Identifying Environmental Variables for Two Stages DEA Analysis of Electricity Distribution Utilities Using Simulated Design of Experiments

Rafael C. Leme*, Anderson P. Paiva, Paulo E. Steele Santos, Pedro P. Balestrassi, and Luis C. Nascimento

Abstract

Benchmarking plays a central role under regulatory scene. Regulator set tariffs according to a performance standard, and let companies extract rents if they can outperform such a standard. Efficiency performance is usually assessed by comparison (or a benchmark) whether against the company's own historical performance or against other companies. In this context, this paper discusses the impact of environmental variables in efficiency performance of electricity distribution companies. For this sake, a two stages data envelopment analysis is used, and a simulated design of experiments is proposed. The discussion is then carried out using real data of Brazilian distribution companies.

Keywords: two-part tariff, electricity distribution pricing, tariff products

* Corresponding Author: tel/fax +55 35 3629 1514; email: leme@unifei.edu.br

1. Introduction

When competition is feasible, the optimal duality of price and quality is left to the market. It is believed that market automatically converges to prices which reflect efficient costs and products deal to consumers' expectation. However, in electricity distribution networks competition is not suitable, since it is a natural monopoly. In this case, the hand of Regulator takes place in order to pursuit optimal price and quality outcomes.

Initially, it has been considered that the utility's costs are all recovered added by a reasonable return. This approach, known as rate-of-return, set prices based on observed costs and no stimulus are made for efficiency. On the other hand, in a regulatory environment, besides the primary focus of Regulator on ensuring non-discriminatory access charges, it must also design charges that reflect efficient costs.

For this sake, many efficient based regulatory approaches has been investigated and adopted around the world (see Jamasb and Pollitt 2001). These approaches are usually based on price or revenue caps regulation, which decouples prices and observed costs. In these regulatory scenarios, the electricity distribution company (DISCO) is strongly stimulated to operate in an efficient manner, since cost saving may be retained, increasing the shareholders profits.

Nevertheless, a drawback may arise when efficient based regulatory approach is adopted for a capital intensive industry, like electricity distribution sector: a lead to degradation in quality, since one can achieve higher cost savings.

In order to deal to this drawback, cap approaches may consider the X-factors. Then, regulatory agency considers a benchmark model for efficiency and quality, and use the X-factors to close eventual inefficiency gaps. Benchmark is set by either a reference firm, designed based on a number of technical and economic information, or the identification of the most efficient practice in the sector. Jamasb and Pollitt (2003) present some approaches for efficiency benchmark models. Also, a discussion on quality regulation approach is presented by Ajodhia and Hakvoort (2005).

Among benchmark techniques, the most widely used by operator are corrected ordinary least squares (COLS), stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The first two approaches select an equation defining the relationship between explanatory variables and dependent variables. They are defined as parametric approaches. Dependent variables are usually considered as costs and explanatory variables of services to be analyzed. Then, the error between the selected equation and the actual value of costs defines the efficiency gap to be closed.

On the other hand, the DEA, firstly proposed by Charnes *et al.* (1978), is a non parametric technique which uses linear programming to define an envelope around observations. The frontier is defined by the efficient firms that envelop the less efficient firms. The distance of inefficient firms to the frontier defines de efficiency gap. Shuttleworth (2005) points that limitation of DEA on electricity distribution business regards on small sample size and statistical inferences. Jamasb and Pollitt (2003), however, state that regulators can use cross-country benchmarking in order to deal to sample size problem. Moreover, these weaknesses may also be overcame using bootstrap techniques (see Odeck 2009), robust solutions of linear programming problems contaminated with uncertain data (see Sadjadi, 2008) or Bayesian inferences (see Tsionas, 2010).

Notwithstanding, an issue arises when some contextual factors may influence the results. In utilities business, these contextual factors are also known as environmental variables. Businessmen argue that environmental variables, that are unmanageable, usually affect firm's costs and quality efficiency performance.

Regarding on environmental variables, Coelho et al. (2003), Domijan et al. (2003), Billinton and Alaan (1984) and Wang and Billinton (2002) show, for example, that weather conditions are high correlated to reliability of the distribution network. On the other hand, one may argue that utilities adapt their operating and investment to mitigate adverse effects of the environment. Indeed, Yu et al. (2009), who have studied the effects of weather condition in the cost and quality performance of UK DISCOs, concludes that the impact is small on average. The authors argue that considering one or another output in the efficiency analysis may internalize the effect of the context factors.

In most countries, context factors are resumed to weather conditions. However, in a wide area country like Brazil, the environmental variables may be extended to regions' diversity conditions such as salary, density and complexity. A recent study of Brazilian Regulator suggests five environmental variables to explain DISCOs inefficiency (see ANEEL, 2010).

In other analyze the impact of environmental variables on efficiency, it has been suggested the use of two-stages DEA (Chilingerian and Sherman, 2004, Ray, 2004, and Ruggiero, 2004). In this approach, the efficiency estimated using traditional DEA (first stage) is regressed on environmental variables (second stage). However, because the first stage efficiency estimates are high data sensitivity and second stage efficiency estimates are serially correlated, one may not use standard approaches to inference. For this sake, Simar and Wilson (2007) propose a data generating process consistent to non parametric efficiency estimates. Then, using bootstrap technique, a consistent inference is possible and feasible.

In this paper, it is proposed an approach based in Design of Experiments (DOE) and Desirability method to indentify the impact of environmental variables on inefficiency among different scenarios, and define the context factor which most affect DISCO inefficiency.

DOE has been extensively used recently in applications related to simulation analysis (see Kleijnen, 2005). Balestrassi *et al.* (2009), for instance, used the Fractional and Full Factorial designs to better determine the parameters of an Artificial Neural Network (ANN) in a problem of nonlinear time series forecasting of short-term daily prices and returns, water consumption or the electricity load for industrial consumers of a production company in Brazil. In the same way, Oliveira *et al.* (2011) presented a novel approach to adjusting the conditional value at risk (CVaR) metric to the mix of contracts on the energy markets using Mixture Design of Experiments (MDE). In this kind of experimental strategy, the design factors are treated as proportions in a mixture system considered quite adequate for treating portfolios in general. Instead of using traditional linear programming, the concept of desirability function was used to combine the mean with the variance equations of a specific portfolio, which in turns, generated an efficient recruitment frontier.

In the analysis of environmental variables, DOE technique may be helpful to evaluate the significance of each factor (environmental variable) on efficiency estimation. DOE is also useful to value the statistical significance of interaction among variables. Then, the regulator may assess the impact of environmental variables in DISCO inefficiency using in the two stages DEA model.

On the other hand, Desirability method is capable of dealing with multiple response problems (Montgomery, 2009). Statistical model is first obtained using regression model and, using a set of transformations based on the limits imposed on the responses, a conversion is conducted for each one of the responses resulting in an individual desirability function. Thus, the environmental variables which most affect the DISCO inefficiency may be assessed.

The test results are carried out using real data obtained from Brazilian DISCOs and Regulator. Here, it is evaluated the efficiency of operational regulatory results. Thus, only operational expenditures (Opex) are considered. Furthermore, the products of DEA method are restricted to regulatory activities. Hence, they are defined by number of costumer, network length and energy delivered. In order to get insights on each product, different scenarios are analyzed.

The reminder of this paper is organized as follows:

2. Two Stages DEA for Electricity Distribution Sector

Data Envelopment Analysis is known as non parametric technique to compute efficiency. The idea is to find the best practices from a sample of firms within a set of comparable decision making units (DMUs). For this sake, it uses linear programming. Feasible production set is generally defined by a convex region containing sample observation of firms' input and outputs. The relative performance of DMUs is obtained according their location within production set. The Pareto-efficient firms then characterize the efficiency isoquant frontier[a], enveloping the less efficient firms. Distance measure of a DMU from the isoquant defines its relative efficiency.

There exist many measure of efficiency. Farrell (1957) proposed a radial measure of efficiency. It may be used either in the input or output spaces. Using radial distance, the efficiency score defines the amount that DMU must reduce (increase) its input (output) in order to lie on isoquant. Thus, radial distance to the frontier is considered as a measure of inefficiency, i.e., it defines the level of inefficiency. In other words, DEA sets the benchmark DMUs and distance of other firms to then. When the mix within inputs and outputs in movements towards the frontier is not preserved, one has non-radial efficiency score. Notwithstanding, this approach is not considered in this paper.

There is a bunch of DEA models developed for different purposes. Basically, DEA can be input or output oriented. The former, computes the minimal resources required to produce a given level of outputs. The latter, maximize the production for a given level of inputs. Depending on the case, one may be interested to reduce inputs and increase outputs altogether. In these cases, non-oriented DEA models may be used.

Furthermore, DEA can be specified as constant return to scale (CRS) or variable return to scale (VRS). CRS approach considers that an increase in the inputs leads an increase in the output in the same proportion. Thus, the relative efficiency is not affected by the size of the firms. On the other hand, VRS is defined when the linearity on input/output does not hold. In this case, firm are more likely to be compared by size. When the return to scale is not constant, non-decreasing (NDRS) and non-increasing (NIRS) return to scale may be also defined.

When unmanageable variables affect the firms' performance, one may use the Two Stages DEA. The first stage is defined by traditional DEA approaches. In the second stage, the efficiency estimated is regressed on environmental variables, which are considered unmanageable. Then, the efficiency score may be corrected considering the contextual factors. However, results may be biased, since environmental variables are highly correlated and efficiency scores do not follow normal distribution. To deal these problems, truncated regression and bootstrap technique are usually applied.

In this paper, we use the Two Stages DEA approach similar to Simar and Wilson (2007), where bootstrap techniques are proposed to make inferences on the second stage regression. The model is described next.

2.1. First Stage DEA

In the regulatory context, DISCOs must provide services to all consumers in their service area considering the operational and maintenance costs allowed by the regulator (Lowry and Getachew, 2009; Jamasb and Pollitt, 2000; Jamasb and Pollitt, 2001). Thus in the first stage of DEA accounting Opex is considered as input. Furthermore, the most commonly outputs used regards on number of costumer (NC) and energy delivered (ED). It is agreed that the former represents commercial costs while the later stands for network density. Besides these outputs, it is also considered the network length (NL), which it is agreed to represent maintenance costs.

Regulator expects that DISCOs use theirs allowed Opex in an efficient manner. If this is not the case, Regulator cuts off the regulatory revenue in order to stimulate DISCO best practices. Thus, in analyzing DISCO performance, input-oriented DEA approach is considered. Note that in this model, only one input is considered. Thus, Farrell (1957) radial measure of efficiency is used, with no loss of generality. Furthermore, DISCOs considered in this study regards on delivery greater than 1 TWh/year. In this case, firms of similar size are compared and NDRS is expected.

The DEA model used in this paper is given as follows:

(1)

In equation (1), is the efficiency parameter for the i-th DMU, and are the input and output matrix, respectively, and is the weight parameter. Furthermore, , , and are the amount of DMUs, inputs and outputs, respectively. The vector is a column vector with all entry equal one[b]. Finally, and are the input and output vector of DMU analyzed.

If reach one, input level is optimized and cannot be reduced for the given level of output. On the other hand, if is less than one, a cut off may be done in the Opex to reach the given level of outputs. Thus, equals one defines the efficiency frontier.

2.2. Second Stage DEA

In the first stage, it is obtained the technical efficiency, i.e., the ability of firms to minimize inputs to produce a given level of outputs. In the second stage, however, we examine the impact of contextual factors. Thus, Two Stages DEA allows environmental variables to be considered in efficiency analysis. For environmental variable one should understand a factor that businessman cannot manage, such as weather conditions, region and period characteristics.

If a firm is faced with environmental variables , one may write the regression:

(2)

In equation (2), is usually a (linear) function of , and is the error independent and identically normally distributed. Moreover, [c]. Thus, to solve this problem, Tobit regression is used. Tobit regression is a truncated regression model. It estimates the relationship between explanatory variable and truncated dependent variables.

When first stage variables are highly correlated to the second stage variables, the regression results are likely to be biased. To overcome this drawback, Simar and Wilson (2007) propose the use of bootstrap technique to make statistical inferences. This approach of bootstrap technique to solve Two Stages DEA is as follows:

I. Compute the first stage efficiency using equation (1);
II. With the help of Tobit regression censored in I by left, estimate of , and the error variance of of equation (2), considering only the inefficient firms;
III. Loop over (a) and (c) times to obtain the bootstrap estimates of and ;
    a. For each inefficient firm, draw as from the normal distribution , with left truncation at ;
    b. Compute efficiencies ;

c. With the help of Tobit regression censored in 1 by left, estimate of , and the error variance of ;

IV. Use the bootstrap values to correct estimate of , and the error variance of and construct estimated confidence intervals.

Once estimated, the impact of environmental variables may be compensated for each firm, considering, for example, the mean scenario for these variables. However, statistical significance of environmental variables should be analyzed. For this purpose DOE technique, discussed next, is used to study the impact of context factors in DISCOs inefficiency.

3. Design of Experiments Concepts

Design of Experiments (DOE) is considered one of the most important methodologies for researchers who deal with experiments in practical applications, with a huge amount of success stories (Balestrassi et al, 2009). Nowadays, DOE resources are incorporated in many statistical software packages that ease calculation and interpretation of results (Chan and Spedding, 2001).

According to Montgomery (2009), DOE is a collection of statistical techniques capable of generate and analyze experimental designs in which several factors are varied together, instead of one at a time. Among the most common available designs are the Screening designs (Plackett-Burmann and Taguchi), Fractional or Full Factorial designs, Response Surface Methodology, EVOP and Mixture Design of Experiments (Montgomery, 2009).

Kleijnen (2005) reviews the use of DOE in analysis of simulated experiments. DOE is used in simulation for sensitivity analysis of the factors considered in the simulation model. Using statistical analysis, one may detect unimportant factors, and simplify the simulation model.

In this paper, we will employ a two-level full factorial design to simulate and analyze the degree of influence of environmental variables in the efficiency score. In this kind of experimental design, the influence of presence (level +1) or the absence (level -1) of each input variables in DEA model is examined. Considering, e.g., three environmental variables that may harm the efficiency score, the full factorial design is presented in Table 1.

Table 1 – Full Factorial Design for Three Environmental Variables

Regression	Intercept	Env. Var. 1	Env. Var. 2	Env. Var. 3
1	+1	−1	−1	−1
2	+1	+1	−1	−1
3	+1	−1	+1	−1
4	+1	+1	+1	−1
5	+1	−1	−1	+1
6	+1	+1	−1	+1
7	+1	−1	+1	+1
8	+1	+1	+1	+1

In analyzing the simulated results, the metamodel considering all main effects and iterations may be used. This metamodel is shown in equation (5).

(3)

In equation (3), , , , …, are known as effects coefficients. On the other hand, is the observed value of environmental variable , in the same way of equation (2). The metamodel of equation (3) may be obtained with the help of ordinary least squares (OLS) or maximum likelihood estimation (MLE). Thus, the error is considered independent and identically normally distributed.

The metamodel is then analyzed with the help of two sample-t hypothesis and nonparametric test. The aim is to verify the difference between the mean response in each one of the two levels. The critical value for the statistics used is obtained using a 5% significance level.

4. Desirability Method

The Desirability Method is a nonlinear optimization method capable of dealing with single or multiple response problems (Montgomery, 2009). In this method, the statistical model is first obtained using an OLS. Then using a set of transformations based on the limits imposed on the responses, a conversion is conducted for each one of the responses resulting in an individual desirability function d_i with $0 \le d_i \le 1$. These individual values are then combined using a geometrical average, such as:

$$D = \left[d_1(Y_1) \times d_2(Y_2) \times \quad \times d_k(Y_k)\right]^{\frac{1}{k}} \tag{4}$$

The global index *D* is maximized using an unconstrained Hooke and Jeeves´ nonlinear algorithm (Rao, 1996), giving a solution of commitment and is restricted to the interval [0, 1]. Index *D* is close to 1 when the responses are close to its specification. The type of transformation depends on the desired optimization direction.

The desirability function approach to a problem of optimization is simple, easy to apply, and allows the user to judge the importance of each response. For the maximization case, e.g., the desirability transformation is (Montgomery, 2009):

(5)

where is the response of interest, and e are, respectively, the lower bound and the target for the th response of interest. Moreover, weights the response. If , then th response is more relevant. On the other hand, if , th response is less relevant. Finally, when , th response behaves linearly from upper limit to target. Figure 1 resumes the dynamics of .

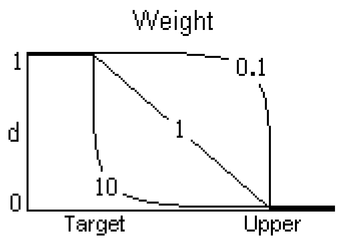

Figure 1- Dynamics of

For environmental variables evaluation, the desirability function may be used as a complementary tool for full factorial analysis. Recall that, when environmental variables are considered, it is expected a greater efficiency score. Hence, we seek to maximize the median of efficiency scores, in such a way that environmental variables are relevant and significant. Desirability function may also be applied to close inefficiency gap as much as possible. In this paper, besides these approaches, we use the desirability function to maximize the median of efficiency scores and minimize inefficiency gap altogether.

5. Methodology

DEA approach described in Section 2 is used in the comparative efficiency analysis. For this sake, accounting Opex is considered the input of DEA model. Regarding on outputs, one may consider NL, NC and ED. Different combinations of outputs may yield different efficiency scores. Thus, considering input-oriented DEA stated in Section 2.1, input/output variables are combined in different scenarios in order to get insights on the variables and models. These scenarios are analyzed and discussed, when we present the data set, prior environmental variables be considered.

Next, in order to analyze the impact of context variables, one should define the environmental variables. In small countries, the number of contextual variables may be few, if any. On the other hand, in a wide area country, it is agreed that is more likely to appear some environmental variables.

For example, in UK, it is agreed that only weather variables affects the DISCO performance (see Yu et al., 2009). However, Brazilian Regulator publishes a study proposing a bunch of environmental variables to explain inefficiency performance around country (see ANEEL, 2010).

Here, we study the Brazilian case, since it suggests a heterogeneous set of environmental variable. Once the first stage is achieved, the context variables are regressed against efficiency score obtained in the first stage scenarios, considering full factorial analysis. The Tobit regression is used jointly with bootstrap, as discussed in Section 2.2.

The results are analyzed with the help of DOE technique described in Section 3. In this stage, a discussion is held analyzing the factors which are statistically significance on efficiency score of DISCOs. For this sake, two sample *t* hypotheses test is performed in the impact factor, identifying the most important (context) factors for inefficiency.

Finally, the Desirability method approach is applied. The impact of environmental variables in DISCO inefficiency is them assessed and a discussion on tradeoffs second stage model is presented.

6. Data Set and Test Results

The data set used is available in the Brazilian Regulator website (ANEEL, 2010), and contains the Opex, NL, NC and ED from 2003 to 2009 for 29 different DISCOs, yielding 203 DMUs. These data are summarized on the histograms presented in Figure 2.

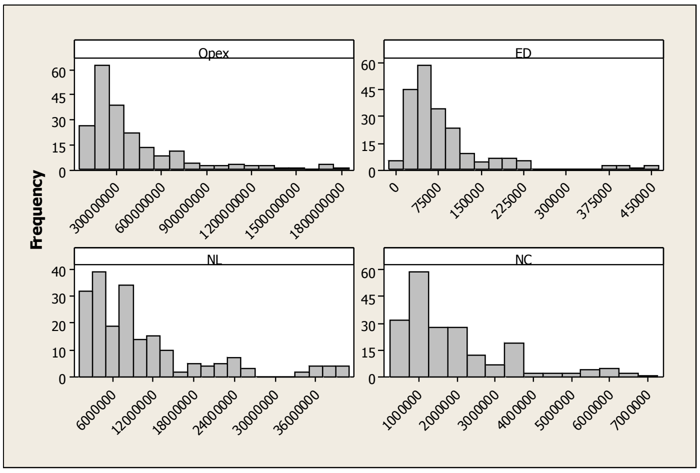

Figure 2- Histograms of data set

Note from Figure 2, that input and output data do not follow any specific parametric distribution. Recall, also, that DEA is a nonparametric method. Thus, when using test statistic here, we consider nonparametric tests.

In the first stage, it is considered four scenarios. All scenarios have Opex as input. For output, NL, NC and ED are considered in different combinations. The analysis here concerns the verification that different set of outputs result in different efficiency score. The scenarios are described in Table 1.

Table 2 - First DEA Stage Models Considered

Model	Input	Output
1	Opex	NC and NL
2	Opex	ED and NL
3	Opex	ED and NC
4	Opex	ED, NC and NL

Considering all DISCOs, the boxplot of efficiency scores for 203 DMUs obtained in each scenario is shown in Figure 3. Descriptive statistics for these results are presented in Table 3. A quick look in Figure 3 may drive us in wrong conclusion. This figure suggests that efficiency distribution on different scenarios is quite the same. However, this analysis does not include the efficiency deviation for each DMU.

Similarly to data set, likelihood of efficiency scores follows no parametric distribution. Thus, to test equality of seven scenarios, one may use the nonparametric Friedman test (see Rice, 2007), as shown in

Table **4**. In this test, null hypothesis considers that the probability distribution generating the observations under various treatments (scenarios) and blocks (DMUs) are identical.

Result in

Table **4** suggests that there exist a systematic difference among scenarios and DMUs, since the probability of null hypothesis is very low. Moreover, one can see from Table 3 that Scenario 4 presents the highest expected mean/median with lowest coefficient of variation. Note also, that Scenario 3 presents the highest discrepancy between mean and median.

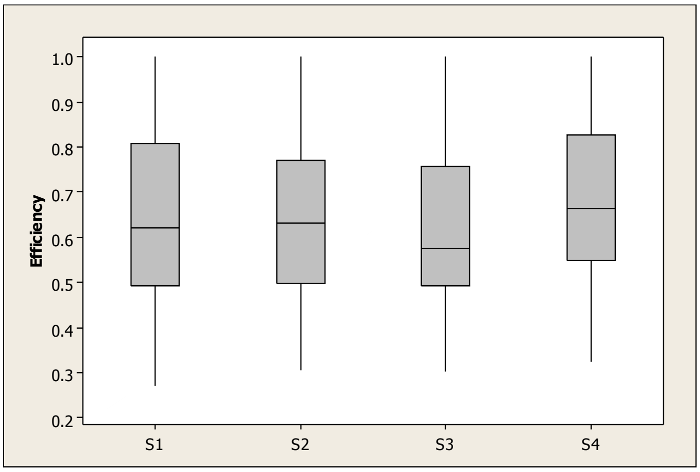

Figure 3- Boxplot of efficiency in each scenario considered

Table 3 – Descriptive Statistics for Efficiency

Scenario	N	Mean	StDev	CoefVar	Minimum	Q1	Median	Q3	Maximum
1	203	0.645	0.183	28.380	0.271	0.493	0.621	0.808	1.000
2	203	0.648	0.181	27.850	0.305	0.499	0.631	0.771	1.000
3	203	0.624	0.173	27.730	0.302	0.492	0.575	0.758	1.000
4	203	0.688	0.170	24.780	0.325	0.550	0.665	0.827	1.000

Table 4 - Friedman Test on Efficiency for Different Scenarios

Source	Sum of Squared Error	Degrees of Freedom	Mean Squared Error	Chi-square statistic	p-value
Scenarios	329.704	3	478.347	232.800	0.000

Error	532.796	606	0.879
Total	862.500	811	

From the above discussion, we could conclude that all scenarios present different efficiency score for discos, and Scenario 4 looks to be the best choice on efficiency calculation. However, DISCOs may face environmental variables, harming their efficiency score in different manners. As aforesaid, in a wide area country, some environmental variables are likely to appear.

Brazilian regulator, e.g., has been suggesting a bunch of variables as environmental variables that may affect efficiency score of DISCOs. Here, we considered five of them:

I. Period (PE): year analyzed;
II. Mean salary (MS): mean employees incomes based in a government database;
III. Consumer per area (CA): number of consumers and service area ratio, i.e, consumer density:
IV. Precipitation index (PI): weather condition index;
V. Complexity index (CI): social economical complexity index.

These context factors are suggested to consider the wide differences among Brazilian regions. For example, the population density is high in the coast and low in the interior, South is richer than North, life cost is different among regions, and the weather conditions widely vary in Brazilian territory. The frequency distribution of environmental variables considered is depicted in Figure 4.

Given the environmental variables described above, nonparametric statistics, DOE and Desirability method are used for sensitivity analysis of environmental variables For this sake, full factorial design is used, yielding (32) simulation experiments. The approach used is given by equation (2), where the environmental variable is presence (+1) and absence (-1) of the model and bootstrap technique discussed in Section 2.2 is used to obtain regression coefficient distribution through a full factorial design. A fraction of the full factorial design is presented in Table 5.

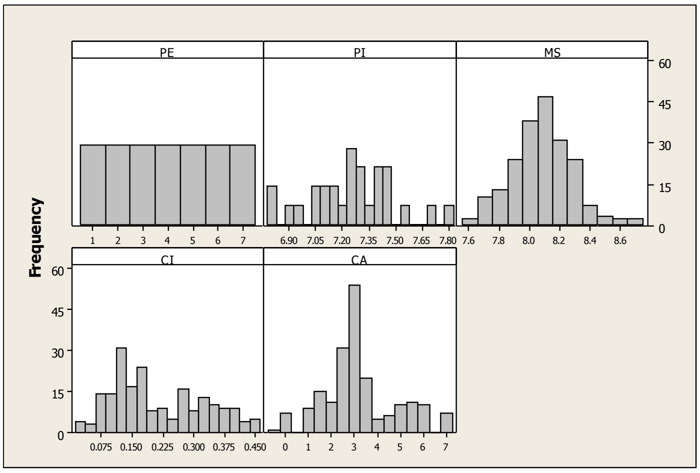

Figure 4- Frequency distribution of environmental variables considered

Table 5 – Fraction of Full Factorial Design for Seven Environmental Variables

Regression	Intercept	TE	MS	SA	CA	DP	PI
1	+1	+1	+1	+1	+1	+1	-1
2	+1	-1	-1	+1	+1	+1	-1
3	+1	-1	-1	-1	-1	-1	+1
4	+1	+1	+1	+1	-1	+1	-1
5	+1	+1	-1	+1	-1	-1	-1
6	+1	+1	+1	-1	-1	+1	-1
7	+1	-1	+1	-1	+1	-1	+1
8	+1	-1	+1	-1	-1	+1	+1
9	+1	+1	-1	-1	+1	+1	-1
10	+1	+1	-1	-1	+1	+1	-1
11	+1	-1	-1	+1	-1	+1	+1

The analysis is carried out using the metamodel similar to equation (3). We consider two different responses: (i) 50th quantile of efficiency score distribution, and (ii) amplitude of efficiency score (R). These responses are chosen because we are interested in the location of efficiency scores, the size of inefficiency gap, and the fact that efficiency score are nonparametric statistics.

The metamodel used is truncated in triple interaction, yielding the metamodel of equation (6). This simplification is due residual analysis: when more interactions are considered in the cases studied, the residuals are not independent and identically normally distributed.

(6)

Plot for main effects for median and R in Scenarios 1 to 4 are depicted in Figures 4 and 5, respectively. These figures suggest different impact of environmental variables for different scenarios considered. For instance, one can see in Figure 5 that MS has great impact in the median when NL is considered in the first stage (Scenario 1, 2 and 4). Moreover, PI appears to have negligible impact in efficiency score, regardless the scenario considered.

Analyzing Figure 6, one can detect the environmental variable which most affect inefficiency gap. Note, for instance, that MS impact on R in all scenarios analyzed. Thus, it should great impact the distance of inefficient DMUs from efficiency frontier. In general, this seems to be the unique environmental variables which affect efficiency gap.

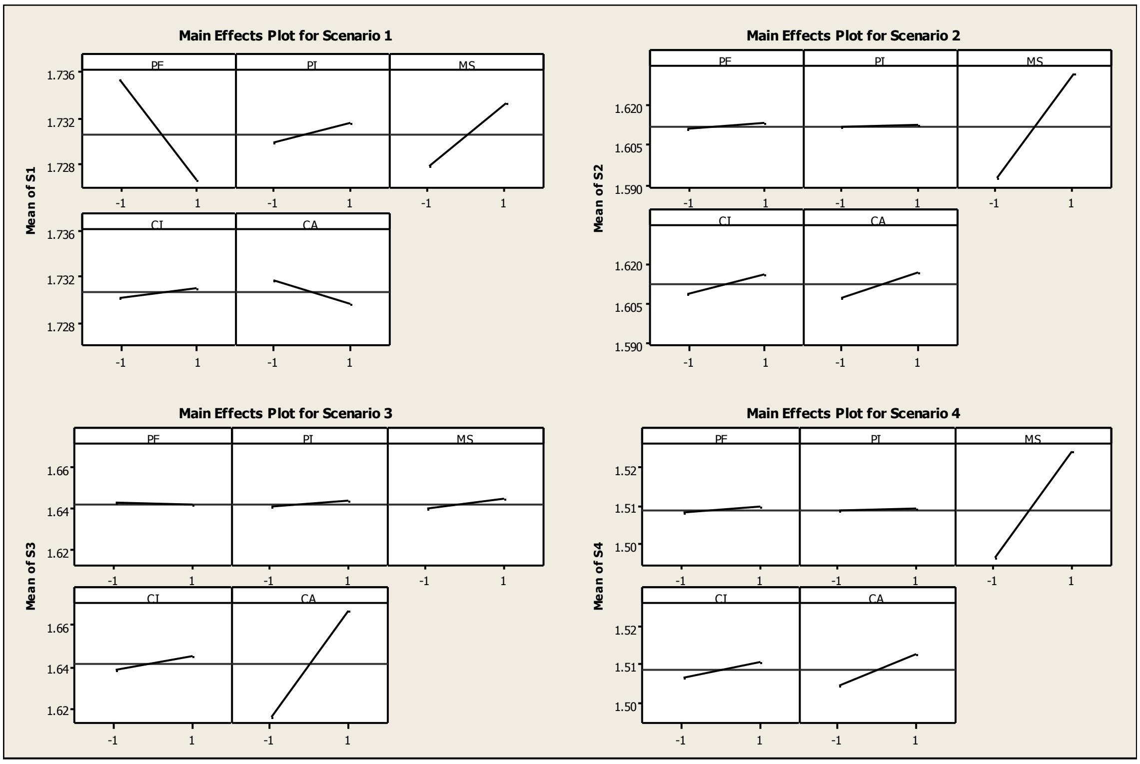

Figure 5- Main effects for median.

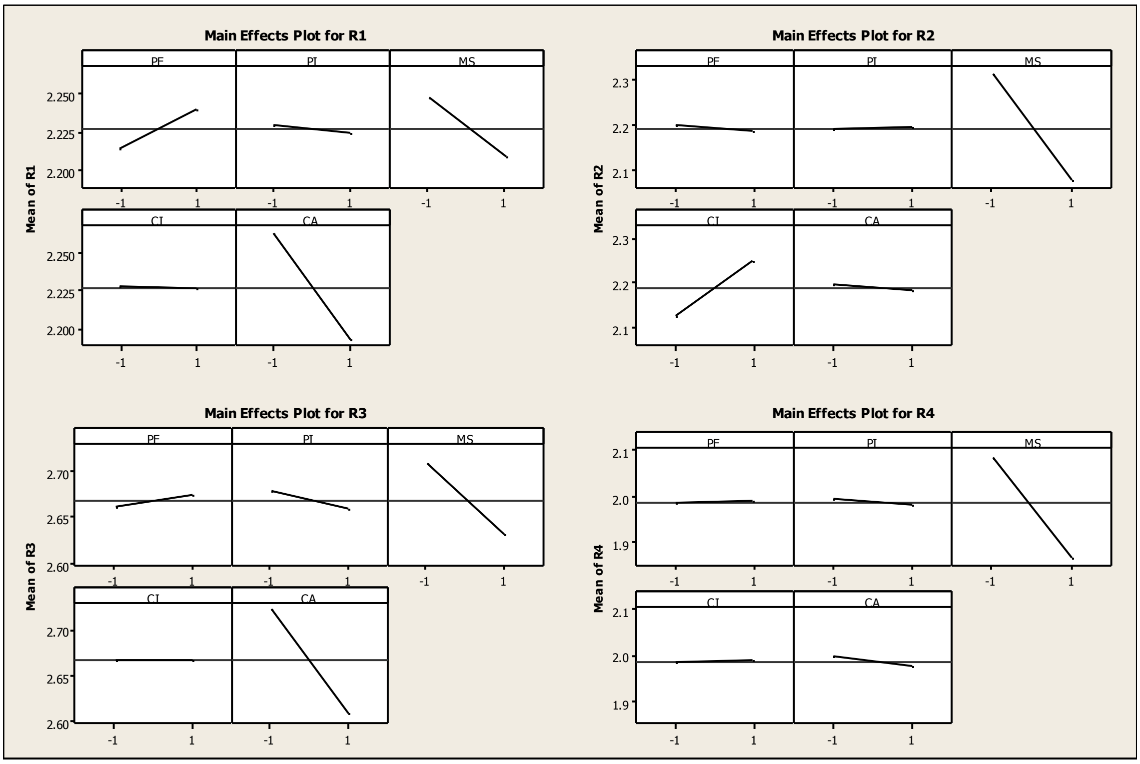

Figure 6- Main effects for R.

In Figures 4 and 5 we can visualize the impact of environmental variables on efficiency score and R, respectively. However, no information is depicted about interaction among these variables on efficiency. For this sake, we can use equation (6) to obtain standardized effects for main effects and their interaction, which may be plot in Pareto charts, as shown in Figures 6 and 7.

Figure 7 depicts standardized effects for the median of , while Figure 8 shows the same for R. In order to simplify the interaction visualization, environmental variables PE, PI, MS, CI, and CA are replaced by the factors A, B, C, D, and E. Moreover, the red line in the figures regards on the coefficient significance of . All factors bellow this line is removed from the metamodel, unless a factor is presented in an interaction. Since a regression based on full factorial analysis, normality test of residuals is of interest. It tests the null hypothesis of residuals being independent and identically distributed under normal distribution. For this sake, we used the Kolmogorov-Smirnov test (see Rice, 2007), and the probability of null hypothesis is greater than 0.15 in all scenarios analyzed.

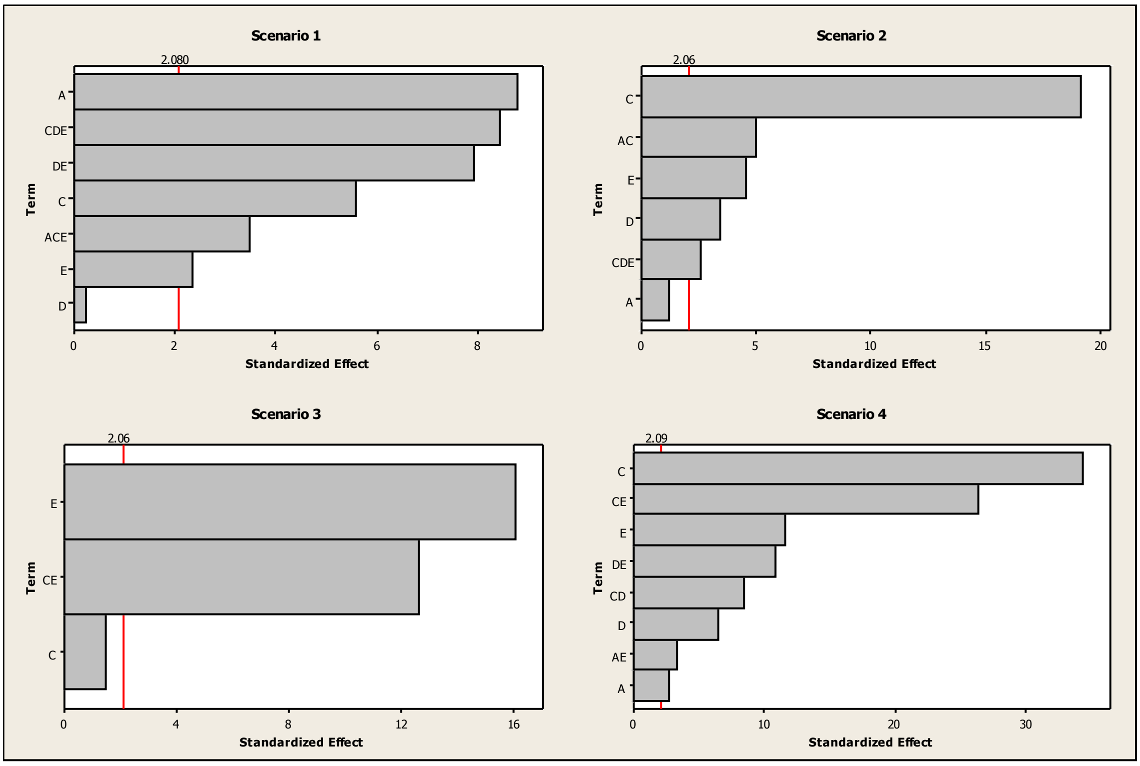

Figure 7- Standardized Effects for Median.

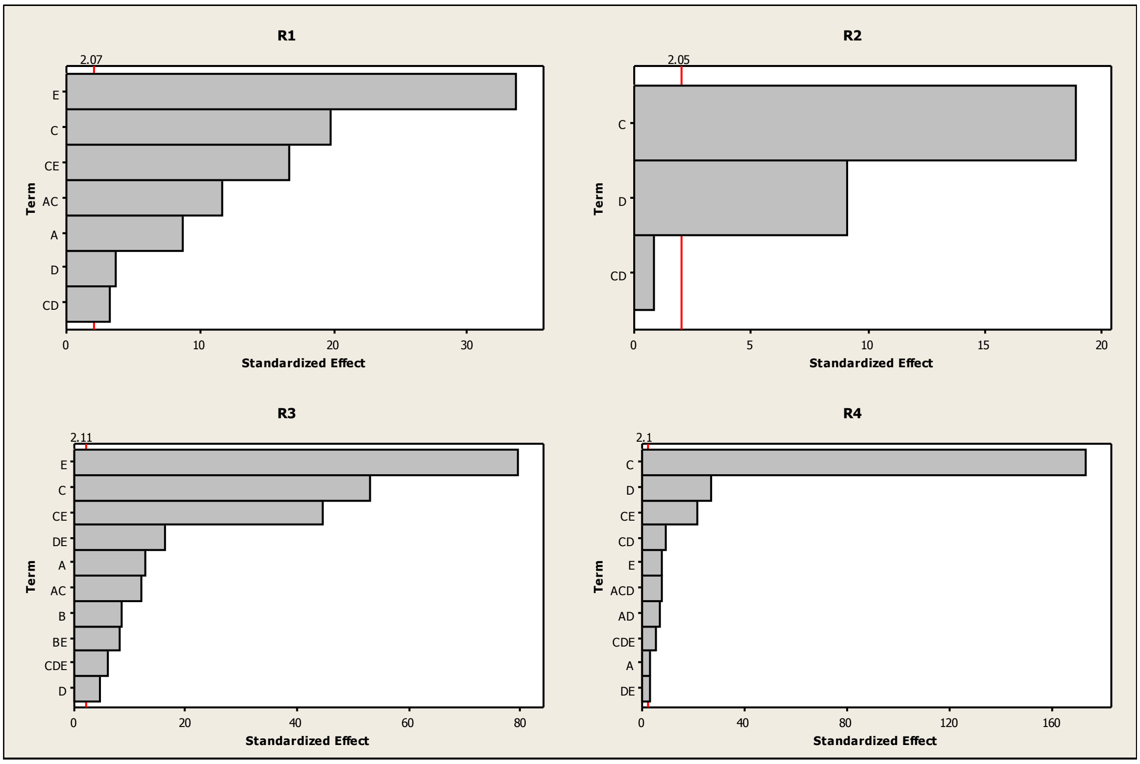

Figure 8- Standardized Effects for R

Figures 6 and 7 confirm that contextual variables impact the efficiency scores (median) and inefficiency gap (R) in different manner, as observed from Figures 4 and 5. Note, however, that metamodel from equation (6) helps in analyzing the real impact of contextual variables, since we can model the main effects and their interaction altogether, making inference on model coefficient. For instance, the contextual variable CI (factor D) is not statistically significant for the median of Scenario 1 (Figure 7). This result was expected from main effects analysis (Figure 5). However, its interaction to MS (factor C) and CA (factor E) is highly significant. Similar results may be observed from Scenarios 2 and 3, where PE (factor A) and MS (factor C) are not statistically significant, respectively. But, when interactions are presented, they should be considered on scenarios analyzed.

In addition, consider, for now, only Scenario 1. The environmental variables PE (factor A) and CA (factor E) impact the median and R in quite different manner. In spite of PE be the most significant contextual factor impacting the efficiency score, it presents less relevance when inefficiency gap is considered. On the other hand, CA is near to threshold of significance level when the median is analyzed, but is highly relevant to close inefficiency gap. Once more, similar results may be observed in Scenarios 2, 3 and 4.

Another important result regards on weather conditions (PI – factor B). This environmental variable is not relevant in almost all scenarios. Indeed, it only presents a small impact on inefficiency gap of Scenario 3, suggesting that PI may be internalized according the output considered, in the same way that it has also been addressed by Yu et al. (2009).

Recall that efficiency analysis defines regulatory revenue of each DISCO. Therefore, when defining a benchmark model for DISCOs, regulator should take into account main aspects related to environmental variables. In regulatory scenario, measuring inefficiency gap may be the main interest. However, when environmental variables are considered in a Two Stage DEA approach, efficiency score may exceed 100%. Thus, regulator may be interested in select environmental variables which maximize efficiency score (minimize) and close inefficiency gap altogether. For this sake, we suggest the use of multi-objective optimization approach known as Desirability Method, described in Section 4, as an auxiliary tool in defining the environmental variables to be considered.

When considering desirability function to minimize an objective, we must select a target value and upper limit. For upper limit, we choose the maximum value observed median and R when full factorial analysis is simulated. For target value, on the other hand, we considered the minimum value observed median and R. In each scenario, we compare the desirability of maximize the median of efficiency score (minimize), minimize inefficiency gap R, and both objectives together. Furthermore, when minimization of and R is of interested, different values for is discussed. Table 6 presents the results when desirability method is applied.

Note, from Table 6, that when the median of and inefficiency gap R are treated separately, the result is simply the target value . These cases define the environmental variables which most contribute to the objective (minimize the median of or inefficiency gap R). The tradeoffs between these objectives are considered when multi-objective approach is applied, i.e, both . The value of is used define the relevance of responses. If regulator is mainly interested in improving the median of , . Otherwise, if inefficiency gap is more relevant, .

Table 6 – Desirability results

Scenario	Median		Inefficiency gap		D	PE	PI	MS	CI	CA
			R							
1	1.7154	1	-	0	1.0000	+1	+1	-1	-1	+1
	-	0	2.1638	1	1.0000	-1	-1	+1	+1	+1
	1.7154	1	2.1987	1	0.8724	+1	+1	-1	-1	+1
	1.7252	1	2.1863	5	0.5269	+1	-1	-1	+1	+1
2	1.5712	1	-	0	1.0000	+1	-1	-1	-1	-1
	-	0	2.0059	1	1.0000	-1	+1	+1	-1	-1
	1.6138	1	2.0072	1	0.7471	-1	+1	+1	-1	-1
	1.5815	5	2.2242	1	0.7060	+1	-1	-1	-1	+0.54
3	1.5951	1	-	0	1.0000	+1	-1	+1	-1	-1
	-	0	2.5180	1	1.0000	+1	+1	+1	+1	+1
	1.6265	1	2.6378	1	0.5986	-1	-1	+1	-1	-0.13
	1.6621	1	2.5547	5	0.3987	-1	-1	+1	-1	+1
	1.5951	5	2.7037	1	0.4953	+1	-1	+1	-1	-1
4	1.4866	1	-	0	1.0000	-1	+1	-1	-1	+1
	-	0	1.8116	1	1.0000	-1	+1	+1	-1	-1
	1.5033	1	1.8320	1	0.8187	-1	-1	+1	-1	-1
	1.5097	1	1.8116	5	0.7819	-1	+1	+1	-1	-1

In Scenario 3, an interesting result is obtained. Note that environmental variables PE and MS improve the median of , while all environmental variables reduces the inefficiency gap R.

However, when the objectives are considered together with a linear desirability transformation, environmental variable CA affects the responses in different manner: in one hand, CA degrade the median of ; on the other hand, CA reduces the inefficiency gap. This difference in response can be viewed in the contour plot presented in Figures 8 and 9. This chart shows the response surface of contextual factors CA and MS as a contour plot, i.e, it shows how the response (median of or inefficiency gap R) behaves as CA and MS change. In the figure, the responses vary from low value (dark blue) to high values (dark green) as the environmental variables change. The remaining variables (PE, PI, CI) are held in -1 (out of the model).

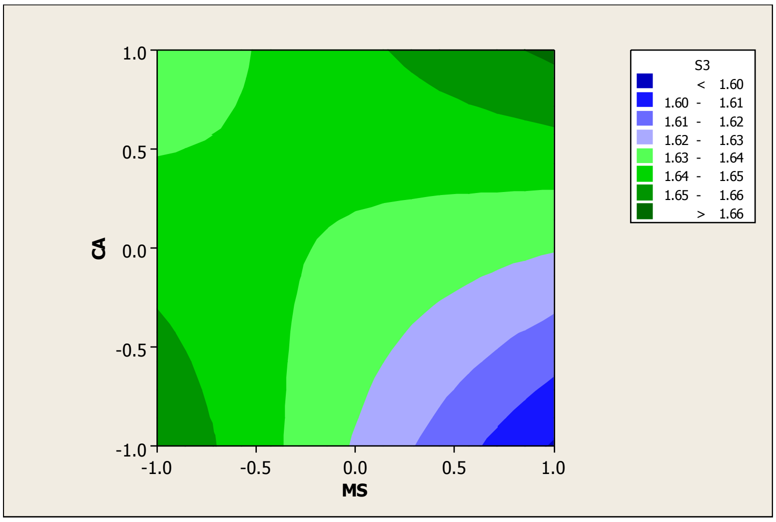

Figure 9- Contour plot for median of

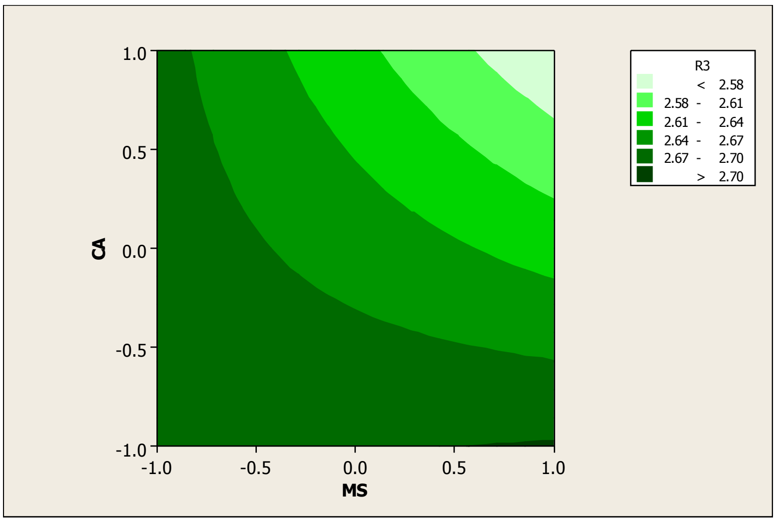

Figure 10- Contour plot for inefficiency gap R

Given Figures 8 and 9, the contextual factor analysis is straightforward. Note that the presence of CA and MS produces lower values of inefficiency gap R. However, to reach low values for the median of , we must consider the presence of MS and absence of CA. When linear desirability transformation is applied, the multi-response optimization suggests the use of a weighted environmental variable in the comparative efficiency analysis. Indeed, this approach is neither usual nor well understood yet, and the regulator must decide by the presence or absence of the variable in the model. A similar result is obtained in Scenario 2. However, in this case, the desirability transformation is no longer linear, and a greater importance is given for the median of (). One may argue that different targets may produce different results. However, since this is a simulated full factorial analysis, targets that have not been observed make no sense.

The desirability method proposed here may be used as a sensitivity analysis of environmental variables. For instance, in Scenario 1, 2, 3 and 4, varying and one may infer which environmental variable affects the median of (inefficiency gap R) when inefficiency gap R (median of) is jointly considered in the model.

7. Conclusions

This paper discusses the use of benchmark two stages DEA approach in electricity distribution companies' efficiency analysis, which is commonly used by regulator to set allowed revenue. The two stages DEA is composed by a traditional DEA model (first stage) and a truncated regression considering environmental variables (second stage). In order to enable statistical inference in the truncated regression, a bootstrap approach is used.

In this context, it is proposed the use of simulated design of experiments to evaluate the impact of environmental variables on decision making units' efficiency, where a full factorial design is used. Using a metamodel for the efficiency score, it is shown that, depending on contextual factor, either the efficiency score or inefficiency gap may be affected. Moreover, it is also shown that the impact of some environmental variable may be internalized according the input/output considered. Thus, regulator should establish a clear objective in selecting environmental variables.

In order to help the efficiency analysis under environmental variables, it is proposed the use of desirability function. This method is a nonlinear optimization procedure capable of dealing with single or multiple response problems, and may be used as a sensitivity analysis of environmental variables. Thus, the analysis may be handled jointly observing the absolute value of efficiency score and inefficiency gap. With this approach, it is shown that tradeoffs between efficiency score and inefficiency gap presents a nonlinear behavior. Moreover, when objective are treated in different manners, weighted environmental variable may be found. However, this approach is neither usual nor well understood yet, and the regulator must decide by the presence or absence of the variable in the model.

The analysis developed in this paper was carried out with the real data available in the Brazilian Regulator website, and the results may be reproduced.

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Notes

a. From now on, isoquant frontier is also referred as isoquant.

b. The last constraint models NDRS DEA.

c. may vary from 1 to ∞, simplifying regression model.