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PARAMETRIC VS. NON-PARAMETRIC EFFICIENCY ASSESSMENT: CASE OF POWER PLANTS IN TURKEY

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Abstract: Throughout the study, the operational and long term investment performances of various power plants in Turkey are assessed and compared using Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). The data set is composed of 65 thermal, hydro and wind power plants with private and public ownership. Efficiency indices, reflecting operational and investment performance, are described and elaborated. Returns to scale, (constant and variable), assurance region, slack based measure, system comparison and bilateral type DEA models as well as stochastic frontier analysis employing the Cobb-Douglas and Translog production functions are used in the analysis. An analysis of returns to scale is carried out. The properties of the production frontiers are described for all efficiency indices. Public-private sector plants, renewable-thermal plants as well as natural gas-coal versus oil fired plants are compared according to their efficiency performance values. Efficiency scores obtained from DEA and SFA are compared and some relationships are identified. Interesting relationship are identified by elaborating the efficiency indices and various input/output factors. Even though natural gas fired power plants outperforms the coal fired ones in terms of investment efficiency, in general, reverse is true for operational performance under variable returns to scale.

Keywords: Efficiency, Stochastic Frontier Analysis, Data Envelopment Analysis, Energy Systems Planning,

Parametrik ve Parametrik Olmayan Verimlilik Değerlendirmesi ve Karşılaştırılması: Türkiye Elektrik Santralleri Örneği

Öz: Çalışma boyunca Türkiye'deki çeşitli enerji santrallerinin operasyonel ve uzun vadeli yatırım performansları Stokastik Sınır Analiz (SSA) ve Veri Zarflama Analizi (VZA) kullanılarak karşılaştırıldı. Veri kümesi, özel ve kamu mülkiyetindeki 65 termal, hidroelektrik ve rüzgâr enerji santrallerinden oluşturuldu. Operasyonel ve yatırım performansını yansıtan verimlilik endeksleri ortaya konup incelendi. Analizde ölçek, sabit ve değişken, güvence bölgesi, gevşek tabanlı ölçüm, sistem karşılaştırma ve bilateral tip DEA modelleri ile Cobb-Douglas ve Translog üretim fonksiyonlarını kullanan stokastik sınır analizi kullanıldı. Ölçek getirisinin analizine yönelik VZA ve SSA modellerinin ortaya koyduğu tüm indisler kullanılarak değerlendirmeler yapıldı. Kamu-özel, termal-yenilenebilir karşılaştırmalarının yanı sıra doğal gaz-kömür-petrol santralleri verimlilik performans değerlerine göre karşılaştırıldı. VZA ve SSA metotlarından elde edilen sonuçlar karşılaştırıldı. İlginç verimlilik endeksi ve çeşitli giriş/çıkış faktörleri arasında ilişkiler ortaya kondu ve değerlendirildi. Doğal gazla çalışan elektrik santralleri, yatırım verimliliği açısından kömürle çalışan santrallerden daha iyi performans gösterse de, değişken getiri oranlarına göre operasyonel performansı için tersi geçerlidir.

Anahtar Kelimeler: Verimlilik, Stokastik Sınır Analizi, Veri Zarflama Analizi, Enerji Sistem Planlama

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1. Introduction

The choice of technology is a key decision to be made for capacity expansion in electricity generation. Currently, renewable and thermal plants form the two main electricity generation categories in Turkey. Total installed capacity of 36824 MW in year 2004 is composed of 65.6% thermal and 34.4% renewable power. Renewables are sub-classified into hydro power plants (34.3%), wind (0.05%) and geothermal (0.04%). Thermals are sub-classified under coal-fired (22.5%), gas-fired (27.6%), oil-fired (7%), biomass-fired (0.07%) and multi-fuel fired (8.4%) power plants (TEİAŞ, 2005). A typical question that arises is "Which technology is advantageous over others and on what ground?". The answer of this question depends on global trends, technological developments, economic considerations and environmental concerns besides the worldwide supply and demand profile of primary energy resources.

Various studies concerning classes of power plants have been proposed regarding the technology selection problem. Frequently, studies are focused on thermal efficiencies of power plants for the basis of comparison, while economic performance of plants are evaluated by monetarization of input and output factors (e.g., Bakos (2003), Kwak *et al.,* 2003, Liu *et al.,* 2003, Park *et al.,* 2000, Sàez *et al.,* 1998). Some Turkey-specific studies on the assessment of power plants was carried out by Sarica and Or (2008), Erdem et. al., (2009) and Sözen et. al. (2010).

A multi input - output performance evaluation is presented in this paper comparing power plants in Turkey based on real data including 65 power plants. Main issue in any such multi-factor analysis is the characterization of the frontier functions to assess the efficiencies of the Decision Making Units (DMU) relative to this function. In this study, two different methodologies are used to overcome this issue. First one is the DEA, which was founded by Charnes et al. (1978). Second one is the Stochastic Frontier Analysis which was introduced by Aigner et.al. (1977), Meeusen and van den Broeck (1977) simultaneously.

2. Model description

2.1 Operational Performance Model

Three parameters constitutes the model for the operational performance of power plants; production quantity (measured in kWh) as a numerical measure of primary purpose of the plant, availability (measured in hours) as a measure of the generation units reliability for the system and total cost of operation (measured in ₺); composed of fuel cost, environmental cost including the damages incurred by SO_2, NO_x and particulates emissions monetarized using the ExternE Project (1995) and other plant related costs over a year. Primary reason to select these factors is the direct relation reflecting primary mission of a power plant; uninterrupted generation of electricity at a fairly reasonable price.

The model developed for the operational performance of renewable power plants differs from the thermal generation units; one input factor (operating cost) and two output factors (production quantity and availability). However, environmental externalities mentioned are negligible in renewable generation units, thus not included related model.

2.2 Long term investment performance Model

Long term investment model to measure performance of the power generation units has three factors: investment cost (measured in US \$) as an input, construction time (measured in months) as an input and potential production (measured in MWh) as an output which is the expected amount of electricity production throughout the economic lifetime of the plant based on historical electricity production data. These parameters are picked to consider the long run effectiveness of an electricity generating facility.

3. Data collection and compilation

Throughout this study data published by Sarica and Or (2008) is deployed. The data published are combined under two sets: i) long term investment performance data set ii) operational performance data set.

Data sets obtained are representative of Turkey's generation mix in total electricity production. Data set representing the thermal plants' operational performance constitutes 71% of Turkey's total thermal power generation in year 2001; while, regarding the renewables, the coverage reaches 82.6%.

4. The Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a nonparametric linear programming (LP) based technique that provides an objective assessment of the relative efficiency of similar organizational units by estimation of production frontiers. Charnes *et al.* (1978) introduced the first DEA model, namely "*Charnes Cooper Rhodes" (CCR)* model. Since then DEA has been successfully deployed in many different fields to assess and compare the efficiency of DMUs (e.g. Banker *et al.*, 1992, Dyson *et al.*, 1987, Golany *et al.*, 1994, Korhonen *et al.*, 2003, Park *et. al*., 2015, Aristovnik *et. al*., 2015).

4.1 The Basic DEA Models

The CCR Efficiency model is also called the technical efficiency model. A major underlying assumption in this model is "constant returns to scale", i.e. the production possibility set is formed assuming constant returns to scale. As Charnes *et al.* (1978) report, the LP model deployed to generate the input oriented CCR efficiency scores of each DMU k_0 considered is as follows.

$$\begin{aligned} &\text{Max} \quad \theta_{CCR}(k_0) = \sum_{j=1}^{n} u_j \, y_{jk_0} \\ &\text{Subject to} \\ &\sum_{i=1}^{m} v_i \, x_{ik_0} = 1 \\ &-\sum_{i=1}^{m} v_i \, x_{ik} + \sum_{j=1}^{n} u_j \, y_{jk} \leq 0 \quad k = 1, \ldots, K \\ &u_j \geq 0 \qquad j = 1, \ldots, n \\ &v_j \geq 0 \qquad i = 1, \ldots, m \end{aligned} \tag{1}$$

where

u_j	= the weight for output j;	K	= the number of DMUs;
v_i	= the weight for input i;	y_{jk}	= the amount of output j of DMU k;
m	= the number of inputs;	x_{ik}	= the amount of input i of DMU k.
n	= the number of outputs;		

Introduced by Banker, Charnes and Cooper (1984) (BCC), this model measures technical efficiency as the convexity constraint ensures that the composite unit is of similar scale size as the unit being measured. As Banker *et al* (1984) report, the LP model deployed to generate input oriented BCC efficiency factors of the DMUs is as follows.

The BCC Model (to be solved for each DMU k_0)

$$\text{Max} \quad \theta_{BBC}(k_0) = \sum_{j=1}^{n} u_j \, y_{jk_0} - u(k_0) \tag{2}$$

Subject to

$$\sum_{i=1}^{m} v_i \, x_{ik_0} = 1$$

$$-\sum_{i=1}^{m} v_i \, x_{ik} + \sum_{j=1}^{n} u_j \, y_{jk} - u(k_0) \leq 0 \quad k = 1, \ldots, K$$

$$u_j \geq 0 \qquad j = 1, \ldots, n$$

$$v_j \geq 0 \qquad i = 1, \ldots, m$$

where $u(k_0)$ is the free scaling variable for each DMU.

The CCR model assumes a radial expansion and reduction of all observed DMUs; while the BCC model only accepts the convex combinations of the DMUs under the production possibility. Thus, it is reasonable to characterize the scale efficiency of a DMU by the ratio of the two scores. Hence, the global efficiency (GE), the local efficiency (LE) and the scale efficiency (SE) concepts are mathematically related as

$$SE = GE / LE = \theta_{CCR}/\theta_{BCC}$$

where θ_{CCR} and θ_{BBC} are the CCR and BCC scores of a DMU, respectively. By definition, SE cannot be greater than 1.

This decomposition depicts the sources of inefficiency, i.e., whether it is caused by inefficient operation (LE) or by disadvantageous conditions caused by scale (SE) or both.

Another interesting property of the BCC model is that we can identify the return to scale (RTS) characteristic of the efficient DMU by looking at the value of $u(k_0)$ at the end of calculations (Banker and Thrall, 1992). Assuming that calculations lead to a point on efficient frontier:

- Increasing returns to scale prevails if and only if $u(k_0)<0$ for all optimal solutions.
- Decreasing return to scale prevails if and only if $u(k_0)>0$ for all optimal solutions.
- Constant returns to scale prevails if and only if $u(k_0)=0$ for any optimal solution.

4.2 The Assurance Region (AR) Models

The input oriented AR models (AR-I) are versions of the CCR and BCC models, where weights of all input and output factors are constrained to be in some predetermined regions (so-called "Assurance Regions" - AR). As Thompson *et.al*. (1986) suggested, the LP model deployed to generate input oriented AR CCR model (AR-I-C) efficiencies of DMUs is just the addition of constraint set (3) given below to equation set (1).

$$\begin{array}{ll} u_i L_{ij} \leq u_j \leq u_i B_{ij} & i = 1, \ldots, m; j = 1, \ldots, n \\ v_j l_{ij} \leq v_i \leq v_j b_{ij} & i = 1, \ldots, m; j = 1, \ldots, n \\ u_j \geq 0 & j = 1, \ldots, n \\ v_j \geq 0 & i = 1, \ldots, m \end{array} \tag{3}$$

where

L_{ij} = lower bound for the ratio of the weight of output factor j to output factor i;
B_{ij} = upper bound for the ratio of the weight of output factor j to output factor i;
l_{ij} = lower bound for the ratio of the weight of input factor i to input factor j;
b_{ij} = upper bound for the ratio of the weight of input factor i to input factor j.

The AR-I-V Efficiency model is a version of the BCC efficiency, where weights of all input and output factors are constrained to be in some predetermined regions ("Assurance Regions"). As Thompson *et al*. (1986) and Tone (1999) stated the LP model deployed to generate AR-I-V efficiency factors of the decision making units considered is just the addition of constraint set (3) to equation set (2). More recent AR model developments can be seen in the studies of Unsal and Örkcü (2016) and Mecit and Alp (2013).

In this study, the values of Assurance Region models' upper and lower bounds are set (subjectively) such that the ratio of any two input (output) factors is at least 0.1 and at most 10. These weight restrictions are based on expert views from the industry.

4.3 The Slack Based Measure (SBM) Model

The SBM efficiency model, proposed by Tone (2001), is a kind of additive DEA model in which input excesses and output shortfalls are taken into account while calculating the efficiency scores. Thus efficiency score does not purely concentrates on radial efficiency measures, it also considers the slack values. In fact this efficiency measure is very suitable for ranking purposes since if a DMU A can dominates DMU B thus $\rho_A \geq \rho_B$ if and only if $x_A \leq x_B$ and $y_A \geq y_B$ The related LP for Constant Returns to Scale (CRS) form (SBM-I-C) can be interpreted as follows:

$$\text{Min} \quad \rho(k_0) = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik_0}}}{1-\frac{1}{n}\sum_{j=1}^{n}\frac{s_j^+}{y_{jk_0}}} \tag{4}$$

$$\begin{aligned} & s.t. \\ & x_0 = X\lambda + s^- \\ & y_0 = Y\lambda - s^+ \\ & \boldsymbol{\lambda \geq ,0\ s^- \geq 0, s^+ \geq 0} \end{aligned}$$

For Variable Return to Scale (VRS) form (SBM-I-V) $\boldsymbol{e\lambda}=1$ constraint should be added to (4).

4.4 The Efficiency Comparison Models between different Systems (SYS):

The DEA models mentioned previously assume that the production possibility set P is convex. That is, if two activities (x_1,y_1) and (x_2,y_2) belong to P, then every point on the line segment connecting these two points belongs to P. However there are situations where this assumption is not valid. Suppose for example that the DMUs under consideration belong exclusively to two systems, i.e. Systems A and B (although we mention two systems, it can be generalized to any multiple system case). As Tone (1993) proposed, for these two systems we divide the input space X to X_A and X_B and Y into Y_A and Y_B. The convexity assumption holds within the same system but does not hold between two systems. The efficiency of a DMU (x_o, y_o) can be evaluated with the following mixed integer LP problem:

$$\begin{aligned} & \text{Min} \quad \theta \\ & s.t. \\ & \theta x_o \geq X_A\lambda_A + X_B\lambda_B \\ & y \leq Y_A\lambda_A + Y_B\lambda_B \\ & Lz_A \leq e\lambda_A \leq Uz_A \\ & Lz_B \leq e\lambda_B \leq Uz_B \\ & z_A + z_B = 1 \\ & \lambda_A \geq 0, \lambda_B \geq 0 \\ & z_A, z_B = 0 \text{ or } 1 \end{aligned} \tag{5}$$

In case of L=0 and U=∞ case formulation becomes CRS (SYS-I-C) and VRS (SYS-I-V) when L=U=1.

From the results secured, not only the efficiency of each DMU can be evaluated but also the efficiency of DMUs in each system can be compared. The comparison of efficiencies between two types of DMUs, e.g. renewable power plants vs. thermal power plants is an important issue. It is necessary to test statistically the difference between two groups in terms of efficiency. Since the theoretical distribution of efficiency scores is unknown, it is inevitable to use nonparametric statistics which are independent of the distribution of DEA score. In this study the rank-sum-test developed by Wilcoxon-Mann-Whitney will be used to identify whether the difference between two groups are significant.

For rank-sum-test the DEA model evaluating each DMU one group with respect to DMUs in opposite group will be deployed. As Cooper and Rhodes (1981) proposed this inter comparison results in sharper discrimination between two groups. Formulation of the idea of bilateral comparison for every DMU in group A can be interpreted as follows:

$$\begin{aligned} &\text{Min } \theta \\ &\theta x_a \geq X_B \lambda_B \\ &y_a \leq Y_B \lambda_B \\ &\lambda_B \geq 0 \end{aligned} \tag{6}$$

5. Stochastic Frontier Analysis

Stochastic Frontier Analysis is a parametric method used to estimate the efficient frontier and efficiency values. With the assumptions about the firm's production technologies, the method recognizes the possibility of stochastic errors but requires the specification of the distance functions (Coelli, et al., 1998).

The stochastic frontier production function based on a Cobb-Douglas production function was independently proposed by Aigner et.al.(1977) and Meeusen/Van den Broeck (1977). The original specification involved a production function specified for cross-sectional data which had an error term which had two components, one to account for random effects and another to account for technical inefficiency. This simple model has been used in a vast number of empirical applications. A number of comprehensive reviews of this literature are available, such as Forsund et.al., (1980), Schmidt (1986), Bauer (1990) and Greene (1993). Some recent applications of the SFA models can be found in Goto/Tsutsui (2006) and Olatubi/Dismukes (2000).

Another form of production function that is used throughout the study for stochastic frontier analysis is the translog production function. Its general form is given as:

$$Y^k = (\alpha_0 + \sum_{i=1}^{n} \alpha_i \ln(x^k{}_i) + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij} \ln(x^k{}_i)\ln(x^k{}_j)) + (\mathrm{V^k - U^k}) \tag{7}$$

where Y^k is the production (or the logarithm of the production) of the i-th firm;

- x^k_i is the k-th input quantity of the i-th firm;
- β_{ij} denotes the unknown parameters
- α_i denotes the unknown parameters
- V^k are random variables which are assumed to be independent and identically distributed (iid). $N(0,\sigma_V^2)$, and independent of the U^k
- U^k are non-negative random variables which are assumed to account for technical inefficiency in production and often assumed to be iid. $|N(0,\sigma_U^2)|$.

The main idea behind using Translog production for SFA is to gain the ability to compute the scale elasticity, scale efficiency, and return to scale analysis under the SFA framework. The methodology proposed by Ray (1998) will be followed. Another benefit by using translog function is to get another efficiency score set under SFA framework to analyze the validity of the results throughout the analysis.

Performance evaluation of considered power plants is done through the DEA and SFA models developed. The input oriented CCR and the input oriented BCC, the AR-I-C, the AR-I-V, SBM, SYS-I-C, SYS-I-V, Bilateral efficiency scores of all plants are determined; then scale efficiencies are calculated based on these scores. Throughout this study, the software package DEA Software Pro developed by Saitech Inc. is used for the basic DEA computations (primarily the embedded LP optimization procedures).

Throughout this study the preceding two models are deployed for SFA part. After calculation of scale elasticities, scale efficiency scores are computed. The suitability of these models is due to the fact that the gathered data of the analyzed power plants is neither panel data nor time series data. The analysis covers only data for year 2001. SFA efficiency estimations are carried out using the computer program FRONTIER developed by Coelli (1992).

6. Model Results

6.1 DEA results

Long term investment performance results

Analysis stage of the study will initiate considering the long term investment performance of power plants with the results of CCR, BCC, AR-I-C and AR-I-V DEA models as well as results for SBM-C, SBM-V, SYS-I-C, SYS-I-V and Bilateral models. Unlike DEA it is not possible to construct a multi-output SFA to measure technical efficiency. In this case a single output version of long term investment and operational performance models are deployed.

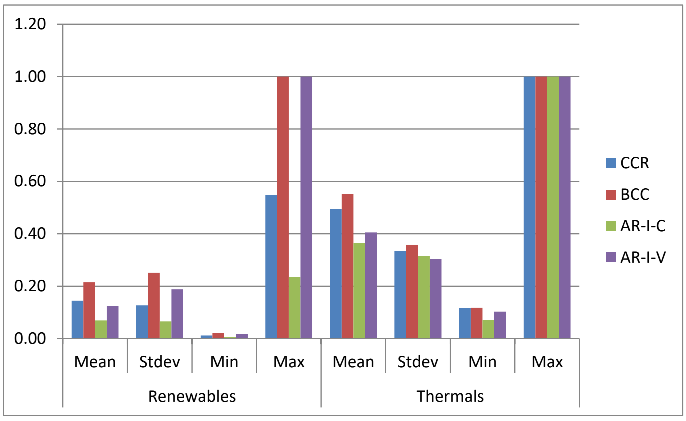

Figure 1:
Renewable vs. Thermal power plants comparison based on CCR, BCC, AR-I-C and AR-I-V models for long term investment performance.

As can be seen from Figure 1 Renewable power plants have lower long term investment performance efficiency scores than the thermal ones. For each corresponding DEA model mean score value, thermal power plants are performing better than the renewable ones. If we look at the minimum of each set it is seen that thermal set’s minimum values are always higher than the renewable ones. A similar situation can be seen also in maximum value case.

After the comparison of renewable and thermals power plants based on basic DEA models, for the completeness of the analysis other DEA model results should also be analyzed. Figure 2 displays other DEA model results regarding long term investment performance. SBM models support the basic CCR model results.

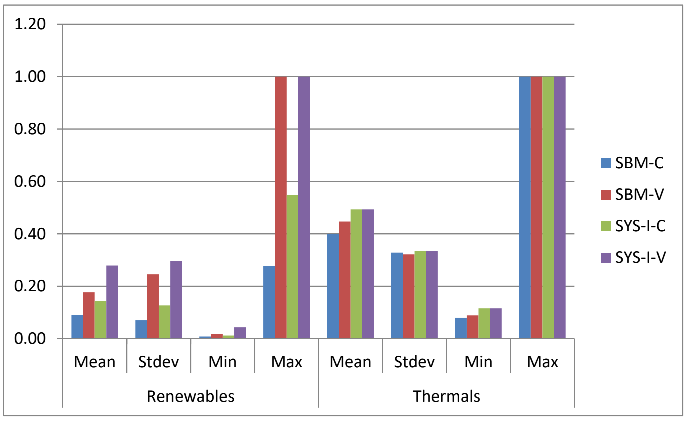

Figure 2:
Renewable vs. Thermal power plants comparison based on SBM-I-C, SBM-I-V, SYS-I-C, and SYS-I-V models for long term investment performance.

Assuming convexity assumption does not hold with in the whole long term investment performance data set but holds within two subgroups than SYS model results again support the previous model findings; regarding long term investment performance, thermal power plants performs better than the renewable ones.

As the final comparison analysis bilateral model results and the related weighted rank-sum-test; model rejected the null hypothesis that the two groups have the same distribution of efficiency score at the significance level of 2,275E-8%; thermal power plants outperform renewable power plants in general.

Privately owned plants have higher long term investment performance value than the public ones, which can be seen in Figure 3 For each corresponding DEA model mean score value, privately owned power plants are performing better than the public ones. If we look at the minimum of each set it is seen that privately owned set's minimum values are always higher than the public ones. A similar situation can be seen also in maximum value case. Another observation is weight restrictions applied in assurance region models has considerably lower the average efficiency value in each sets which highlights the presence of slack values in CCR and BCC model results.

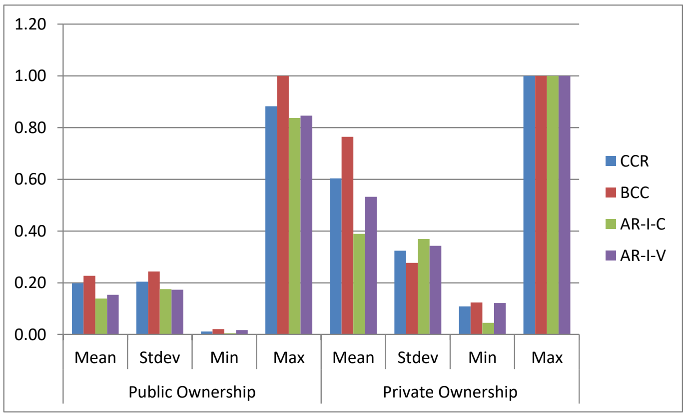

Figure 3:
Public vs. Private power plants comparison based on CCR, BCC, AR-I-C and AR-I-V models for long term investment performance.

SBM and SYS based model result is displayed in Figure 4.We can see the slack value presence as a drop down effect on mean efficiency scores of SBM-I-C and SBM-I-V with relative to CCR and BCC models respectively. Besides, SBM model results support the basic

DEA model results: Privately owned power plants' mean efficiency scores of SBM models are higher than the public ones. As the final comparison analysis bilateral model results and the related Weighted rank-sum-test; model rejected the null hypothesis at the significance level of 0.00047 %. Thus privately owned power plants outperform publicly owned power plants in general.

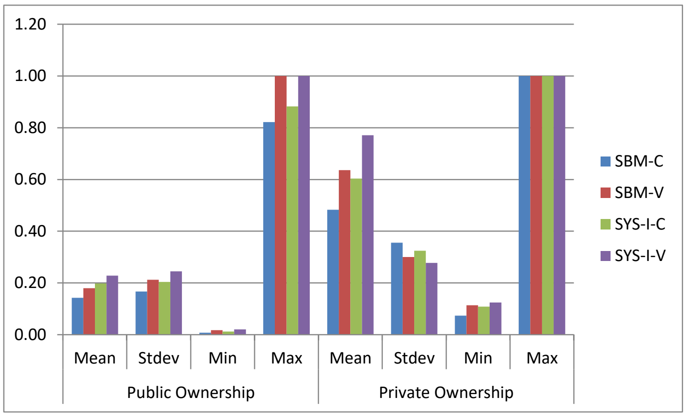

Figure 4:
Public vs. Private power plants comparison based on SBM-I-C, SBM-I-V, SYS-I-C, and SYS-I-V models for long term investment performance.

Figure 5 displays the coal-natural gas fired power plant comparison based on CCR, BCC, AR-I-C and AR-I-V models. A first look reveals that natural gas fired power plants has higher long term investment performance than the coal fired ones. For each corresponding DEA model mean score value, natural gas fired power plants are performing better than the coal fired ones ranging between 0.2 and 0.3. If we look at the minimum of each set it is seen that natural gas fired set's minimum values are always higher than the coal fired ones except for the case AR-I-V model. For the maximum value case, except for the BCC model result, each corresponding maximum value of natural gas fired power plant is higher than the coal fired ones. Another observation is weight restrictions applied in assurance region models has minimum effect on average efficiency value in each sets which highlights the rare presence of slack values in CCR and BCC model results.

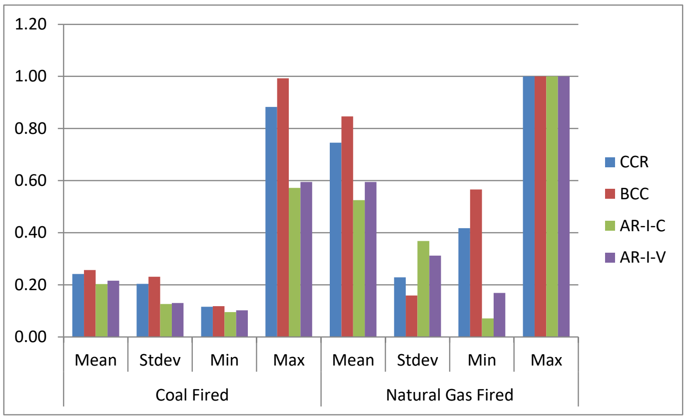

Figure 5 :
Coal fired vs. Natural Gas fired power plants comparison based on CCR, BCC, AR-I-C and AR-I-V models for long term investment performance.

SBM model results also support the basic DEA model results. Natural gas fired power plants' mean efficiency scores of SBM models are higher than the coal fired ones. Also minimum values of Natural gas fired power plants are higher. For the case of maximum values SBM model results show privately owned power plants outperforms coal fired ones. Considering the convexity assumption with in the long term investment performance data set, it is seen that for the current case SYS models results support the previous model findings. As the final comparison analysis bilateral model results and the related weighted rank-sum-test, model rejected the null hypothesis at the significance level of 0.0000456%. Thus natural gas fired power plants outperform coal fired power plants in general.

Operational performance results

As can be seen from Figure 6 renewable power plants have lower operational performance value than the thermal ones. For each corresponding DEA model mean score value, thermal power plants are performing better than the renewable ones. If we look at the minimum of each set it is seen that thermal set's minimum values are always higher than the renewable ones. A similar situation can be seen also in maximum value case.

Beginning with the basic DEA models can lead to the preliminary result that renewable power plants perform better than the thermal ones. But a closer look at the figure shows us a different situation. If the CRS models mean value is compared it natural to come up with the above conclusion. But if the VRS models values are investigated one cannot find a significant difference between these two subgroups. Also AR-I-V model seems to place the thermal power plants performance higher than the renewable one. This situation also may highlight significant scale inefficiency with in thermal power plants operation.

SBM-I-C model results shows renewable ones are more efficient than the thermal ones, while SBM-I-V model reveals the fact thermal ones performs better than the renewable ones which can be seen in Figure 7. From this point, we can conclude that renewable power plants outperforms thermal power plants globally (CRS efficiency), but thermal ones outperforms renewable ones locally. Thus if the disadvantage of size was not present within thermal power plants, they would strictly outperform the renewable ones. As the last analysis for the comparison of renewable and thermal power plants, bilateral model results with weighted rank-sum-test should be checked. Rank sum statistics with bilateral DEA model rejected the null hypothesis at the significance level of 5.63E-10 %. Thus test result obtained supports the previous conclusion renewable power plants outperform the thermal ones globally in general.

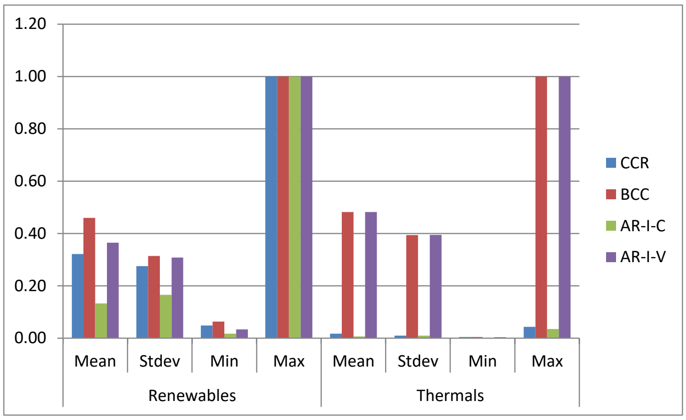

Figure 6:

Renewable vs. Thermal power plants comparison based on CCR, BCC, AR-I-C and AR-I-V models for operational performance.

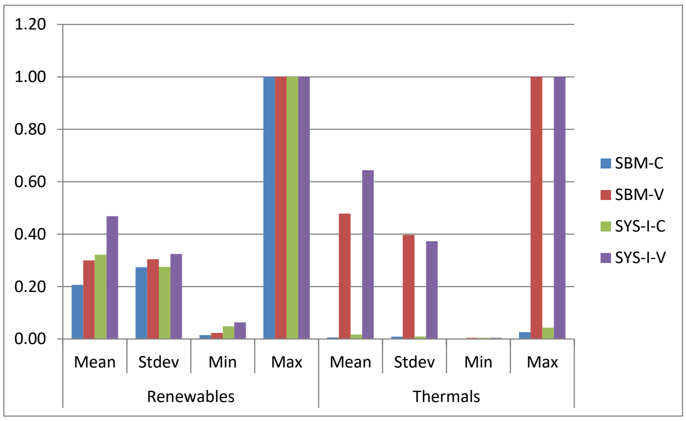

Figure 7:
Renewable vs. Thermal power plants comparison based on SBM-I-C, SBM-I-V, SYS-I-C, and SYS-I-V models for operational performance.

CCR model mean efficiency score suggests publicly owned power plants outperform the privately owned ones which can be seen in Figure 8. For AR-I-C model situation is not apparent i.e. mean values of efficiency score are very close, max values efficiency score are the same etc. But when the focus of analysis becomes BCC and AR-I-V models, the dominancy of the privately owned power plants is significant.

As can be seen form Figure 9, SBM-I-C type model, which is CRS, does not lead to any conclusion. But SBM-I-V type model reveals the fact that privately owned power plants are more efficient. With the higher discrimination power of SYS-I-C model it is seen that publicly owned thermal power plants outperform the privately owned ones. But also SYS-I-V based models show that privately owned power plants outperforms the public ones under. Rank sum statistics with bilateral DEA model rejected the null hypothesis at the significance level of 5.80E-02%; public power plants outperform the privately owned ones globally in general.

At the operational level next comparison will be between coal and natural gas fired plants. As can be seen Figure 10, analysis reveals the fact that according to basic DEA models natural gas fired power plants outperform coal fired ones. An interesting note is that there is huge efficiency score differences between weight restricted and non-restricted models, which is a clue for significant number of slack values in basic DEA model results.

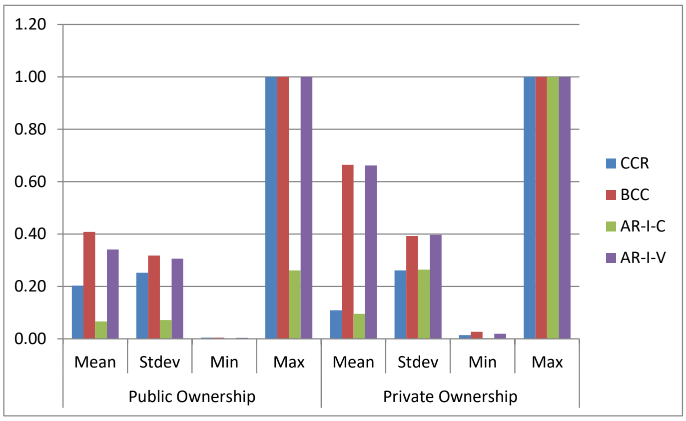

Figure 8:
Public vs. Private power plants comparison based on CCR, BCC, AR-I-C and AR-I-V models for operational performance.

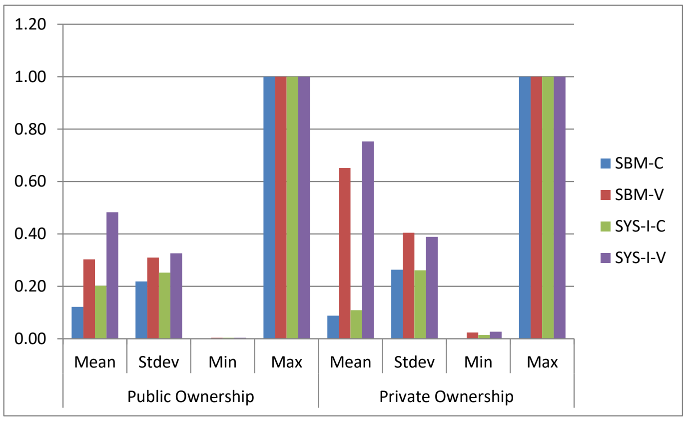

Figure 9:

Public vs. Private power plants comparison based on SBM-I-C, SBM-I-V, SYS-I-C, and SYS-I-V models for operational performance.

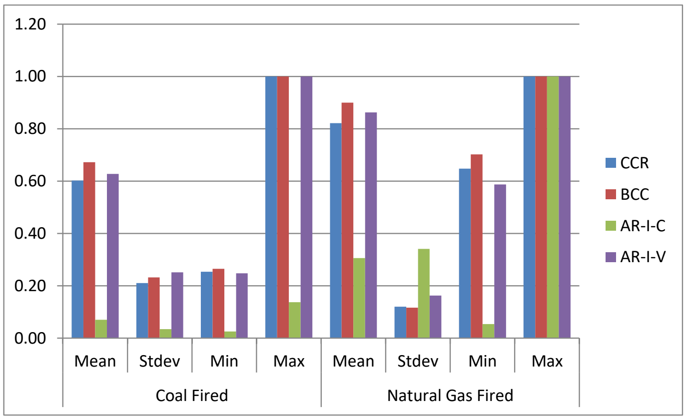

Figure 10:

Coal fired vs. Natural Gas fired power plants comparison based on CCR, BCC, AR-I-C and AR-I-V models for operational performance.

The effects of slacks with in basic DEA models are reflected to SBM-I-C efficiency scores by suppressing the efficiency scores which can be seen in Figure 11. Nevertheless SBM based models support the basic DEA model results. SYS-I-C models mean and min efficiency scores show that natural gas fired power plants outperform coal fired ones but SYS-I-V model results point out the opposite. Thus globally (CRS) natural gas fired power plants are dominating group but locally (VRS) coal power plants outperform natural gas fired ones.

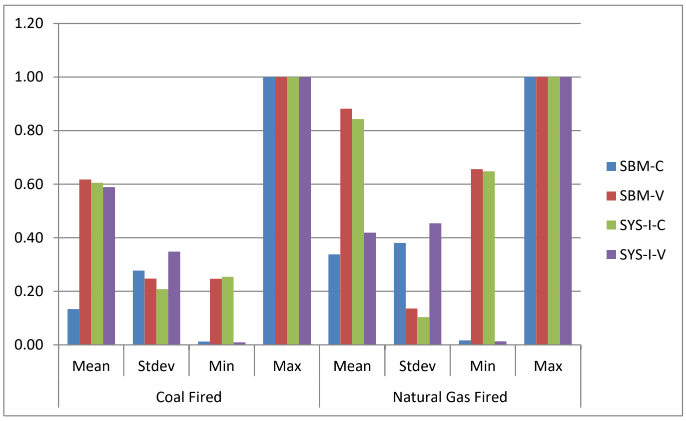

Figure 11:

Coal fired vs. Natural Gas fired power plants comparison based on SBM-I-C, SBM-I-V, SYS-I-C, and SYS-I-V models for operational performance.

As the last checkpoint bilateral model with weighted rank-sum-statistics should be investigated. The rank sum statistics with bilateral DEA model rejected the null hypothesis that the two groups have the same distribution of efficiency score at the significance level of 0.159% stating that natural gas fired power plants outperform coal fired power plants in general.

6.2 SFA results

Long term investment performance results

Throughout the stochastic frontier analysis, a comparison based on types of power plants will be made. Our initial analysis starts with long term investment performance of power plants.

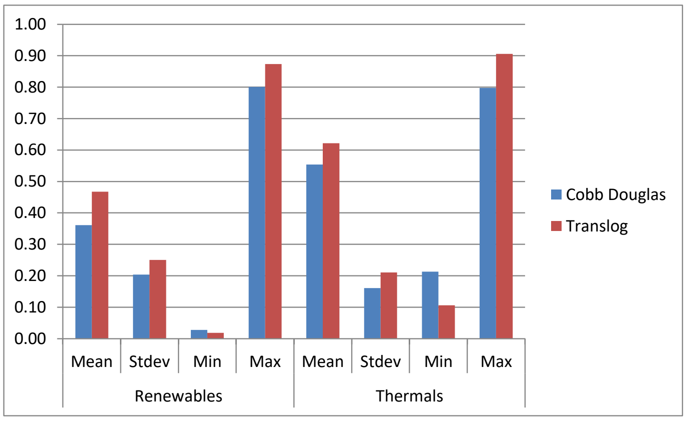

Figure 12:

Renewable vs. Thermal power plants comparison based Cobb-Douglas and Translog production functions for long term investment performance.

As can be seen from Figure 12 it is possible to say thermal power plants outperform renewable ones according to SFA models deployed. Statistically speaking the null hypothesis is rejected at significance level of 0.011% and 0.757% for Cobb-Douglas and Translog production functions respectively, stating that thermal ones outperform renewable ones in general for long term investment performance.

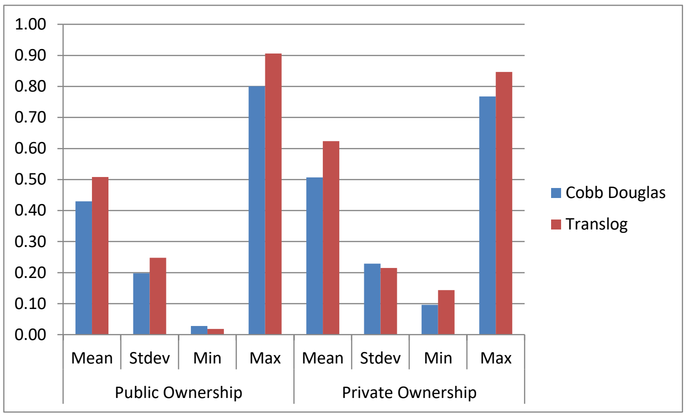

Figure 13:

Public vs. Private owned power plants comparison based Cobb-Douglas and Translog production functions for long term investment performance.

For the comparison of private vs. public plants, one cannot detect any dominancy as shown in Figure 13. Statistically speaking, the null hypothesis (hypothesizing that privately and publicly owned power plants have same efficiency distribution) is rejected at significance level of 13% and 5% for Cobb-Douglas and Translog production functions respectively. In the Cobb-Douglas based model two subgroups' efficiency score distribution is indifferent. But from the Translog production based SFA model it can be concluded that privately owned power plants outperform the publicly owned ones.

The dominancy of natural gas fired power plants over coal fired ones can be seen directly in Figure 14. Statistically speaking null hypothesis (hypothesizing that coal fired and natural gas fired power plants have same efficiency distribution) is rejected at significance level of 2.4% and 4.2% for Cobb-Douglas and Translog production functions respectively. As expected natural gas fired power plants outperform coal fired ones.

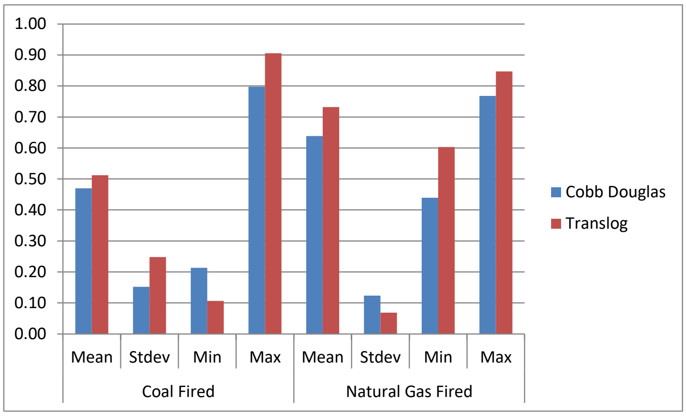

Figure 14:

Coal vs. Natural Gas fired power plants comparison based Cobb-Douglas and Translog production functions for long term investment performance.

Operational performance results

Next step of the analysis will start with operational performance of power plants. An important reminder is that it is not possible to find a SFA model that can handle a multi-output model in literature to measure technical efficiency. Therefore, a single output operational performance model is formed where production is the single output.

From Figure 15 it can be seen that average efficiency scores are very close each other with renewables being a little bit in front of thermal ones. The max values also support these observations. Statistically speaking null hypothesis (hypothesizing that renewable and thermal power plants have same efficiency distribution) is rejected at significance level of 5.17% and 2.04% for Cobb-Douglas and Translog production functions respectively, revealing that renewable power plants outperform the thermal ones.

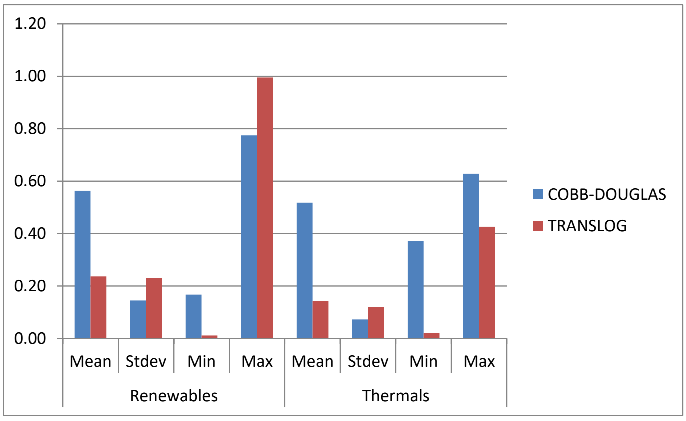

Figure 6 *Renewable vs. Thermal power plants comparison based Cobb-Douglas and Translog production functions for operational performance.*

Regarding the comparison of privately and publicly owned power plants, Figure 16 displays the relevant SFA model results. Again, average efficiency scores seem to be very close each other with renewables being a little bit in front of thermal ones. Also max values support these finding. Statistically speaking null hypothesis (hypothesizing that renewable and thermal power plants have same efficiency distribution) is rejected at significance level of 8.89% and 15.5% for Cobb-Douglas and Translog production functions respectively. According to Cobb-Douglas base SFA results one may say that renewable power plants outperform thermal ones. But accordingly to the Translog based SFA results these two groups have the same efficiency score distribution.

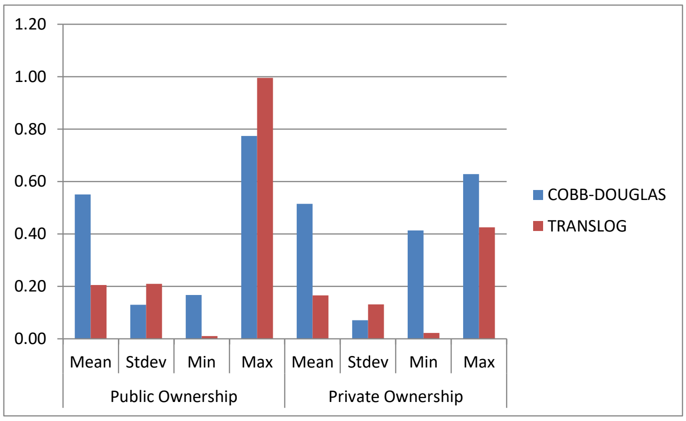

Figure 7 *Public vs. Private owned power plants comparison based Cobb-Douglas and Translog production functions for operational performance.*

As the last point, comparison of coal and natural gas power plants based on operational performance efficiency scores are investigated. The related SFA model results reveal that subgroups efficiency scores are very close to each other and standard deviations values are comparable to the average efficiency score making hard to come up with a decision. Switching to statistical measures reveals the fact that null hypothesis (hypothesizing that coal and gas fired thermal power plants have same efficiency distribution) is rejected at significance level of 25% and 37.36% for Cobb-Douglas and Translog production functions respectively. We can conclude that they are statistically indifferent.

6.3 Scale efficiency results

Initially, our analysis will start with long term investment performance of power plants. First of all Returns to Scale (RTS) characteristics of data set based on the models will be helpful to understand results obtained within two preceding sections, which are presented in Table 1 below.

Table 1. Returns to scale characteristics of Long Term Investment performance data.

	BCC Based	AR-I-V Based	Translog Based
Increasing	45	55	3
Decreasing	0	0	53
Constant	11	1	0

Regarding RTS characteristics of production possibility frontiers (PPS) formed by DEA models, a composition of two parts (CRS and IRS) parties seen. Without weight restrictions more power plants drop onto the CRS portion of the frontier. RTS characteristic of PPS formed by SFA is totally different. Most of the power plants fall on to DRS portion of the PPS.

Figure 17 displays the scale efficiency score statistics within the long term performance data set. It can be seen that global efficiency values contain a significant amount of scale inefficiency. Inefficiency levels rise up to more than 80% for DEA Basic and AR models. Another important observation is that the renewable power plant set inherits more scale inefficiencies than the thermal one independent of whatever model is used.

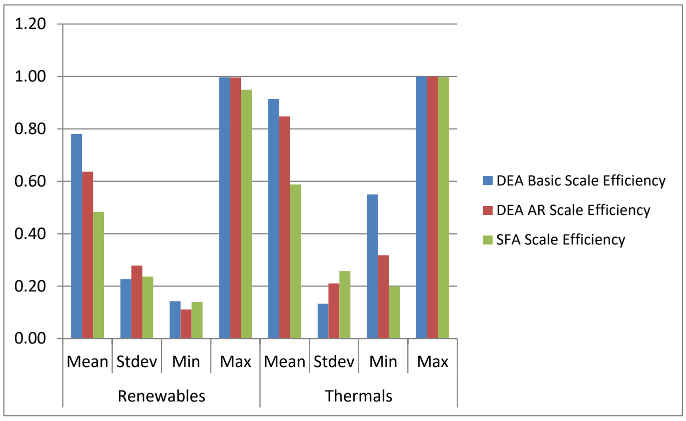

Figure 17:

Renewable vs. Thermal power plants comparison based on scale efficiency for long term investment performance.

Figure 18 displays the scale efficiency data of the long term investment efficiency score regarding the comparison of publicly and privately owned power plants. Keeping in mind that standard deviation levels are nearly equal, it is seen that privately owned power plants long term investment performances suffers from the scale inefficiencies present for DEA based models. For SFA case, the opposite becomes true. Also, on average each subset suffers around 20% scale inefficiency.

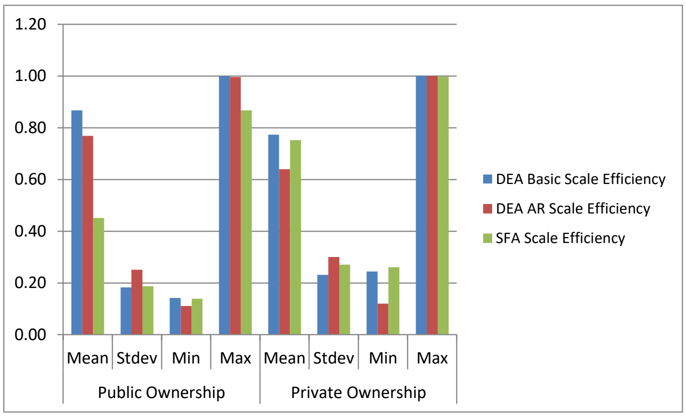

Figure 18:

Public vs. Private owned power plants comparison based on scale efficiency for long term investment performance.

Figure 19 shows the results of scale efficiency calculation for coal-natural gas fired plant comparison. From DEA perspective it is clear that natural gas fired power plants suffer from scale inefficiency more than coal fired ones. But from SFA point of view coal fired power plants have a major scale inefficiency disadvantage thus lowering the general efficiency scores.

As a next step in our analysis, the operational performance of power plants will be investigated. First of all Returns to Scale (RTS) characteristics of data set based on the models will be helpful to understand results obtained within two preceding sections.

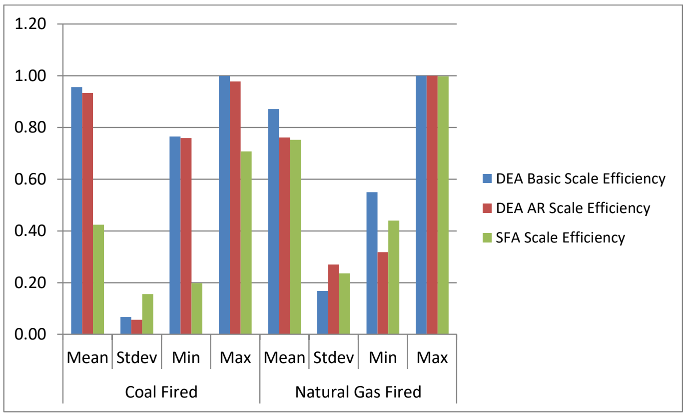

Figure 19:

Coal vs. Natural gas fired power plants comparison based on scale efficiency for long term investment performance.

Table 2 shows that without weight restrictions DEA model produces a PPS such that nearly one third of the power plants is in the IRS portion. The rest is mainly localized at DRS portion. Weight restrictions push the power plants at IRS part to CRS part as can be seen. The PPS produced by Translog based SFA model shows a similar pattern to basic DEA model PPS.

Table 2. Returns to scale characteristics of operational performance data.

	BCC Based	AR-I-V Based	Translog Based
Increasing	22	0	21
Decreasing	35	34	44
Constant	8	31	0

For the comparison of renewable and thermal power plants based on operational performance model results reveals that except for the weight restricted DEA model results basic

DEA and SFA scale efficiency pattern points out that thermal power plants suffer from their size significantly while operating.

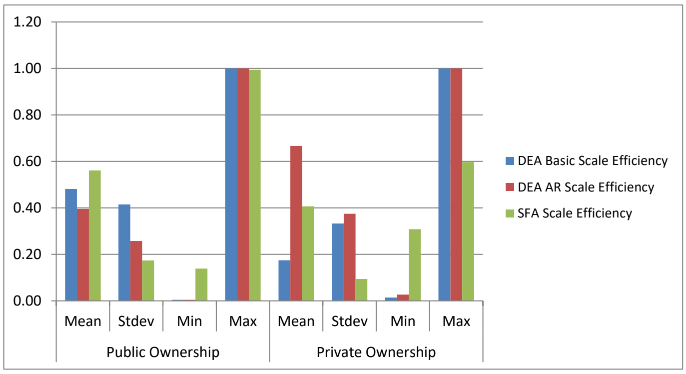

Figure 20:

Public vs. Private owned power plants comparison based on scale efficiency for operational performance

For the comparison of publicly and privately owned power plants based on operational performance model results displayed in Figure 20 should be analyzed. Except for the weight restricted DEA model result basic DEA and SFA scale efficiency pattern reveals that privately owned power plants suffer from their size significantly while operating.

Natural gas and coal fired power plants based operational performance scale efficiency is in line with the basic DEA model results; each subgroups suffers from scale inefficiency considerably. But coal fired power plants is the most disadvantageous subgroup. This situation is also valid with SFA scale efficiency and AR based DEA scale efficiency score.

7. Conclusions

In this study, the performance of 65 power plants owned by the public and private sectors in Turkey has been assessed and compared through Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). SFA models Cobb-Douglas and Translog; and DEA models; CCR, BCC, AR-I-C, AR-I-V, SBM-C, SBM-V, SYS-I-C, SYS-I-V and bilateral types; are used in the analysis. Various performance comparisons have been conducted and the relationships between efficiency scores and input/output factors have been elaborated. Several conclusions that can be drawn from the study can be summarized as follows:

Regarding DEA models:

- Thermal power plants perform better than the renewable ones for long term investment performance.
- Privately owned power plants perform better than the publicly owned ones for long term investment performance.
- Natural gas fired power plants performs better than the coal fired ones for long term investment performance.
- For operational performance, renewable power plants outperforms thermal power plants globally (CRS efficiency), but thermal ones outperforms renewable ones locally showing better managerial capacity.
- For operational performance, privately owned power plants operate under the disadvantage of their size, making them less efficient globally. If the scale effect was not present privately owned power plant would outperform the public ones.
- For operational performance, natural gas fired power plants are globally (CRS) dominant, but locally (VRS) coal power plants outperform natural gas fired ones.

Regarding SFA models:

- Thermal ones outperform renewable ones in general for long term investment performance.
- It can be concluded that privately owned power plants outperform the publicly owned ones for long-term investment efficiency.
- Natural gas fired power plants outperform coal fired ones for long term investment efficiency.
- Renewable power plants outperform the thermal ones regarding the long term investment efficiency.

Regarding Scale efficiency:

- Renewable power plant set inherits more scale inefficiencies than the thermal one showing the size disadvantage of installed ones independent of whatever model is used for long term investment performance.
- Basic DEA and SFA scale efficiency pattern reveals that thermal power plants suffer from their size significantly while operating
- Basic DEA and SFA scale efficiency pattern reveals that privately owned power plants suffer from their size significantly while operating.

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