | 29,94 | 36,13 | 33,51 | 35,11 |
| *Minimal* | 0,32 | 0,32 | 0,58 | 0,58 | 0,66 | 0,65 | 0,51 | 0,43 | 0,29 | 0,51 |
| *Maximum* | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *Efficient* | 9 | 6 | 8 | 8 | 5 | 9 | 4 | 8 | 5 | 6 |
| **Government** | | | | | | | | | | |
| **Parameter** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** |
| *Average* | 23,89 | 24,98 | 24,89 | 24,67 | 24,43 | 25,63 | 25,36 | 23,12 | 22,98 | 22,33 |
| *Median* | 7,92 | 9,64 | 11,27 | 11,12 | 11,37 | 11,93 | 11,06 | 10,07 | 10,58 | 8,40 |
| *Standard deviation* | 33,44 | 34,30 | 33,64 | 32,25 | 31,61 | 33,14 | 32,23 | 31,70 | 30,97 | 31,20 |
| *Minimal* | 0,33 | 0,46 | 0,49 | 0,52 | 0,56 | 0,61 | 0,48 | 0,41 | 0,44 | 0,42 |
| *Maximum* | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| *Efficient* | 5 | 5 | 6 | 4 | 5 | 5 | 5 | 5 | 5 | 5 |
| **Combined** | | | | | | | | | | |
| **Parameter** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** |
| *Average* | 26,22 | 25,20 | 27,78 | 28,43 | 26,42 | 27,13 | 23,50 | 25,77 | 24,14 | 23,45 |
| *Median* | 9,75 | 9,19 | 12,47 | 14,88 | 11,19 | 12,02 | 11,17 | 12,13 | 8,28 | 9,32 |
| *Standard deviation* | 30,39 | 28,99 | 31,09 | 30,42 | 27,89 | 29,42 | 26,94 | 28,71 | 28,43 | 28,02 |
| *Minimal* | 0,40 | 0,42 | 0,53 | 0,53 | 0,56 | 0,59 | 0,49 | 0,43 | 0,40 | 0,49 |
| *Maximum* | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| *Efficient* | 2 | 2 | 2 | 2 | 1 | 3 | 2 | 2 | 1 | 1 |

For each dimension evaluated, as well as for the Combined Efficiency Index – which is the arithmetic mean of the results from the three measurement perspectives – the following parameters are presented for each year: mean, median, standard deviation, minimum value, maximum value, and number of efficient units in the sample.

Only one of the 48 units in the sample was efficient across all three perspectives over the evaluation period. An analysis of its indicators shows that this concessionaire had the lowest operating costs among the group, despite achieving only average or unsatisfactory results in the other evaluation variables.

Doyle and Green (1994) explain that, when considering variable returns to scale, production units with the lowest levels of inputs or the highest levels of outputs in at least one variable are classified as weakly efficient or 'Maverick.' Angulo-Meza and Estellita Lins (2002) further note that this type of efficiency does not necessarily reflect superior performance compared to other units, but rather arises from the lack of sufficient information to establish meaningful comparisons. This is a limitation inherent to the DEA mathematical model that accounts for variable returns to scale.

The adopted model considers variable returns to scale and is input-oriented, favoring units that allocate fewer resources. Although it did not achieve satisfactory results in other output measures, the only efficient unit in the analysis maintained the lowest input usage over the 10-year period. This highlights the lack of a direct relationship between investments made and the performance of concessionaires, as noted by Giannakis et al. (2005), Ramos-Real et al. (2009), and Growitsch et al. (2010). In other words, the superior performance of this concessionaire is not tied to positive outcomes for Investors, Consumers, or the Government, but rather to its low resource allocation, which does not accurately reflect the true performance of the concessionaires.

An analysis of the descriptive statistics for each evaluation perspective reveals a certain homogeneity across the dimensions. All compared parameters show comparable results: the means range from 20% to 30%, the medians vary between 4% and 15%, the standard deviation remains around 30% to 40%, the maximum value in all analyses is 100%, and the minimum values are less than 1%.

However, the low mean and median efficiency values, the high standard deviations, and the significant difference between the minimum and maximum values indicate considerable heterogeneity within the sample. This suggests that the concessionaires operate under quite different exogenous and managerial conditions, leading to significant variation in their performance regarding resource allocation and the production technologies they adopt.

Under the existing circumstances, certain factors and characteristics of a favorable operating environment may enable utilities to achieve lower operating costs, even if their production functions do not fully align with market requirements. The results suggest that companies operate in different environments – favorable or unfavorable to their performance – highlighting the need to adjust the evaluation data to account for the operating environment (Fried et al., 2002).

To quantify the environmental effects captured by the slacks in the operational cost variable, a stochastic regression model is employed to distinguish managerial inefficiency from random effects (Avkiran and Rowlands, 2008). This is followed by regressing the total slacks in operating costs against a set of exogenous variables, using a Cobb-Douglas functional form, as the problem involves a single dependent variable. This approach applies logarithmic transformations to the quantitative variables in the stochastic cost frontier model to mitigate heteroscedasticity. The coefficients are estimated using the Maximum Likelihood method, with the results presented in Expression 9.

The equation presented in (9) shows the expected value of the effect of each exogenous variable. The parameters estimated in the empirical model indicate the impact of the environment on the performance of the production units. Positive coefficients suggest that the environment is unfavorable to the concessionaires' performance, as a marginal increase in these variables results in an increase in the total slack variable, which is used to assess inefficiency. Conversely, variables with negative coefficients indicate that the environment is favorable to performance, as their increase leads to a reduction in the slack variable.

$$
\begin{aligned}
\ln(\bar{s}_{opex}^{-}) = &\underset{(1{,}012)^{*}}{-227{,}643} + \underset{(0{,}067)^{*}}{0{,}972}\ln(area) - \underset{(0{,}140)^{*}}{0{,}759}\ln(decl) \\
&+ \underset{(0{,}121)^{*}}{0{,}603}\ln(desc) - \underset{(0{,}074)^{*}}{0{,}418}\ln(veg) - \underset{(0{,}304)^{*}}{0{,}415}\ln(chuva) + \underset{(0{,}210)}{0{,}082}\ln(BT) \\
&+ \underset{(0{,}117)}{0{,}128}\ln(MT) + \underset{(0{,}017)^{*}}{0{,}101}\ln(AT) + \underset{(0{,}049)}{0{,}045}\ln(V) - \underset{(0{,}136)^{*}}{0{,}945}\ln(sub) \\
&+ \underset{(0{,}022)^{*}}{0{,}094}\ln(MVA) + \underset{(0{,}157)^{*}}{1{,}197}\ln(porte) + \underset{(0{,}001)^{*}}{0{,}123}year + u + v
\end{aligned}
\tag{9}
$$

The numerical values in parentheses represent the standard errors of the estimated parameters for the corresponding variables. By calculating the ratio of the estimated value of each variable to its respective standard error, one can infer the statistical significance of each variable in the model. Parameters flagged with an asterisk (*) are statistically significant at the 99% confidence level.

It is noteworthy that there is a performance difference between small and large units, with small companies being favored. This result is consistent with the size of the concession area: the size of a company is proportional to the area in which it operates. Therefore, since large concessionaires exhibit greater slacks, those operating in larger areas also display higher inefficiency.

Another notable observation concerns the reference year (year). There was an increase in total slack over the analyzed period, indicating a decline in the performance of concessionaires over time. This trend can be attributed to the rise in average costs between 2002 and 2013, without a corresponding increase in outputs.

It is important to note that not all the exogenous variables chosen were statistically significant. The number of voltage transformers (V) and the medium and low voltage markets (MV and LV) did not show a significant effect on the sample, even though their economic impact is well-documented in the literature (Jamasb and Pollitt, 2001; Jamasb et al., 2004).

Using the equation from the stochastic model (9), the predicted gap value can be calculated. For the adjusted operating costs introduced in Section 3, described by equation (7), an upward adjustment is applied to the operating costs, leveling the exogenous effect to match the worst-case scenario in the sample for the operating environment and random noise. This adjustment raises the input variable for all units, placing them in a common and unfavorable operating environment.

The purpose of the third stage is to reassess the efficiency of electric power distribution utilities using the same specifications as in the first stage. However, the operating cost variable is replaced by the Adjusted Operating Cost variable, calculated in the second stage.

When analyzing the results from the third stage, it was observed that a group of concessionaires showed a positive change in their efficiency scores, while others experienced a reduction, and some exhibited little or no variation.

In general, the units that showed improved performance in the third stage (64.6%) had the highest operating costs in the sample during the first stage evaluation. Although these units achieved good results in the output vectors, they performed poorly in the first stage due to their high operating costs. Since these concessionaires were already operating in unfavorable environments, the adjustment of the opex variable to account for exogenous effects resulted in only a small change in their operating costs, leading to higher efficiency scores in the third stage evaluation.

Another group of units (18.8%) experienced a significant drop in their efficiency scores, as they were well-evaluated in the first stage. This decline was attributed to their low operating costs, which resulted from operating in a favorable environment. In the second stage, the adjustment for exogenous effects on the operating costs variable led to a large variation, as the predicted value of cost inefficiency for these exogenous variables was exceptionally low. Since this predicted effect was compared to the maximum value in the sample, the adjustment caused a substantial increase in operating costs for these concessionaires. Thus, if their robust performance in the first stage was due to their low opex, the third stage saw a significant decline in their efficiency scores, as operating costs increased when adjusted for the operating environment.

Finally, other distributors (16.7%) showed little or no variation in their combined efficiency scores. Although there was a difference between the maximum exogenous effect and the observed exogenous effect, the adjustment of the opex variable had minimal impact on the efficiency reassessment in the third stage, resulting in similar combined efficiency scores across both evaluations. The descriptive statistics for efficiency in each dimension are presented in Table 4.

**Table 4**

Descriptive Statistics for the efficiency scores obtained in the third stage

| | | | | **Investors** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Parameter** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** |
| *Average* | 60,5 | 58,7 | 65,8 | 64,8 | 62,7 | 56,9 | 55,1 | 51,5 | 43,2 | 60,2 |
| *Median* | 60,6 | 59,8 | 60,6 | 55,6 | 55,0 | 46,7 | 41,0 | 34,0 | 29,8 | 51,3 |
| *Standard deviation* | 20,1 | 21,8 | 13,3 | 18,5 | 18,5 | 21,2 | 25,7 | 29,7 | 26,9 | 18,9 |
| *Minimal* | 23,0 | 13,8 | 54,1 | 48,2 | 46,5 | 39,5 | 31,6 | 24,2 | 20,6 | 42,3 |
| *Maximum* | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| *Efficient* | 4 | 4 | 4 | 6 | 6 | 6 | 7 | 7 | 7 | 4 |
| | | | | **Consumers** | | | | | | |
| **Parameter** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** |
| *Average* | 61,6 | 50,4 | 74,8 | 67,0 | 69,6 | 66,3 | 52,0 | 48,3 | 49,7 | 45,5 |
| *Median* | 67,1 | 53,1 | 75,0 | 63,5 | 67,4 | 63,0 | 48,4 | 43,0 | 46,7 | 47,0 |
| *Standard deviation* | 28,0 | 31,8 | 17,2 | 16,3 | 14,6 | 19,6 | 18,1 | 21,2 | 22,1 | 23,7 |
| *Minimal* | 19,0 | 9,1 | 54,1 | 48,2 | 46,5 | 39,6 | 31,9 | 24,2 | 20,6 | 10,5 |
| *Maximum* | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| *Efficient* | 4 | 5 | 8 | 5 | 3 | 7 | 2 | 2 | 3 | 3 |
| | | | | **Government** | | | | | | |
| **Parameter** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** |
| *Average* | 34,2 | 25,7 | 64,1 | 59,1 | 58,1 | 52,2 | 45,7 | 39,3 | 36,5 | 43,1 |
| *Median* | 27,5 | 17,7 | 61,1 | 55,8 | 54,6 | 49,0 | 42,1 | 35,3 | 31,6 | 40,1 |
| *Standard deviation* | 20,3 | 22,9 | 11,2 | 12,4 | 13,0 | 14,7 | 16,5 | 18,1 | 19,1 | 16,1 |
| *Minimal* | 19,0 | 9,1 | 54,2 | 48,3 | 46,4 | 39,2 | 31,5 | 24,2 | 20,6 | 28,8 |
| *Maximum* | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| *Efficient* | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 1 |
| | | | | **Combined Index** | | | | | | |
| **Parameter** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** |
| *Average* | 52,1 | 44,9 | 68,2 | 63,6 | 63,5 | 58,5 | 50,9 | 46,4 | 43,1 | 49,6 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *Median* | 51,0 | 40,7 | 66,5 | 59,9 | 60,3 | 52,7 | 46,8 | 44,6 | 38,6 | 46,6 |
| *Standard deviation* | 16,5 | 18,8 | 11,1 | 12,0 | 11,6 | 14,2 | 15,4 | 16,2 | 17,5 | 14,1 |
| *Minimal* | 28,0 | 17,2 | 54,7 | 48,8 | 47,1 | 39,6 | 32,0 | 24,2 | 20,6 | 27,4 |
| *Maximum* | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 95,3 |
| *Efficient* | 2 | 2 | 2 | 2 | 1 | 2 | 1 | 1 | 1 | 1 |

Similarly, to the observations from the first stage (Table 3), the efficiency evaluation in the third stage shows a certain homogeneity across the different dimensions. All compared parameters present related results: (i) mean values range from 40% to 70%; (ii) medians range from 30% to 60%; (iii) standard deviations are between 12% and 25%; (iv) the maximum values for all analyses are 100%; and (v) minimum values are above 20%.

Although there remains a high standard deviation and a significant difference between the minimum and maximum scores, it is evident that the dispersion of performance indicators decreased when comparing the results of the first and third stages. By analyzing the results in Table 3 and Table 4, it can be observed that: (i) the mean and median values increased; (ii) the standard deviations decreased; (iii) the minimum values increased, narrowing the gap between the minimum and maximum values; and (iv) the number of efficient units increased.

Consistent with the findings of Hsu and Hsueh (2009), the increase in technical efficiency suggests that, without accounting for the operating environment, companies operating under unfavorable conditions were penalized more heavily than those benefiting from favorable conditions. After controlling for exogenous effects, the advantage gained by companies previously in unfavorable situations began to outweigh the decrease in efficiency experienced by companies that were initially favored by more convenient operating conditions.

Regarding the reduction in the dispersion of efficiency scores, Fried et al. (2002) explain that companies operating in favorable environments tend to have an upward-skewed standard deviation. The application of the third stage reduces this bias, resulting in less dispersed efficiency scores.

## 5. CONCLUSION

Tariff review is one of the primary responsibilities of the energy regulatory agency. The complexity of this task is reflected in the periodic changes to the procedures used to define efficient costs, as well as in the numerous studies found in the literature. Various approaches have been debated, each with its own advantages and disadvantages, and no universal strategy has been established for their evaluation.

The theoretical framework highlights the importance of considering the impact of exogenous factors on the performance of concessionaires, aiming to understand how adversities and external operating environment characteristics influence the technical efficiency of energy distribution companies. In this context, the present research established a methodology that incorporates environmental effects into the direct evaluation of the performance of energy supply concessionaires. To achieve this, an integration of the DEA model with SFA was adopted, using a three-stage procedure to adjust efficiency for exogenous effects.

The results from the first stage indicated a favoring of units with the lowest operating costs, highlighting the lack of a direct relationship between investments made and the performance of concessionaires. In other words, good performance is not necessarily tied to the level of satisfaction among Investors, Consumers, or the Government. These results do not necessarily reflect the superiority of these units over others but rather their low resource allocation.

Considering the heterogeneity in the concession areas where distribution companies operate and the regional differences across Brazil, the second stage incorporated the influence of these characteristics on operating costs. As a result, operating costs were increased, leveling the distributors by adjusting them to reflect a less favorable operating environment. This adjustment allowed for a reassessment of efficiency in the third stage, using the adjusted operating cost as an input variable. The other variables and specifications in the DEA model for the third stage remained the same as those in the first stage. The results obtained in the third stage differed significantly from those found in the first stage.

The high dispersion in efficiency scores from the first stage suggests the presence of varying operating environments, which allowed certain units to achieve high technical efficiency without necessarily demonstrating strong market performance. However, when the effect of the operating environment and statistical noise is accounted for, these previously favored companies experience a reduction in their efficiency scores. Conversely, companies that were initially disadvantaged by their operating environment benefit from the new evaluation, leading to an increase in their technical efficiency.

The result, distinguishing the performance between the first and third stages, is the reduction in sample heterogeneity. The adjustment made in the second stage proved satisfactory, as it not only reduced the degree of result dispersion but also increased the average efficiency of the concessionaires. Therefore, it is crucial to include exogenous factors in the direct calculation of efficiency when using benchmarking techniques in the regulation of the energy distribution sector, ensuring a more accurate evaluation of the operational efficiency of concessionaires.

## 5.1. Theoretical and practical implications

This work proposes a benchmarking model that integrates DEA and SFA. The primary theoretical contribution lies in the introduction of an approach capable of assessing regulated entities operating in different environments. By adjusting operating costs to account for the operating environment of energy utilities, the model allows for a more accurate evaluation of their efficiency. It helps to understand the impact of exogenous factors, such as geographic and market characteristics, on the operational efficiency of utilities. Thus, this research contributes to the literature by offering a framework that combines manageable and non-manageable variables, providing a more rigorous and realistic analysis of the efficiency of regulated companies.

In practice, this model can be used by regulators to conduct a fairer and more accurate assessment of electric utilities. The adjustment of operating costs based on the operating environment provides a foundation for defining more appropriate tariffs and controlling quality standards. This model offers regulators an effective tool for determining the frequency of tariff reviews, considering the actual operating conditions of concessionaires, while ensuring that companies in more challenging environments are not unfairly penalized. Additionally, the results suggest that the model can be adapted to other regulated sectors, providing a strong basis for applying benchmarking techniques across different industries.

## 5.2. Study limitations

The study has some limitations that should be considered. First, the significant heterogeneity among the energy utilities analyzed may complicate comparisons, as the characteristics of the concession areas – such as size and geography – vary widely, directly influencing operating costs. Additionally, the research relies on a limited sample of 48 Brazilian utilities over a 10-year period (2003-2012), which may not capture all the variability within the sector, limiting the generalizability of the results.

Another important limitation relates to the impact of exogenous factors. Although the model accounts for external variables to adjust for differences in the operating environment, not all of these variables were statistically significant, which may affect the accuracy in capturing all elements influencing the operating costs of the concessionaires. Finally, the external validity of the study is limited, as the proposed model was developed specifically for the Brazilian electricity sector. This may hinder its applicability to other regulated sectors or international contexts with different characteristics.

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