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EFFICIENCY ANALYSIS IN ELECTRICITY TRANSMISSION UTILITIES

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Abstract. In those countries where the electric production chain has been disintegrated, transportation utilities (transmission as well as distribution) are subject to regulation or are under supervised activity. Regulation of activities considered as natural monopolies in network economies requires knowing or assessing efficient capital and operating expenditures (CAPEX and OPEX) depending on the output levels. The problem of determining the tariffs that transmission utilities can charge is tightly related to efficient OPEX levels. This work discusses the use of Data Envelopment Analysis and Stochastic Frontier Analysis to determine efficient frontiers for electricity transmission activity. The results include relative efficiency and productivity indicators, as well as benchmarking peers. This information can be useful to the regulator to foster efficient performance of transmission utilities.

1. **Introduction.** As many other countries, Colombia carried out institutional and economic reforms in the nineties, which focused the State action on long term planning, regulation and specialized supervision, as well as on social services provision. In the case of the electricity sector, as in other public utilities, the industry was unbundled, allowing free entry of private investors. A wholesale market was organized in 1995. Incentive regulation has been adopted to foster efficiency improvements in transmission and distribution activities. The Energy and Gas Regulatory Commission (CREG) is in charge of setting the rules to achieve optimal performance levels. In addition it must design the market operating rules to guarantee free entrance of agents and to avoid the use of market powers.

Electricity transmission was defined as power transportation through a set of lines, including their connecting modules, operating at voltages equal or greater than 220 kV [9]. The Colombian Interconnected National System (SIN) networks was functionally classified in three types of systems: National Transmission System (STN), Regional Transmission Systems (STR) and Local Distribution Systems (SDL). The first one corresponds to transmission activity while the other two are related to distribution activity.

There are currently eleven transmission utilities, four of which are private or mostly private. Two of these 11 utilities own the 83% of the network assets and

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four of them own just some few modules. Three of these utilities exhibit a high degree of vertical integration.

CREG has adopted a revenue cap method to remunerate the firms. In the case of existent infrastructure the maximum allowable revenue is established in accordance with the assets effectively own in the STN [10]. Capital expenditures (CAPEX) are determined by assessing a regulatory asset base through its replacement value, which corresponds to its reinstatement as new. The operating expenditures (OPEX) for the existent infrastructure are paid as a percentage of the electrical assets value. The allowed percentage was initially determined by the international advisors when the market was settled and nowadays CREG is making use of benchmarking methods in order to achieve economic efficiency in the use of OPEX. A planning process followed by solicitations were set forth after 2000 for new expansions. Construction and operation of new lines and equipments are assigned to the company that demands the minimum present value of the annual expected income for the next 25 years of operation [10].

Transmission utilities must ensure the reliability of the network. Quality standards are applied in conjunction with non-attainment penalties or compensation schemes. Transmission charges are paid by consumers and correspond to a stamp price that recovers efficient CAPEX and OPEX (a rule that does not take into account the benefits each consumer obtains from the network). Maximum power losses to be paid by consumers are settled by the regulator.

This paper presents a a methodological proposal to measure efficient OPEX for electricity transmission utilities. The analysis can be easily extended to distribution utilities. The principal aim of this work is to support the regulatory decisions related with those expenditures in the Colombian transmission sector. The efficiency measurements are based on a definition of the microeconomic function of the transmission activity. We used two different methodologies to asses efficiency of the firms: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). DEA determines an efficient frontier made up with those firms considered as efficient and compares other firms against the frontier. The proposed models are input oriented with discretionary and non-discretionary variables. Efficiency measures were calculated using variable and constant returns to scale models. Based on DEA models, Malmquist indexes were used to evaluate the dynamics of efficiency changes in OPEX. However, the use of time windows hinders their interpretation. The models developed using SFA build a production function considering inputs and environmental variables as the entries of the function, and nominal transport capacity as the output. The frontier yields information about relative efficiency of the firms at product (output) delivery.

In section 2 we present a brief summary of DEA and SFA; in section 3, the microeconomic conceptualization of power transmission activity is presented. In section 4 we present the variables included in the analysis classified as inputs, outputs and environmental variables. Section 5 presents the specific DEA and SFA models and their results. Finally section 6 states some conclusions about the relative efficiency values obtained from the application of the mentioned models, as well as how these measures together with a series of indicators per company might help the regulator to take decisions at the time of establishing the allowable revenue related to OPEX that each utility can earn.

2. Benchmarking Methodologies for Efficiency Measurement.

Frontier production estimates can be seen as an extension of microeconomic output function estimates. The basic premise comes from considering that the output function represents some "ideal" entity that maximizes the output for a given input. The minimization of inputs for a given level of product(s) and the optimization of benefits are variations of the same concept. In this sense, frontier productions are useful for the relative efficiency analysis since the performance of a specific entity can be compared against the ideal entity to determine the degree of relative efficiency. This explains the synonymy between production and efficiency frontiers.

In a consequent manner the efficiency measurement can be made through the comparison of each observation with the best observed practice (the frontier). This measurement can be used to estimate different efficiency quantities that capture different dimensions of efficiency [5]. Some of these concepts are the technical efficiency (TE), which is the capability to make use of the inputs such that the output is maximized; allocative efficiency (AE), which is related to the capability of the entity to combine the inputs making the marginal substitution rate equal to the relative price of the inputs; and productive efficiency (PE), which is the capability to produce at minimum cost.

If the frontier is built up from production functions (output as a function of input), its estimation informs about technical inefficiency. The frontier can also be constructed from cost functions (total cost as a function of output level and input cost) and its estimation informs about productive inefficiency.

Two basic approaches are usually exploited in empirical studies about production frontier analysis: Data Envelopment Analysis (DEA), and Stochastic production Frontier models (SFA)[5]. Furthermore, the use of multivariate statistical techniques can be mentioned (mainly principal components and factor analysis). The first two approaches were explicitly developed for an empirical study of boundaries to determine a hierarchical organization of units (firms, individuals, entities) in terms of output or cost efficiencies. The other approaches are related to the the exploitation of basic characteristics of those techniques.

Many countries have implemented incentive regulation in the power sector and have used benchmarking techniques to assess relative efficiency. The main frontier-based benchamarking techniques used and reported by literature are DEA, SFA and COLS (Corrected Ordinary Least Square). In the case of power transportation, most of the studies reported have been preformed to measure efficiency in the distribution utilities [18], [11], [16], [20], [19]. Tranmission is a natural monopoly and in many countries the service is rendered by only one utility. Nonetheless Colombia has 7 transmission utilities and therefore the use of benchmarking techniques such as DEA and SFA, could be relevant for regulation purposes.

2.1. Data Envelopment Analysis.

DEA is a family of non-parametric methods based on optimization techniques that allow the computation of the relative efficiency of a set of firms [8]. The firms with the best relative performance are those that use a minimum amount of resources for a given result (input-oriented) or those that produce the best results from a given amount of resources (output-oriented). These firms are considered efficient and are used to construct the efficient frontier, against which all the other firms will be compared.

In the case of electricity transportation, the supplied power is a variable ruled by the market and is beyond the control of the firms. Nevertheless this power must be provided according to quality and reliability standards. Therefore, the efficiency of the electricity transportation firms measures its ability to provide the power according to those standards and with minimum amounts of resources. These resources are related to capital assets, transportation losses, and administrative, operative and maintenance expenses.

Charnes, Cooper and Rhodes [4] developed the first DEA model to assess the relative efficiency of a set of schools under different programs. This model was especially designed to deal with firms or units that have multiple inputs and outputs, and their production function is hard to specify. The basic model can be characterized by n units, m inputs and s outputs, where the j-th firm requires x_{ij} units of the i-th input and produces y_{rj} units of the r-th output, for $j = 1, \dots, n$, $i = 1, \dots, m$ and $r = 1, \dots, s$. The linear programming problem to determine the efficiency of a specific firm (o) can be formulated as [8]:

$$\begin{aligned} \theta^* = \min \quad & \theta \\ \text{s.t.} \quad & \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \quad r = 1, 2, \dots, s \\ & \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io} \quad i = 1, 2, \dots, m \\ & \lambda_j \geq 0 \quad j = 1, 2, \dots, n, \end{aligned}$$

where θ is the pure technical efficiency that must be minimized to reveal the possible gaps in the behavior of the entity. The variables λ_j for $j = 1, \dots, n$ reveal the weight that each of the entities in the set receive for the evaluation of the firm o under analysis. In this case, the model is input-oriented, since the resources are multiplied by the variable θ, that reveals the factor by which the entity must contract its input usage to become efficient.

Many developments have been done since the introduction of this first model. Of special interest for this work are the extensions to allow variable returns to scale [2], since the firms under analysis show different productive structures. Other important extensions are related to the possibility of dealing with non-discretionary inputs and outputs[8], the inclusion of principal components in the models [1] and the restrictions to the values of the weights given to each input and output in the analysis of each firm. These characteristics are relevant for this study in order to include several conditions that affect the performance of transmission utilities, some of which might not be under their control, e.g. geographic factors and saline environments. How to treat with these issues inside the DEA framework can be found in [8] and [7] and references therein.

2.2. **Stochastic Frontier Analysis - SFA.** For the case of the transportation utilities an output function can be formulated to relate the final product to a set of inputs. Kumbhakar and Lovell [15], Coelli *et al* [5] have extensively discussed the basic notions of the SFA model. The the basic idea is to estimate a production function of the form

$$y = X\beta + \epsilon \tag{1}$$

where y is usually the output's natural logarithm and matrix X encloses the variables associated to inputs (or their logarithms) and to environmental factors. The term ϵ is formed by two elements: $\epsilon = v - u$. The vector v is related to the residual and it is considered as a normally distributed symmetrical noise. The term u represents the efficiency; it is non-negative in output functions and non-symmetric. Since u is present, then ϵ is non-symmetric with expected value $\mathrm{E}[\epsilon] = \mathrm{E}[v - u] = -\mathrm{E}[u] < 0$. Finding symmetry or normality when specifying output functions using ordinary least squares (OLS) or finding positive skewness implies that the SFA model is not adequate to explain input-output relations.

The next step in the procedure is to deduce the distribution of ϵ from the joint distribution of v and u (in this work u has a semi-normal distribution). Then the likelihood function for the distribution of ϵ is calculated and the parameters are estimated in order to obtain the technical efficiencies for each entity involved. The last step is carried out using the approach proposed by Battese and Coelli [3], in which the technical efficiency is computed from the conditional expectation of e^u given ϵ.

3. **Economics of Electric Power Transmission and Distribution.**

3.1. **Electric Power Transmission.** The main objective of electric power transmission is to carry electric power generated at electric power plants, usually located at long distances from consumption centers, to the sites where it is finally consumed. The generic transmission problem is then to move $P(t)$ units of electric power a distance of L units at a given time t. To accomplish this task, an electric current $I(t)$ generated at power plants is sent through a wire of electric conducting material of length L at some voltage V. This process occurs repeatedly at home distribution circuits at the low mains voltage and in high and very high voltage distribution and transmission lines and transformers. The power transmitted $P(t)$ is given by

$$P(t) = V \cdot I(t) \cdot \phi, \tag{2}$$

where the coefficient ϕ is a variable number close to 1.

3.2. **Electric Power Losses.** Transmission of an electric power $P(t)$ a distance L results in power losses $\Pi(t)$ caused by heat dissipation in the electric conductor given by

$$\Pi(t) = R \cdot I(t)^2, \tag{3}$$

where R is the electrical resistance of the wire given by

$$R = \rho \cdot \frac{L}{S}, \tag{4}$$

where S is the cross section of the wire and ρ is the electrical resistivity of the conductor material.

Electric power losses are economically important because they constitute the electric power that needs to be produced by generators along with electric power delivered to customers no matter if they are dissipated as heat in the transmission and distribution systems. Since they grow with the square of electric current transmission, voltage is usually increased so as to reduce electric current and losses to economic levels when transmitting large quantities of electric power.

3.3. **Input/output Model of Electric Power Transmission.** Electric power transmission can be analyzed in economic terms as a black box with inputs and outputs. Output variables of the electric power transmission are transmitted power $P(t)$ and distance L. Inputs are related to the following transmission system production factors:

- Transmission system elements providing adequate electric insulation and mechanical support of the electric conductor at the transmission voltage V such as high voltage transmission line towers, electric insulators, step-up and step-down transformers, supervisory control and protection equipment, etc.
- Wire or cable of electrical conducting material in amount M:

$$M = S \cdot L. \tag{5}$$

- Electric power losses $\Pi(t)$ required in addition to the transmitted power $P(t)$ at the sending end (generating plant) of the transmission element in order to deliver the amount $P(t)$ to the user.

3.4. **Production Function of Electric Energy Transmission.** Input variables V, M and $\Pi(t)$ and the electric resistivity parameter ρ completely determine electric power transmission output variables $P(t)$ and L via equations (2), (3), (4) and (5) for each element of the transmission system. The following equation relates the two output variables to the three input variables

$$P(t) \cdot L = V \cdot \left(\frac{M}{\rho}\right)^{1/2} \cdot \Pi(t)^{1/2} \cdot \phi. \tag{6}$$

This production function belongs to the *Cobb-Douglas* type. The economically relevant output is the arithmetic product of the two output variables [17]. This function exhibits constant returns to scale in voltage and decreasing returns in amount of conductor and power losses. Production function (6) can be cast in terms of time averages of electric energy transmitted $\bar{P}$ and electric energy losses $\bar{\Pi}$ in a given period of time T

$$\begin{aligned}
\bar{P} &= \frac{1}{T}\int_0^T P(t)dt \\
\bar{\Pi} &= \frac{1}{T}\int_0^T \Pi(t)dt \\
\sigma_P^2 &= \frac{1}{T}\int_0^T \left(P(t) - \bar{P}\right)^2 dt = \frac{1}{T}\int_0^T P^2(t)dt - \bar{P}^2,
\end{aligned}$$

where σ_P^2 is the average variance of transmitted energy. The corresponding electric energy production function is then

$$\bar{P} \cdot L = V \cdot \left(\frac{M}{\rho}\right)^{1/2} \cdot \bar{\Pi}^{1/2}\gamma^{-1/2} \cdot \phi, \tag{7}$$

where γ is the loss factor assumed to be constant and given by

$$\gamma = 1 + \left(\frac{\sigma_P}{\bar{P}}\right)^2.$$

3.5. **Transmission Losses and Congestion.** Input congestion is said to occur if increasing one or more inputs decreases some outputs without improving other inputs or outputs [6]. Consider the average electric power delivered ($\bar{P}$) as the model output and the average of actual electric power ($\bar{P}_{sent}$) sent through the transmission system as the model input. The input and output of the model are related by

$$\bar{P} = \bar{P}_{sent} - \bar{\Pi}. \tag{8}$$

Using equations 7 and 8 we obtained

$$\bar{P} = \bar{P}_{sent} - k\bar{P}_{sent}^2, \tag{9}$$

where k is a constant with dimension equal to the inverse of electric power, given by

$$k = \left(\frac{L}{V\phi}\right)^2 \frac{\gamma\rho}{M}.$$

Therefore increasing the input by a small amount $\Delta\bar{P}_{sent}$ produces a change in the output equal to

$$\Delta\bar{P} = \Delta\bar{P}_{sent} - 2k\Delta\bar{P}_{sent}.$$

For $\bar{P}_{sent}$ greater than $\frac{1}{2k} = \frac{V^2\phi^2 M}{2L^2\gamma\rho}$ then the transmission system shows congestion. In terms of percentage of losses this amounts to the fact that congestion in electric power transmission appears whenever losses are greater than 50%. Since losses in electric transmission systems are usually less than 5% because of economic reasons as shown in the next section congestion in power transmission systems is far from becoming a real problem and it has not been taken into account in the model described in this paper.

4. **Variables.** The next step after defining the economic model for the transmission activity corresponds to the identification of the variables to be used in the frontier-based benchmarking models. Jamasb and Pollit [13, 14] have summarized different groups of inputs and outputs used in different studies and their frequency of use. The previous economic description of the electric power transmission provides us with the first set of input and output variables to measure efficiency of the utilities, to determine efficient OPEX. Environmental variables were defined in order to capture specific conditions that affect the performance of the utilities. Those variables were built according to the availability of the information.

4.1. **Input Variables.** Transmission activity seen from a microeconomic point of view has tree important input variables: the voltage level (V), the amount of electric conducting material (M), and the electric power losses (Π). As seen from the model above, the amount of material is a key indicator of industry size. On the other hand, the voltage level is associated with electric energy transmission infrastructure for voltage support, such as 230 KV and 500 KV transmission lines, transformers and substation equipment. Finally, energy losses in Colombia are presently taken into account and passed directly to consumers through a tariff formula and were not considered explicitly in the present study. Thus, the input variables used in the model are:

1. Amount of electric conducting material (Material): the amount of material is a proxy variable of the utilities size. It was defined as the sum over all the transmission lines of the conductor cross section S (given in MCM) times its length L (in kilometers). Another approximation for this variable is the valuation of the electrical-related assets (EA), that is, the electrical assets were assessed using the monetary valuation carried out by the Colombian Energy and Gas Regulatory Commission (CREG). Transmission lines, transformers and substation equipment were included.

2. Non-electrical assets (NEA): although non-electrical assets are not part of the inputs presented in the microeconomic model, they are necessary to perform the electric transmission activity besides the electrical assets. In order to differentiate the utilities owning the non-electrical assets from those renting them, the investment in non electrical assets was taken as the sum of the bills of non-electrical assets depreciation and their rental fees. This procedure enables the efficiency evaluation between those two types of utilities.
3. Operating expenditures (OPEX): these are the administration, operation and maintenance expenses for the transmission activity of the utilities. As it was seen above some Colombian electric utilities are vertically integrated; therefore, a separation between the expenses of the activities of the electricity chain was made. The utilities were inquired directly about that division. Moreover, retirement pensions and local taxes, which are highly variable among the utilities, were excluded from the OPEX with the purpose of homogenizing the evaluated utilities.

4.2. **Output Variables.** Following the model, the obvious output variable should be the transmitted energy. However, the unavailability of information made this variable unusable for the Colombian transmission activity and we used an alternative variable. On the other hand, output variables that were not considered in the simple electric energy transmission model described above, and which are important factors in determining efficient performance, are related to the quality of the electric energy service such as continuity of delivery, security and reliability. Therefore, for the Colombian utilities benchmarking the output variables are:

1. Power capacity (MVAKM): instead of the transmitted energy, we used the power capacity of the lines measured in MVA·km. This computed as the sum over all transmission lines of its power capacity times its length.
2. Quality of the electric energy service (Quality) measured as the weighed average of the number of available hours of each line given by

$$\text{Quality} = \frac{\sum_{i \in \text{lines}} \text{Number of available hours }_i \cdot \text{length}_i}{\sum_{i \in \text{lines}} \text{length}_i}. \tag{10}$$

4.3. **Environmental Variables.** Besides the input and output variables the OPEX are affected by some environmental factors beyond the control of the utilities, such as degree of salinity in coastal regions, access to network, dispersion, etc. After analyzing the impact of each variable on the efficiency performance, we determined the following environmental set as the most relevant:

1. Length of lines exposed to salinity in coastal regions (LinesSal)
2. Substation equipment (bays) exposed to salinity in coastal regions (SubSal)
3. Electrical assets exposed to salinity in coastal regions (EASal). The lines and substation equipment exposed to salinity were assessed using the monetary valuation of the electrical assets performed by the CREG.
4. Infrastructure Complexity: This additional variable was constructed in order to reflect the different network configurations that the utilities may have. The complexity is not exactly an environmental variable because it can be under utility control. The difficulty is that it can not be changed in the short term and, consequently, it can be classified as an environmental variable. Network configuration can be described through different descriptors, such as dispersion, substation structures, etc. This wide range of descriptors produces

many different definitions of the complexity variable some of which we used in the DEA and SFA models:

(a) Substation complexity (SubComplex): this index reflects the amount of substation equipment of each utility. It was used to capture the possible increasing of the maintenance costs with the amount of equipment. It is given by

$$\text{SubComplex} = \frac{\text{Number of bays}}{\text{Number of substations}}. \tag{11}$$

(b) Area complexity (AreaComplex): this index was constructed to include the dispersion of the electric network and, therefore, the difficulty level of maintenance. It is given by

$$\text{AreaComplex} = \frac{\text{Service area}}{\text{Total lines length}}. \tag{12}$$

(c) Configuration complexity (ConfigComplex): this third index is a weighed average of the substation complexity of the utility. The substation complexity was evaluated depending on its configuration (single and double busbars with or without transfer bus, double circuit breaker or one-and-half circuit breaker, etc.) using the following indicators:
   - *Flexibility* is the property of the substation to accommodate itself to different conditions that may arise, especially due to operational changes of the system and, further, to contingencies and/or maintenance.
   - *Reliability* is the probability that a substation can supply energy during a given time after executing an internal operation (for instance, commutation of the adequate relays), under the condition that at least one substation component (switch, etc.) be out of service by either failure or maintenance.
   - *Security* is the property of a substation to supply energy continuously without any interruption whatsoever during equipment failure, especially switches and busbars. Security implies reliability.

(d) Electric network complexity (NetComplex): this index is a proxy of network dispersion and is given by

$$\text{NetComplex} = \frac{\text{Number of substations}}{\text{Total lines length}}. \tag{13}$$

4.4. **Information Issues.** The efficiency analysis was performed for years 2001 through 2004. The information employed to develop the models was taken from three different sources:

1. The most important source was the utilities themselves, which filled out some forms with information about OPEX.
2. The national account database for public utilities.
3. The National Transmission and Administrator of Accounts database. This is the Colombian entity in charge of liquidating and billing the national transmission system bills. Thus it has information about all the assets of the utilities involved.

There are currently eleven transmission utilities in Colombia but in this study we evaluate seven of them because the other four utilities have just some few modules.

The principal descriptors for those seven utilities are presented in Table 1 so the obtained results of the efficiency evaluation can be better understood.

Utility	Ownership	Integration level	Relative size	Salinity level
A	Private	Transmission	0,41%	
B	Public	Transmission	7,29%	
C	Public	Complete	7,63%	
D	Private	Complete	2,72%	
E	Public	Complete	1,51%	
F	Private	Transmission	69,74%	7,20%
G	Private	Transmission	9,73%	52,69%

Table 1. Principal descriptors of the Colombian transmission utilities

5. **Efficiency Measurement models.** Based on the microeconomic characterization of the transmission activity and the previously presented variables two types of models were developed. The differentiation is related to the variables used to include the electrical assets in the analysis. In models Type 1 the electrical assets are physical variables and the included variables are shown in Table 2.

Inputs	**Outputs**	**Environmental Variables**
Material	MVAKM	LinesSal
NEA	Quality	SubSal
OPEX		Complexity

Table 2. Variables of Type 1 models

In models Type 2 the variables used to describe the characteristic of the utilities are mostly in monetary units. In this sense the length of the lines in the previous model is removed and the value of the electrical assets is used as an input for the operation of the entities. Equivalently, the length of the lines exposed to salinity and the substation equipment exposed to the same effect are replaced by the total value of the assets exposed to corrosion. Furthermore, the variables included in model 1 that were already in monetary units are also included in this model: NEA and OPEX. It must be noted that all these values are in constant monetary units. The included variables are shown in Table 3.

Inputs	**Outputs**	**Environmental Variables**
EA	MVAKM	EASal
NEA	Quality	Complexity
OPEX		

Table 3. Variables of Type 2 models

5.1. **DEA Models.** In this section we make some precisions about the DEA models used for assessing the efficiency of the transmission utilities using both type 1 and 2 models. First, the model is input-oriented since this orientation allows the measurement of the efficiency related to the OPEX and the NEA, that are resources of the process. Thus for a given level of Quality, MVAKM, amount of electric conducting material and environmental variables, the most efficient utility is the one with the minimum level of OPEX and NEA. These two variables and the Quality are the only ones that are controllable by the utility. Therefore these variables are considered as discretionary, while all others are considered as non-discretionary.

The environmental variables are non-isotonic variables, since complexity and salinity are issues that make the operation of the utilities difficult, increasing their costs. These variables are included in the DEA models as output variables, such that each utility is compared with those that have at least the same level of complexity and salinity exposure. Therefore if two utilities have the same level of OPEX expenditures and NEA, the one with the greater level of complexity or salinity exposure will perform better in the evaluation.

5.1.1. *Type 1 DEA models.* Based on the model presented in Table 2 different variable sets were tried for Model 1, as can be seen in Table 4. These different sets were designed to capture the environmental aspects through different complexity variables. To include the salinity level, all models make use of a principal component built with the information of the two related variables: the length of lines and the amount of substation equipment exposed to salinity. Specifically this component captures the 88.53% of the variability of the original descriptors. On the other hand, depending on the complexity variable there are five different models DEA type 1: the first four models use the different complexity variables and the last model does not take into account complexity aspects.

Model Name	**Inputs**	**Outputs**	**Environmental Variables**	
			Salinity level	**Complexity**
Sub	Material NEA OPEX	MVAKM Quality	PCSal	SubComplex
Area				AreaComplex
Config				ConfigComplex
Net				NetComplex
NonComplex				

TABLE 4. Variables of Type 1 DEA models

5.1.2. *Type 2 DEA models.* As can be seen in Table 5, we designed five different variations for this model. All of them have the same input and output variables but differ in the environmental descriptors in a similar fashion as for model type 1.

Model Name	**Inputs**	**Outputs**	**Environmental Variables**	
			Salinity level	**Complexity**
Sub	Material NEA OPEX	MVAKM Quality	EASal	SubComplex
Area				AreaComplex
Config				ConfigComplex
Net				NetComplex
NonComplex				

TABLE 5. Variables of Type 2 DEA models

5.2. **Results for DEA models.** In this section we present the results for DEA models type 1 and 2. It is important to note that this section presents just a sample of the considerable amount of simulations that we performed in order to check the coherence of the model with the microeconomic formulation of the activity as well as the relevance of the environmental variables. We include the efficiency indexes, where 100% implies total relative efficiency and 0% total inefficiency. As the number of the utilities included is small (seven) in relation to the number of variables included in the analysis, we use a time window to make the number of utilities larger [22]. Thus we analyze the behavior of the utilities during four years in a whole set. In this set each utility in each year is analyzed as a different entity. Consequently the number of entities is larger, resulting in a better discrimination among the efficient and the inefficient entities.

It must be noted that the utilities analyzed in this work do not have a constant behavior in relation to their operating expenditures since many of their operations change every year according to long run maintenance programs. This is also true for the length of the lines and the value of the electric assets since new interconnection projects were built during the years included in the analysis, affecting these variables. The results included in table 6 show the efficiency indexes for every utility in each of the years under analysis.

The results for models type 1 and 2 are consistent and do not show significant changes in the ordering of the entities. The extreme utilities, the largest one and the smallest one, are consistently evaluated against themselves. This is due to the fact that there are no other utilities with similar characteristics in the sample. In the case of utility B, its ranking is highly dependent on the variable used to represent the complexity issues.

In all the models, the integrated utilities showed low levels of relative efficiency. This is clear in the models with physical variables as well as in those with monetary variables. Utility C showed a decreasing pattern in its efficiency evaluation, which can be explained from the increase in its OPEX in every year included in the analysis. On the other hand, utilities D and C present highly variable results along the period of observation. Nevertheless these entities do not show important changes in the variables related to the environmental issues. The changes are consequently explained by their extremely different results for the variables under their control. These results are evident among the different models and their variations.

5.2.1. *Benchmark peers for the utilities.* A relevant result from the DEA models is the information about the efficient peers against each of the utilities are compared. Table 7 presents the peers for the case of the model 1-Config. The sets of peers for each entity are highly stable for most of the models type 1 and 2. From these results it is clear that the largest and the smallest utilities are only comparable against themselves, due to the important differences between them and the other utilities included in the analysis. Nevertheless, the models give information about the behavior with time of such utilities, showing that their performance was better in some years than in others.

5.2.2. *Efficient OPEX.* Table 8 presents the efficient percentage of OPEX for each one of the utilities for every year. This percentage was computed by taking the value of the OPEX from the efficient peer in the frontier and dividing this value by the value of each utility electric asset. This gives the relative efficient value of the OPEX for each utility.

		Model type 1					Model type 2				
Utility	Year	Sub	Area	Config	Net	NonComplex	Sub	Area	Config	Net	NonComplex
A	2001	100	100	100	100	100	100	100	100	100	100
	2002	100	100	100	100	100	100	100	100	100	100
	2003	100	100	100	100	100	100	100	100	100	100
	2004	48	48	48	48	48	48	48	48	48	48
B	2001	100	77	77	77	77	92	77	77	77	77
	2002	100	96	96	97	96	100	96	96	97	96
	2003	100	100	100	100	100	100	100	100	100	100
	2004	100	100	100	100	100	100	100	100	100	100
C	2001	100	54	100	54	54	100	54	100	54	54
	2002	93	45	100	45	44	92	45	100	45	44
	2003	70	41	99	41	41	70	41	99	42	41
	2004	64	38	100	38	38	64	38	100	38	38
D	2001	100	100	100	100	100	100	100	100	100	100
	2002	42	31	30	32	30	42	31	30	32	30
	2003	31	31	31	31	31	31	31	31	31	31
	2004	45	45	45	45	45	45	45	45	45	45
E	2001	100	100	100	100	100	100	100	100	100	100
	2002	67	67	67	67	67	67	67	67	67	67
	2003	68	68	68	68	68	68	68	68	68	68
	2004	72	72	72	79	72	72	72	100	72	72
F	2001	100	100	100	100	100	100	100	100	100	100
	2002	100	100	100	100	100	100	100	100	100	100
	2003	100	100	100	100	100	100	100	100	100	100
	2004	100	100	100	100	100	100	100	100	100	100
G	2001	89	100	89	100	89	79	77	77	77	77
	2002	100	100	100	100	100	100	100	100	100	100
	2003	100	100	100	100	100	100	100	100	100	100
	2004	100	100	100	100	100	100	100	100	100	100

TABLE 6. Technical efficiency (%) for transmission utilities for types 1 and 2 DEA models

Utility	**2001**	**2002**	**2003**	**2004**
A	A2001 (100%)	A2002 (100%)	A2003 (100%)	A2001 (100%)
B	E2001 (80.39%) F2003 (4,45%) B2004 (15,16%)	E2001 (93,95%) F2003 (5,19%) B2004 (0,86%)	E2001 (91,23%) F2003 (5,05%) B2004 (3,72%)	B2004 (100%)
C	C2001 (100%)	C2002 (100%)	C2002 (61,4%) C2004 (38,6%)	C2004 (100%)
D	D2001 (100%)	E2001 (99,7%) F2002 (0,3%)	E2001 (99,7%) F2002 (0,3%)	E2001 (99,7%) F2002 (0,3%)
E	E2001 (100%)	E2001 (100%)	E2001 (100%)	E2001 (100%)
F	F2001 (100%)	F2002 (100%)	F2003 (100%)	F2004 (100%)
G	E2001 (5,08%) F2002 (0,37%) G2002 (69,28%) G2003 (24,31%) G2003 (0,96%)	G2002 (100%)	G2003 (100%)	G2004 (100%)

TABLE 7. Benchmark Peers for DEA model 1-Config

Utility	Year	Model type 1					Model type 2				
		Sub	Area	Config	Net	NonComplex	Sub	Area	Config	Net	NonComplex
A	2001	2,42	2,42	2,42	2,42	2,42	2,42	2,42	2,42	2,42	2,42
	2002	5,26	5,26	5,26	5,26	5,26	5,26	5,26	5,26	5,26	5,26
	2003	3,76	3,76	3,76	3,76	3,76	3,76	3,76	3,76	3,76	3,76
	2004	2,42	2,42	2,42	2,42	2,42	2,42	2,42	2,42	2,42	2,42
B	2001	2,98	2,30	2,30	2,31	2,30	2,75	2,30	2,30	2,31	2,30
	2002	3,02	2,90	2,90	2,92	2,90	3,02	2,90	2,90	2,92	2,90
	2003	2,75	2,74	2,74	2,75	2,74	2,75	2,74	2,74	2,75	2,74
	2004	2,65	2,65	2,65	2,65	2,65	2,65	2,65	2,65	2,65	2,65
C	2001	1,43	0,76	1,43	0,76	0,76	1,43	0,76	1,43	0,76	0,76
	2002	1,59	0,76	1,72	0,76	0,76	1,58	0,76	1,72	0,76	0,76
	2003	1,29	0,76	1,83	0,76	0,76	1,29	0,76	1,83	0,76	0,76
	2004	1,30	0,76	2,02	0,76	0,76	1,30	0,76	2,02	0,76	0,76
D	2001	2,16	2,16	2,16	2,16	2,16	2,16	2,16	2,16	2,16	2,16
	2002	1,28	0,94	0,90	0,98	0,90	1,28	0,94	0,90	0,98	0,90
	2003	0,89	0,89	0,89	0,89	0,89	0,89	0,89	0,89	0,89	0,89
	2004	0,89	0,89	0,89	0,89	0,89	0,89	0,89	0,89	0,89	0,89
E	2001	1,37	1,37	1,37	1,37	1,37	1,37	1,37	1,37	1,37	1,37
	2002	1,37	1,37	1,37	1,37	1,37	1,37	1,37	1,37	1,37	1,37
	2003	1,40	1,40	1,40	1,40	1,40	1,40	1,40	1,40	1,40	1,40
	2004	1,25	1,25	1,25	1,37	1,25	1,25	1,25	1,74	1,25	1,25
F	2001	1,70	1,70	1,70	1,70	1,70	1,70	1,70	1,70	1,70	1,70
	2002	1,49	1,49	1,49	1,49	1,49	1,49	1,49	1,49	1,49	1,49
	2003	2,26	2,26	2,26	2,26	2,26	2,26	2,26	2,26	2,26	2,26
	2004	2,36	2,36	2,36	2,36	2,36	2,36	2,36	2,36	2,36	2,36
G	2001	2,78	3,12	2,78	3,12	2,78	2,48	2,41	2,41	2,41	2,41
	2002	2,85	2,85	2,85	2,85	2,85	2,85	2,85	2,85	2,85	2,85
	2003	2,95	2,95	2,95	2,95	2,95	2,95	2,95	2,95	2,95	2,95
	2004	2,80	2,80	2,80	2,80	2,80	2,80	2,80	2,80	2,80	2,80

TABLE 8. Efficient OPEX(%) as a percentage of the electrical assets for DEA models

Table 9 shows the average for the OPEX percentage for every model. It can be seen that the efficient OPEX as a percentage of the electrical assets may be used to divide the utilities in two groups: the integrated and the non integrated ones. The first group shows an average OPEX percentage lower than 2%, while the second group shows an average percentage above this value. The utilities with the largest and the smallest scale are included in the last group. In this group are also the utilities with a similar incidence in their operation due to the environmental variables.

A separated treatment of the utilities for the OPEX remuneration is proposed from these results. This is clearly a consequence of the different structures of the utilities, which imply different levels of OPEX. Nevertheless, it would be extremely expensive for the regulator to design a different remuneration scheme for each different utility in the market. From these results, the utilities can be grouped as indicated to develop a different remuneration for integrated and non-integrated utilities. Furthermore, the largest utilities in the sample receive a lower OPEX

	Model type 1					Model type 2				
Utility	Sub	Area	Config	Net	NonComplex	Sub	Area	Config	Net	NonComplex
A	3,47	3,47	3,47	3,47	3,47	3,47	3,47	3,47	3,47	3,47
B	2,85	2,65	2,65	2,66	2,65	2,79	2,65	2,65	2,66	2,65
C	1,40	0,76	1,75	0,76	0,76	1,40	0,76	1,75	0,76	0,76
D	1,30	1,22	1,21	1,23	1,21	1,30	1,22	1,21	1,23	1,21
E	1,35	1,35	1,35	1,38	1,35	1,35	1,35	1,47	1,35	1,35
F	1,95	1,95	1,95	1,95	1,95	1,95	1,95	1,95	1,95	1,95
G	2,84	2,93	2,84	2,93	2,84	2,77	2,75	2,75	2,75	2,75

Table 9. Average efficient OPEX percentage(%) for model type 1 and 2

percentage than the smallest ones, which is an alternative way to take into account the different scales of the utilities for remuneration purposes.

5.2.3. *Productivity indexes.* A well-known method to compute the productivity indexes from DEA evaluations is the Malmquist index [7, 24]. For the computation of these indexes it is necessary to have at least two time periods to observe the change in the frontier as well as the change in the performance of each entity. Because of the reduced number of entities (7) and years of information available (4), we built two observation blocks. The first one includes the behavior of the entities in the first three years and the second one the data from the three last years; with this division, the number of entities in each window is large enough to avoid discrimination problems in the model. Nevertheless, the so called frontier-shift is not adequately captured since the observations of the two years in the middle are included in both time windows. This issue makes difficult the interpretation of the results and consequently their applicability. In order to make use of these indexes the sample size in every year should be large enough to allow the adequate behavior of the DEA models.

5.2.4. *Efficient OPEX with constant return to scale.* All the results presented in the previous section where computed assuming variable returns to scale. This approach allows that firms with increasing or decreasing returns to scale can still be rated as efficient, focusing the analysis on pure technical efficiency [7, 23]. Nevertheless the regulator may be also interested in scale efficiency as well as in pure technical efficiency. This information might be used by the regulator as long run goals in order to provide signals to the firm to move to the most productive scale size [23]. Taking this into account we compute efficiency indexes assuming that the firms show constant returns to scale. The average of these indexes over the different model configurations are shown in Table 10. These indexes are always lower or equal than those computed under the variable returns assumption [8] and this difference shows how important is the scale inefficiency for each entity. This information can be used by the regulator to identify the firms with largest deviations from the most productive scale size and to define long run goals in OPEX efficiency.

5.3. **SFA Models.** The final basic SFA model presented in this article follows the microeconomic model for the transmission activity previously presented. The dependent variable is the natural logarithm of the power capacity (MVAKM). The independent variables are those of the model type 1 (see Table 2): the amount of electric conducting material (Material), non-electrical assets (NEA) and operating

Utility	1 - Sub	1 - Config	2 - Sub	2 - Config
A	2,42	2,42	2,42	2,42
B	1,72	1,52	1,91	1,91
C	0,79	0,80	0,79	0,76
D	0,90	0,89	0,90	0,90
E	1,38	1,38	1,38	1,38
F	1,95	1,95	1,95	1,95
G	2,93	2,83	2,75	2,75

Table 10. Average efficient OPEX percentage (%) for model type 1 and 2 with constant return to scale

expenditures (OPEX). Furthermore, the environmental factors that were included in the SFA model are those related to salinity: bays and lines exposed to salinity (SubSal and LinesSal, respectively). Although the number of evaluated utilities is only seven, as in DEA models the analysis was made from 2001 to 2004 using a time window, so the firms were arranged successively for each period obtaining 24 observations. This procedure have the advantage that allow the detection of changes in technical efficiency not only between the utilities but within each one throughout the horizon of four years.

As it was mentioned before the basic idea of SFA models is the estimation of the stochastic production frontier. Nevertheless, before using SFA the evaluation of some conditions should be done. Thus the existence and gravity of multicollinearity are checked and the basic assumptions of heteroscedasticity and autocorrelation are verified using Ordinary Least Squares (OLS). In addition, it is necessary at this stage to check whether the skewness coefficient is negative and to test if the residuals are not symmetrically distributed, so that SFA might be applied.

With the previously mentioned input, environmental and output variables, the existence of multicollinearity between them was revealed using OLS. This first obstacle was solved using the first two principal components of the three inputs: Material, NEA and OPEX, named PC1 and PC2[1]. The first one represents the 96.07% of the set variability and the second one represents, accumulated with the previous one, the 99.12% of the set variability.

Using the first two principal components the following production function was stated (in this case a semi-logarithmic function):

$$\ln(\mathrm{MVAKM})_i = \beta_1 + \beta_2 \mathrm{PC1}_i + \beta_3 \mathrm{PC2}_i + \beta_4 \mathrm{SubSal}_i + \beta_5 \mathrm{LinesSal}_i + \epsilon_i. \quad (14)$$

The procedure continues analyzing the basic assumptions of the model using OLS trying to detect if heteroscedasticity and autocorrelation are present in the estimates. A certain heteroscedasticity associated to the first component was detected, thus SFA was applied to correct it. Notwithstanding slight differences in the estimates, the results of the hierarchical order of the transmission utilities turned out identical to the situation without any correction. That is the reason to present the results without any adjustment for heteroscedasticity.

Finally, the behavior of the residuals was studied in this first step by estimating their skewness coefficient (Skewness = -0.77) and checking if the residuals distribution was not symmetric. In this last case the null hypothesis that the distribution

[1] $\mathrm{PC1} = 0.582 \cdot \mathrm{Material}_i + 0.579 \cdot \mathrm{OPEX}_i + 0.571 \cdot \mathrm{NEA}_i$ and $\mathrm{PC2} = -0.282 \cdot \mathrm{Material}_i - 0.515 \cdot \mathrm{OPEX}_i + 0.809 \cdot \mathrm{NEA}_i$, $\forall i = 1, \ldots, 24$.

was normal was tested. Tables 11 (a) and (b) show different statistics which exhibit the rejection of the null hypothesis. These results validate the final model presented.

Test	**Statistic**		**DF**	**p Value**	
Kolmogorov-Smirnov	D	0.2243		Pr>D	<0.010
Cramer-von Mises	W-Sq	0.1883		Pr>W-Sq	0.007
Anderson-Darling	A-Sq	1.1668		Pr>A-Sq	<0.005
Chi-Square	Chi-Sq	9.3853	2	Pr>Chi-Sq	0.009

(a) Goodness-of-Fit Tests for Normal Distribution

Equation	**Test Statistic**	**Value**	**Prob**
lx	Shapiro-Wilk W	0.89	0.0067
System	Mardia Skewness	3.06	0.0804
	Henze-Zirkler T	2.16	0.0306

(b) Normality Test

Table 11. Rejection of null hypothesis

An additional analysis about the impact of the salinity variable was performed using the following production function, which is the original function (eq. 14) without that environmental variable. All the analyses of assumptions were also done for this model.

$$\ln(\text{MVAKM})_i = \beta_1 + \beta_2 \text{PC1}_i + \beta_3 \text{PC2}_i + \epsilon_i \tag{15}$$

Consequently the were established two SFA models to perform the efficiency evaluation: model 1 (equation 14) and model 1-nonSal (equation 15).

5.4. **Results for SFA models.** Once the production function is defined, noise (symmetric) and efficiency (non-negative) perturbations are added to the function and a probabilistic distribution is assumed for these efficiency perturbations (in this case the half-normal). The parameters of interest for the model 1 are estimated using maximum likelihood and are presented in Table 12.

	Coefficient	Standard Error	z	$P > \|z\|$	95% confidence interval	
PC1	0,7428	0,0001	6.573,6700	0	0,74	0,7430504
PC2	-0,6517	0,0001	-5.577,1700	0	-0,65	-0,6515074
SubSal	-9,21E-04	1,00E-05	-9,21E+01	0	-9,41E-04	-9,02E-04
LinesSal	0,0010	0,0000	523,35	0	0,00	0,0009844
Constant	13,1116	0,0001	.	0	13,11	13,11184
/lnsig2v	-32,3757	330,6993	-0,1000	0,922	-680,53	615,7829
/lnsig2u	0,5423	0,2673	2,0300	0,042	0,02	1,066074
σ_v	9,33E-08	1,54E-05			1,70E-148	5,20E+133
σ_u	1,3114	0,1752			1,01	1,7041
σ_2	1,7199	0,4597			0,82	2,620784
λ	1,41E+07	1,75E-01			1,41E+07	1,41E+07
Likelihood-ratio test of $\sigma_u = 0$: chibar2(01) = 16.48. Prob $\geq$ chibar2 = 0.000						

Table 12. SFA Parameters.

As can be seen, the coefficients associated to the explanatory variables are all significant. The hypothesis test of absence of technical efficiency in the model is measured through the null hypothesis that the standard deviation of the technical efficiency term is zero ($\sigma_u = 0$ in the table). The associated p-value (Prob$\geq$ chibar2 = 0.000) rejects the null hypothesis with a good level of significance against the alternative of the presence of technical efficiency model.

With the estimated parameters, the evaluation of the relative technical efficiency for each utility was done for models 1 and 1-nonSal. The SFA models performed an analysis of the whole transmission activity; nevertheless, the obtained results can not be seen as an input reduction that the utilities have to do in order to become efficient. They give information about the utilities relative position, which is presented in the Table 13 for the two SFA models.

First of all, from Table 13 utilities can be divided in two groups: those with relative technical efficiencies quite close to the frontier and those companies far away from the frontier. The first ones have technical efficiency above 0.9 (i.e. utilities B, G, C and F with the exception of F in the fourth period), and the other ones below 0.40 (i.e. utilities D, E and A). Utility A has the lowest technical efficiency. This utility is the smallest one and this fact can be the reason of its evaluation since it has a relative small output compared to its relative high inputs.

On the other hand, we can perform an analysis of the performance of the utilities through the four years. Utility F had the most dramatic decline: it was in the most efficient group in 2001 but came down to very worrisome efficiency levels in the quadrennium. In addition, a comparison between the two models allows an analysis about the impact of the salinity level on the utilities performance. In particular, utility G obtained a better technical relative efficiency when this variable is included in the model since it is the utility with highest salinity levels (see Table 1).

Utility	Year	1	1-nonSal	Utility	Year	1	1-nonSal
A	2001	0,0490	0,0467	E	2001	0,3172	0,3029
	2002	0,0486	0,0460		2002	0,3145	0,2983
	2003	0,0482	0,0463		2003	0,3122	0,2982
	2004	0,0481	0,0460		2004	0,3119	0,3002
B	2001	1,0000	0,9689	F	2001	1,0000	0,5705
	2002	1,0000	0,9744		2002	0,9904	0,7169
	2003	0,9776	1,0000		2003	0,3769	0,3570
	2004	0,9692	0,9988		2004	0,3279	0,3291
C	2001	1,0000	0,8235	G	2001	1,0000	0,8670
	2002	0,9542	0,8171		2002	0,9630	0,9118
	2003	0,9391	0,8070		2003	0,9397	0,9148
	2004	0,9177	0,7943		2004	0,9095	1,0000
D	2001	0,3802	0,3385				
	2002	0,3787	0,3276				
	2003	0,3653	0,3301				
	2004	0,3644	0,3417				

TABLE 13. Technical efficiency for transmission utilities for SFA model

5.5. **Regulatory use of efficiency measurements.** Regulatory reforms have been introduced to provide utilities with the right incentives to improve efficiency in capital and operating expenditures and to allow consumers to benefit from the efficiency gains. Incentive regulation schemes use benchmarking methods such as DEA and SFA. As established by Jamasb and Pollit [13], the primary function of this work is to serve as a decision-support tool. The value of the efficiency estimates obtained using DEA and SFA relies on the useful information they provide to the regulator to design the right incentives when facing the determination of prices that regulated firms are allowed to charge.

Determination of the efficiency indices is done by taking into account several aspects of the firms' production processes. In the case of SFA this is done through the specification of a production function that fits the observable combination of inputs and outputs. Even though in DEA there is no such specification, the weights of the input and output variables in the evaluation of each firm are assigned such that each firm receives the best [8]. These characteristics imply that the regulator does not affect the efficiency results but these are given by the selected variables and the data. Naturally, the reliability of the results is closely related to the availability of adequate sources of information. Regulatory accounting is one way to ensure this.

As it was pointed out, identification and selection of relevant variables is a difficult task. In general, the firm's processes are too complex to be completely described with a small variable set. As suggested by Thanassoulis [23, 22], in this study we tried different combinations of variables to capture their influence on the efficiency measurements. We found that the results obtained with the different variable sets were stable in most of the cases using both DEA and SFA. Another way to determine how reliable the efficiency estimates are, is the use of bootstrapping [21]. With this technique, it is possible to construct confidence intervals of the efficiency indices [12, 21, 25]. However, due to the stability of our results under the diverse alternatives, we do not have to resort to bootstrapping techniques to evaluate reliability of efficiency estimates. Additionally, some of the estimated efficiencies might be small enough to require large reductions of inputs (in this case OPEX) in some of the firms to become efficient. The regulator then should use the indices as input information to fix short, mid and long run goals for the different firms.

6. **Conclusions.** In this study a methodological proposal to measure efficient OPEX of electricity transportation utilities was developed and applied to the Colombian case. The first step was the analysis of the electric power transmission in economic terms as a black box with inputs and outputs. A *Cobb-Douglas* production function was found. This function exhibits constant returns to scale in voltage and decreasing returns in amount of conductor and power losses.

Based on this production function different types of models to measure relative efficiency were defined. For each model the set of input and output variables was defined. Input variables were CAPEX (electrical and non electrical assets) and OPEX. Some expenses like local taxes, pensions and terrorist attacks were excluded to homogenize the sample. Output variables represent utility product, i.e. the transported energy, with adequate quality levels. Therefore, power capacity and availability factors were used.

Since the evaluated utilities operate in different surroundings, besides the input and output variables some environmental factors were considered. Those variables are beyond the utilities control and may restrict the way in which factors are combined or may affect firm productivity. Among these variables we included assets and their value exposed to salinity and complexity of the transmission systems. Complexity of the firms was represented by configuration of substations, number of bays per substation, number of substations per kilometer and operation area of the companies. It is important to point out that it was not possible to build a variable that reflects the network and equipment accessibility. The keraunic level was not included in the environmental set because it must be considered at design time.

Once the microeconomic model and variables were defined we used DEA and SFA to measure utilities efficiency. DEA models measure the relative efficiency in which OPEX and NEA are combined by utilities to transport electric power with a given availability level, amount of conducting material, and environmental variables. For this benchmarking technique we propose two types of input-oriented models that differ in the electric assets variable. One uses them in physical units and the other one in monetary units. The results for these two models were consistent, which suggest that remuneration can be done distinguishing among utilities, as long as they present very different structures and environments.

In order to deal with the dimensionality problems caused by having only seven firms under evaluation, a time window of four years was used. In this way the discriminatory power of the DEA models is improved, providing meaningful results. Furthermore, an analysis of the change in the productivity was tried by using Malmquist indices. Nevertheless the use of the time window hinders the interpretation of the frontier shift effect. This is so because some entities are part of the two time windows built. This analysis would be possible with a data set including more time periods, as each time window could be constructed large enough to avoid dimensionality problems of the DEA technique. Additionally DEA models under constant returns to scale, that take into account the optimal size of the company in the technical efficiency measurement, can be seen as a good long term reference for the desirable efficiency level. Furthermore, the firms are not able to change their productive scale in the short term and, in many cases, this has been inherited from the time when the firm was part of the public sector.

SFA models performed an analysis of the complete transmission activity following its production function. Its results yield relevant information about the relative behavior of the companies and allow an analysis about the effect of environmental variables, e.g. salinity. Even though the proposed microeconomic model is a Cobb-Douglas function in SFA we obtained better fittings using a semi-logarithmic function. For this technique a significant number of models were estimated with inputs in physical and monetary variables and one single output. The first two principal components of the factors (EA, NEA and OPEX) were used as inputs, which explained over 99% of its variability. The results allows the comparison among firms as well as the analysis of the performance of the utilities through the observation period.

This study presents a set of models that allow the regulator to establish efficiency references or targets by using performance comparisons among electricity transmission utilities. Satisfactory results were obtained, despite the few international references to successful studies, the reduced sample of transmission utilities in Colombia, the high heterogeneity among firms and the common knowledge that considered unfeasible the use of techniques like DEA and SFA to estimate efficient frontiers for electric energy transmission and OPEX. Regulator decisions must be supported on objective technical studies and tools, and models are a fundamental assistance to such purpose. It is also important to point out that any work measuring efficiency must count on reliable information with a high disintegration level. An effort on regulatory accounting is necessary in all countries opting for market liberalization.

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