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Assessing the Performance of Electric Distribution Companies Using SFA and DEA Methods

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Abstract: This paper proposes non-parametric and parametric approaches to measure the performance of electric distribution companies. Two different cost frontier models are applied and their estimators are: (1) in which a cost function is estimated to identify appropriate cost variables and efficiency frontiers are computed using stochastic frontier analysis (SFA), (2) data envelopment analysis (DEA). One of the important steps in the design of the benchmarking model is to select input and output variables. Principal component analysis is used to reduce the number of input and output variables under study. These methods are applied to 41 Iranian electric distribution companies. To analyze the sensitivity of efficiency estimates, a correlation analysis of different estimations is also carried out. The correlation tests show a weak consistency between the obtained results from different methods.

Key words: Benchmarking, data envelopment analysis, principal component analysis, stochastic frontier analysis.

INTRODUCTION

During recent years, regulators have tried to make competitive condition and to grant distribution companies to private sectors. Most of the regulation schemes used in practice are based on benchmarking that is, measuring a company's efficiency against a reference performance (Farsi *et al.*, 2007). Benchmarking is a valuable tool in energy policy analysis and to promote efficiency improvement in distribution companies. Efficiency benchmarking can be used to put up a pseudo competition between the distribution companies, since such companies do not face normal competition due to their natural monopoly position. Various methods have been developed for estimating efficiency scores of electricity distribution companies. The main frontier benchmarking methods are Data Envelopment Analysis (DEA), Corrected Ordinary Least Square (COLS), and Stochastic Frontier Analysis (SFA). DEA is based on linear programming while COLS and SFA are statistical techniques (Jamasb and Pollitt, 2001). The advantages and disadvantages of using DEA over SFA to measure efficiency are well known in the literature. Non-statistical approaches such as DEA have the disadvantage of deterministic nature and no easy statistical inference, but have the advantages of the possibility to implement it with a small data set and requiring few assumptions about the underlying technology. SFA models on the other hand have the attraction of allowing for statistical noise, but have the disadvantage of requiring strong assumptions as to the form of the frontier (Jacobs, 2000). Mortimer (2002) reviewed empirical results drawn from published simulation studies with the purpose of highlighting the pros and cons of competing methods for frontier estimation and efficiency measurement. A summary review of the 41 real-world DEA versus SFA comparisons identified in the literature is provided by Mortimer (2002). None of these articles demonstrated that either DEA or SFA have an absolute advantage over their competitors. There is a number of articles describe the use of DEA and SFA in the assessment of electricity distribution. Filippini *et al.* (2004) estimated a cost frontier function on a sample of Slovenian electricity distribution utilities over the 1991–2000 period. Their results showed that Slovenian distribution companies are cost inefficient. They have also proved the presence of increasing returns to scale with most utilities not achieving the minimum efficient scale. Thus, the Slovenian regulatory authority should consider how to induce mergers of small electricity distribution utilities into larger units. Kopsakangas-Savolainen and Svento (2008) examined the cost-effectiveness of Finnish electricity distribution utilities. They estimated several panel data stochastic frontier specifications using both Cobb–Douglas and Translog model specifications and concluded that the random effects models produce very similar inefficiency scores and rankings.

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Lavado (2004) computed the efficiency of electric cooperatives (ECs) in Philippines using SFA and DEA. The efficiency of each cooperative was then ranked and compared for consistency checks. The SFA reports that on the average, ECs are 34 percent away from the cost frontier while that of DEA estimates 42 percent. Hirschhausen *et al.* (2006) applied non-parametric and parametric tests to assess the efficiency of electricity distribution companies in Germany. Relatively high correlations were found between the two methods and East German utilities featured a higher level of average efficiency than their West German counterparts. Jamasb and Pollit (2003) applied parametric and non-parametric approaches to 63 electric distribution companies in Europe and concluded that there are substantial variations in estimated efficiency scores. Estache *et al.* (2004) computed efficiency scores of South America's main electric distribution companies. The results showed weak consistency between parametric and non-parametric methods. In recent years, DEA has become one of the preferred benchmarking methods. Resende (2002) used DEA model for evaluation of Brazilian electricity distribution companies. The study discussed potential and difficulties with the implementation of yardstick Schemes. Edvardsen and Forsund (2003) studied the performance of 122 electricity distributors in the Denmark, Finland, Norway, Sweden and Netherlands in 1997 using DEA and Malmquist index. They found that Finnish electricity distributors have the most productivity among other countries. The DEA methodology is used to determine the efficiency of the 50 largest (based on megawatt-hour sales) electric distribution utilities in the U.S by Pahwa *et al.* (2003). The research considered distribution systems losses, distribution operation and maintenance expenses, distribution capital additions expenses, distribution line transformers and distribution lines as inputs. The results of paper include performance efficiency, gaps in inputs and outputs of inefficient utilities, sensitivity-based classification of utilities, and a gap report of utilities. Chien *et al.* (2003) applied a DEA study to measure the relative efficiencies of 17 service centers of the electricity distribution district of Taiwan Power Company (TPC). They compared the efficiencies of service centers by three outputs (i.e., total number of customers, distribution network, and transformer capacity) and two inputs (i.e., total number of staff and general equipment) and suggested the specific improvement directions for the corresponding inefficient districts by district reorganization. Sanhueza *et al.* (2004) applied a DEA to determine the distribution added value in Chile and for increasing the reliability of the obtained results, a bootstrap technique was applied. A summary review of previous studies is provided in a Table 1.

Input - Output Selection:

Efficiency evaluation is highly dependent on input and output selection. According to Keeney and Raiffa (1993) a desirable set of measurement factors should be complete, decomposable, operational, nonredundant, and minimal (Lo *et al.*, 2001). Inclusion of more variables can increase the efficiency of an inefficient utility and very large number of variables could make all the utilities efficient and make the analysis meaningless. Therefore, only the most significant variables must be included. The existing literature on this topic uses a wide range of input and output variables for modeling of electric distribution companies. Therefore, there is not a universally agreed set of input and output variables for define an appropriate model of DEA to measure the efficiency of electric distribution companies. Jamasb and Pollitt (2001) reviewed published papers which different input and output variables are used to model electric distribution companies. We developed a three-stage process to select appropriate variables. At the first stage, we gathered all variables that influence the costs of distribution network. At this stage, we discussed with authority expert as well as industry expert. At the second stage, we divided variables into input, output and environmental variables. Finally, significant variables were selected based on the expert and authority groups' opinion. Table 2 presents the key input, output and environmental variables were chosen in the analysis.

Structure of the Methods:

***Method 1: the Stochastic Cost Frontier Model*:**

Stochastic frontier analysis is a parametric method used to estimate the efficient frontier and efficiency scores. The theory of stochastic frontier production functions was originally proposed by Aigner *et al.* (1977) as well as Meeusen and van den Broeck (1977). This approach requires the definition of an explicit production or cost function and recognizes the possibility of stochastic errors. This is caused by an underlying assumption splitting the error term into a stochastic residuum (noise) and an inefficiency-term. The statistical noise is assumed to follow a normal distribution, and the inefficiency term u_i is generally assumed to follow either a half-normal or truncated normal distribution.

Hence, the mathematical expression of the production process is (Hirschhausen *et al.* (2006)):

Table 1: A summary review of previous studies

Author	Data	Inputs	Outputs	Method
Filippini *et al.* (2004)	sample of Slovenian electricity distribution utilities over the 1991–2000 period	prices of capital prices of labor customer density load factor	total number of kWh delivered	cost frontier function
Kopsakangas-Savolainen and Svento (2008)	Finnish electricity distribution utilities	price of capital labor price load factor	total distributed quantity of electricity	several panel data stochastic frontier
Lavado (2004)	electric cooperatives (ECs) in Philippines	total operating and maintenance expenditure distribution network transformer capacity	total Sales	SFA DEA
Hirschhausen *et al.* (2006)	electricity distribution companies in Germany	labor grid size peak load	units sold the number of customers the inverse density index	Parametric non-parametric
Jamasb and Pollit (2003)	63 electric distribution companies in Europe	operating expenditures total expenditures network length distribution/transmission losses non-discretionary inputs network length	units delivered no. of customers network length	Parametric non-parametric
Estache *et al.* (2004)	South America's main electric distribution companies	number of employees distribution network transformer capacity	total sales	Parametric non-parametric
Resende (2002)	Brazilian electricity distribution companies	transformers' capacity network extension number of employees	concession area number of consumers industrial sales of electric energy non-industrial sales of electric energy	DEA
Edvardsen and Forsund (2003)	122 electricity distributors in the Denmark, Finland, Norway, Sweden and Netherlands in 1997	loss total operating and maintenance costs replacement value total lines	energy delivered number of customers	DEA Malmquist index
Pahwa *et al.* (2003)	50 largest electric distribution utilities in the U.S	distribution systems losses distribution operation and maintenance expenses distribution capital additions expenses distribution line transformers distribution lines	distribution system peak load retail sales retail customers	DEA
Chien *et al.* (2003)	electricity distribution district of Taiwan Power Company (TPC)	total number of staff general equipment	number of customers distribution network transformer capacity	DEA
Sanhueza *et al.* (2004)	electricity distribution in Chile	distribution added value total kilometers of lines energy that has not been billed number of workers salaries	total energy sold coincident power during peak hours number of customers	DEA

The main purpose of this paper is to propose non-parametric and parametric approaches to measure the efficiency of electric distribution companies and study the sensitivity of different methods for assessment of the efficiency of companies.

Table 2: Input, output and environmental variables

output	inputs	Environmental variables
Quantity of energy supplied(ENSUPP)	Total asset(M$)(TOTAST) Number of staff(NO.ST) Operation expenditure(M$)(OPEXP) Distribution network (Km)(DISNET) Transformer capacity(MVA)(TRANSCAP) Energy loss rate(%)(ENLOSS)	Service area (Km^2) (SAREA) Peak load (MW)(PLOAD) Density of customers (C/Km)(DENS)

$$Y_i = x_i\beta + (v_i - u_i) \quad i = 1,...,n \tag{1}$$

Where

Y_i : is output (or the logarithm of output) of the i-th firm,

x_i : is a $k\times1$ vector of input quantities of the i-th firm,

β: is a vector of parameters to be estimated,

v_i : are random variables which are assumed to be i.i.d. $N(0,\sigma_v^2)$, independent of u_i .

u_i : are non-negative random variables usually assumed to be half normal distributed, thereby accounting for individual technical inefficiency.

The SFA technique can be used to predict efficiency scores of models involving multiple outputs by estimating input distance functions (see Coelli and Perelman, 1999). Translog form of input distance function is shown in Eq. (2).

$$\begin{aligned}-\ln(x_{Ki}) &= \alpha_0 + \sum_{m=1}^{M}\alpha_m \ln y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln y_{mi}\ln y_{ni}\\ &+\sum_{n=1}^{M}\sum_{k=1}^{K-1}\beta_k \ln(\frac{x_{ki}}{x_{Ki}}) + \frac{1}{2}\sum_{k=1}^{K-1}\sum_{l=1}^{K-1}\beta_{kl}\ln(\frac{x_{ki}}{x_{Ki}})\ln(\frac{x_{li}}{x_{Ki}})\\ &+\sum_{k=1}^{K-1}\sum_{m=1}^{M}\delta_{km}\ln(\frac{x_{ki}}{x_{Ki}})\ln y_{mi} - \ln D_{Ii}\end{aligned} \tag{2}$$

$M(m = 1,..., M)$ and $K(k = 1,..., K)$ are the number of outputs and inputs, respectively. -InD_{Ii} can be interpreted as error term which reflects the difference between the observed data realizations and the predicted points of the estimated function. -InD_{Ii} is re-written as v_i - u_i. The relationship between technical efficiency and -u_i is defined as TE_i = exp (-u_i) (Kumbhakar and Lovell, 2000) where TE_i represents the technical efficiency. The efficiency scores are bounded between 0 and 1; a value of 1 indicating relative efficiency.

Coelli *et al*, (1999) suggest that the literature offers two alternative approaches to consider environmental factors. In case 1, they consider that the environmental factors influence the shape of the technology and hence that these factors should be included directly into the production functions as regressors. It is assumed that in this case each firm faces a different production frontier. In case 2, environmental variables are assumed to directly affect technical efficiency. In this case, the environmental factors have an influence only on the distance that separate each firm from the best practice function. To account for environmental influences in SFA, we use environmental variables directly into the production functions as regressors in order to predict how companies would be ranked if they were able to operate in equivalent environments. Once developed and taking into account the variables considered in the application, the function to be estimated is:

$$\begin{aligned}-\ln(OPEXP_i) &= \alpha_0 + \alpha_1\ln(ENSUPP_i) + \beta_1\ln(\frac{No.ST_i}{OPEXP_i}) + \beta_2\ln(\frac{ENLOSS_i}{OPEXP_i})\\ &+\frac{1}{2}\beta_{11}\ln(\frac{No.ST_i}{OPEXP_i})^2 + \frac{1}{2}\beta_{22}\ln(\frac{ENLOSS_i}{OPEXP_i})^2 + \frac{1}{2}\beta_{12}\ln(\frac{No.ST_i}{OPEXP_i})\ln(\frac{ENLOSS_i}{OPEXP_i})\\ &+\delta_{11}\ln(\frac{No.ST_i}{OPEXP_i})\ln(ENSUPP_i) + \delta_{21}\ln(\frac{ENLOSS_i}{OPEXP_i})\ln(ENSUPP_i)\\ &+\gamma_1\ln(SAREA_i) + \gamma_2\ln(PLOAD_i) + \gamma_3\ln(DENS_i) - \ln D_{Ii}\end{aligned} \tag{3}$$

Method 2: Conventional Data Envelopment Analysis:

Data Envelopment Analysis (DEA) is a non-parametric method that calculates the efficiency in a given set of decision-making units (DMUs). DEA measures the efficiency of a DMU with multiple inputs and outputs by ratios of weighted outputs to weighted inputs (Charnes *et al*. (1978)). Assuming that there are *n* DMUs, each with *m* inputs and *s* outputs, the efficiency scores can be computed as a solution to the following linear programming (LP) problem:

$$\min \theta_o \tag{4}$$

Subject to:

$$\theta_o x_{io} \geq \sum_{j=1}^{n} \lambda_j x_{ij}, \quad i = 1, 2, \ldots, m \tag{5}$$

$$y_{ro} \leq \sum_{j=1}^{n} \lambda_j y_{rj}, \quad r = 1, 2, \ldots, s \tag{6}$$

$$\lambda_j \geq 0, \quad j = 1, 2, \ldots, n \tag{7}$$

Where,

θ_o : Overall efficiency (OE) of DMUs,

x_{kj} : Amount of input *k* utilized by DMU *i*,

y_{kj} : Amount of output *k* produced by DMU *i*,

$\lambda_1, \ldots, \lambda_n$: The weights for the inputs and outputs of the *n* DMUs.

In this method, all environmental variables are considered as inputs, so we will have six inputs (energy loss rate, number of staff, operation expenditure, service area, peak load and number of customers per distribution network) and one output (Quantity of energy supplied).

Number of customers per distribution network is an undesirable input and needs to be increased rather than decreased to improve the efficiency. To overcome this problem, we used the method proposed by Seiford and Zhu (2002). We multiply each undesirable input by "-1" and then find a proper translation vector *k* to let all negative undesirable inputs be positive. The number of customers per distribution network is converted by

$$\bar{x}_{kj} = x_{kj} + k \succ 0 \tag{8}$$

Where x_{kj} is the number of customers per distribution network, *k* let all negative undesirable inputs be positive and $\bar{x}_{kj}$ is the transformed number of customers per distribution network.

Application:

The Iranian electricity distribution companies, established in 1992, are public and act under the supervision of TAVANIR Company which is responsible for electricity generation, transmission and distribution in Iran and acts under the supervision of Ministry of Energy. During the recent two decades, Ministry of Energy has tried to grant economic activities and service rendering electricity distribution companies to private sectors. In order to demonstrate the performance of the proposed methods, we have used the information of Iranian Distribution Companies (IDCs) as a case study and an efficiency score is calculated for each company. There are 41 electricity distribution companies in Iran and the information of these companies is available at: www.tavanir.org. Table 3 presents the summary statistics of IDCs' variables.

Variable Selection:

In this study principal component analysis (PCA) is used to reduce the number of variables under study. PCA is widely used in multivariate statistics such as factor analysis. PCA involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components. The mathematical background lies in eigen analysis. Table 4 shows correlation matrix of the input variables. A PCA was run on the six inputs and the results are shown in Table 5. This Table shows eigen values, proportion, cumulative and order importance of variables, respectively. The first two variables represent 74% of the variance of the data matrix and the first three represent 90%. The results suggest that reasonably the first three variables represent the whole information contained in the original six variables. Finally, we have three inputs which are: energy loss rate, number of staff and operation expenditure.

Table 3: Summary statistics of IDCs' variables

	Max	Min	Mean
Service area (Km^2)	128811	90	35619.07
Distribution network (Km)	34586	5178	13429.41
Transformer capacity(MVA)	4682	392	1572.853
Total asset(M$)	36.143	3.802	14.465
Number of customers	975369	125978	490436
Number of staff	2238	198	577
Operation expenditure(M$)	544.1	50	138.790
Peak load (MW)	2871	148	882.446
Quantity of energy	12257	818	3641.732
Energy loss rate (%)	42.03	7.87	15.828

Table 4: Correlation matrix of the input variables

	TOTAST	NO.ST	OPEXP	DISNT	TRANSCAP	ENLOSS
TOTAST	1.000					
NO. ST	0.476	1.000				
OPEXP	0.503	0.910	1.000			
DISNT	0.678	0.312	0.357	1.000		
TRANSCAP	0.757	0.493	0.509	0.510	1.000	
ENLOSS	0.237	-0.006	0.162	0.026	0.418	1.000

Table 5: Result of PCA algorithm

Order important variable	ENLOSS	NO.ST	OPEXP	DISNT	TOTAST	TRANSCAP
Eigen value	3.282	1.160	0.945	0.348	0.198	0.067
Proportion	0.547	0.193	0.158	0.058	0.033	0.011
Cumulative	0.547	0.740	0.898	0.956	0.989	1.000

RESULTS AND DISCUSSION

Two different cost frontier models are applied to Iranian Distribution Companies (IDCs). For estimating efficiency with SFA method, a translog distance function is applied to estimate the SFA parameters. The estimated parameters of the cost frontier by using the Frontier 4.1 by Coelli (1994) are listed in Table 6.

Parameters σ^2 and μ are defined as follows:

$$\sigma^2 = \sigma_u^2 + \sigma_v^2 \tag{9}$$

$$\mu = \sigma_u^2 / \sigma^2 \tag{10}$$

The parameter μ in Eq. (10) shows the percentage of error term that the efficiency may have and must be between 0 and 1. A value of $\mu = 0$ indicates that the deviations from the frontier are due entirely to noise, while a value of one would indicate that all deviations are due to technical inefficiency. The results show all coefficients have the expected signs. The output and two inputs elasticity are positive i.e increase in output or inputs will increase operation expenditure. For instance, according to the results presented in Table 6, the output coefficient suggests that on average, a one percent increase in the quantity of energy supplied will increase the operation expenditure by about 0.65 percent. The results also indicate that the peak load and service area have positive effect on the operation expenditure. A 1 percent increase in the peak load will increase operation expenditure by approximately 0.18 percent. As expected, the customer density has a negative effect on the operation expenditure.

Table 6: Distance function parameters

Parameters	Coefficient	Standard-error	t-test
α_0	-0.87	0.94	-0.93
α_1	-0.65^a	0.17	-3.76
β_1	-2.77^a	0.87	-3.20
β_2	-1.60^b	0.78	-2.06
β_{11}	-0.48	0.49	-0.97
β_{22}	-0.36^a	0.12	-2.95
β_{12}	0.60^c	0.31	1.91
δ_{11}	0.46^a	0.12	3.96
δ_{21}	0.10	0.08	1.31
γ_1	-0.07^c	0.04	1.91
γ_2	-0.18^b	0.07	-2.75
γ_3	0.27^a	0.06	4.11
σ^2	0.04		
μ	0.32		
Log-likelihood	16.09		

^{a}, ^{b}, ^{c} : significant at %1, %5, %10, respectively.

The efficiency estimates from two methods on IDCs are given in Table 7. It shows that the average efficiency scores under method 1 (parametric method) are equal to 0.7247 and change from 0.4961 to 0.9985.

The average efficiency scores are 0.8552 from method 2. Efficient companies have efficiency scores equal to one. These are the companies that serve as a reference set to the others. For example, the number of efficient companies obtained in method 2, with overall efficiency scores equal to one are 16 and around %61 of IDCs require reducing their inputs if they are to become efficient.

Sensitivity analysis is based on changes in efficiency score upon inclusion or exclusion of one or more variables from the method (Pahwa et al. (2003)). Table 8 summaries the sensitivity analysis of the relative efficiencies by removing energy loss rate (as an example) in the methods. The values with brackets in Table 8 presented the differences between the original efficiency values and the removing energy loss rate in the methods. If there are significant differences between the original efficiency score and the efficiency scores from eliminating input factor, we can examine the input factor advantages for the corresponding DMU.

For example, the efficiency of DMU 3 decreases significantly when calculating the efficiency score without energy loss rate from two methods. Thus, the energy loss rate is an important factor for this DMU. However, the efficiency of DMU 19 does not change for most situations. This Table shows that some companies are very sensitive to changes in data and could become inefficient very quickly by changing a few variables.

Pearson and Spearman correlation coefficients of the efficiency scores obtained from different methods are computed in order to analyze the different estimation results in more detail. The correlation matrixes are shown in Table 9. Method 1 (parametric approach) shows no correlation with method 2. The correlation results suggest that there is a weak positive relationship between both parametric and non-parametric approaches. This suggests that the estimates obtained from different non-parametric methods are not significant.

Table 7: Efficiency estimates from different methods

No. DMU	Method 1 (SFA)	Method 2 (DEA)
1	0.7278	0.6708
2	0.5210	0.8223
3	0.8316	0.9778
4	0.7441	1.0000
5	0.6908	0.7552
6	0.8438	0.6380
7	0.6551	0.8169
8	0.7674	1.0000
9	0.9115	0.8224
10	0.6719	0.5694
11	0.7759	0.7641
12	0.8211	0.7841
13	0.6565	0.8999
14	0.9138	1.0000
15	0.8405	0.7841
16	0.6794	1.0000
17	0.6885	1.0000
18	0.7690	0.9468
19	0.7436	1.0000
20	0.5622	0.9867
21	0.7677	0.8271

Table 7: Continue

22	0.9301	1.0000
23	0.7238	1.0000
24	0.8226	1.0000
25	0.6282	0.8149
26	0.7291	0.9178
27	0.5371	1.0000
28	0.9985	1.0000
29	0.6190	0.7033
30	0.7856	0.7980
31	0.6018	0.8737
32	0.6184	0.7485
33	0.6968	0.7521
34	0.4961	1.0000
35	0.9282	0.9137
36	0.6083	1.0000
37	0.6973	0.4862
38	0.8423	0.7405
39	0.5615	0.8838
40	0.6180	0.6710
41	0.6864	0.6927

Table 8: Sensitivity analysis of removing energy loss rate in the methods

No. DMU	Method 1(SFA)		Method 2(DEA)	
1	0.4371	[0.2907]	0.6611	[0.0097]
2	0.4601	[0.0609]	0.8167	[0.0056]
3	0.7066	[0.1250]	0.7002	[0.2776]
4	0.5462	[0.1979]	1.0000	[0.0000]
5	0.8565	[-0.1657]	0.7529	[0.0023]
6	0.9283	[-0.0845]	0.6380	[0.0000]
7	0.7706	[-0.1155]	0.8169	[0.0000]
8	0.8622	[-0.0948]	1.0000	[0.0000]
9	0.9120	[-0.0005]	0.8224	[0.0000]
10	0.6259	[0.0460]	0.4925	[0.0770
11	0.8416	[-0.0657]	0.7217	[0.0424
12	0.9004	[-0.0793]	0.7841	[0.0000]
13	0.6195	[0.0370]	0.8999	[0.0000]
14	0.8409	[0.0729]	0.8994	[0.1006]
15	0.8443	[-0.0038]	0.7429	[0.0412]
16	0.8253	[-0.1459]	1.0000	[0.0000]
17	0.1755	[0.5130]	1.0000	[0.0000]
18	0.9335	[-0.1645]	0.9466	[0.0002]
19	0.7445	[-0.0009]	1.0000	[0.0000]
20	0.7574	[-0.1952]	0.9867	[0.0000]
21	0.9182	[-0.1505]	0.8273	[0.0000]
22	0.6220	[0.3081]	0.9648	[0.0352]
23	0.9461	[-0.2223]	1.0000	[0.0000]
24	0.5986	[0.2240]	1.0000	[0.0000]
25	0.8829	[-0.2547]	0.8138	[0.0011]
26	0.5959	[0.1332]	0.9178	[0.0000]
27	0.9516	[-0.4145]	0.9436	[0.0564]
28	0.7396	[0.2589]	1.0000	[0.0000]
29	0.8478	[-0.2288]	0.7024	[0.0009]
30	0.7552	[0.0304]	0.7939	[0.0041]
31	0.7632	[-0.1614]	0.8694	[0.0043]
32	0.7449	[-0.1265]	0.7463	[0.0022]
33	0.5288	[0.1680]	0.7521	[0.0000]
34	0.9227	[-0.4266]	1.0000	[0.0000]
35	0.7647	[0.1635]	0.9053	[0.0084]
36	0.8296	[-0.2213]	0.9999	[0.0001]
37	0.8860	[-0.1887]	0.4826	[0.0036]
38	0.6689	[0.1734]	0.7405	[0.0000]
39	0.5477	[0.0138]	0.8836	[0.0002]
40	0.8488	[-0.2308]	0.6599	[0.0111]
41	0.9092	[-0.2228]	0.6893	[0.0034]

Table 9: Pearson and Spearman correlation coefficients

		Spearman correlation	
		Method 1	Method 2
Pearson correlation	Method 1	1.0000	0.0683
	Method 2	0.0875	1.0000

Conclusion:

In this paper, two different cost frontier models were applied to measure the efficiency of electric distribution companies. Inclusion of more variables without increasing the number of DMUs would make more DMUs efficient so, only the most significant variables must be included. Details of input and output variables selection using PCA have been provided. To analyze the different estimation results, Pearson and Spearman correlation coefficients were computed. The correlation tests show a weak consistency between the obtained results from different methods. Practical experience shows that regulators converting efficiency scores into X-factors tend to adopt arbitrary standards. Regulators using benchmarking to determine a company's inefficiency level, set the target for their costs and also determine the revenue allowance for each company. The paper shows the results in term of efficiency are sensitive to the approach used, so it will be unclear which results the regulator should use. Therefore, it is concluded that a regulator should use these methods with caution because different results create regulatory risk over the revenues that a company will be allowed. This paper suggests that regulator should not directly use these scores in the regulation scheme and as an alternative method of setting revenues allowance of companies. Also, this paper suggests that if a number of sets of efficiency scores estimations are available, regulator can use a combination of different techniques to set standards.

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