

EFFICIENCY MEASURES AND REGULATION:
THAI ELECTRICITY GENERATION

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ABSTRACT

This paper aims to estimate the efficiency improvement target or the X factor for regulating the Thai electricity generation state owned enterprise. Efficiency is measured by employing a modern, standard application of parametric and nonparametric approaches, namely Stochastic Frontier Analysis and Data Envelopment Analysis respectively. The results from evaluating the Thai power plants are beneficial to internal management. Single X factor for an enterprise can be adopted for the next review of revenue requirement.

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1 Introduction

In Thailand, national energy policy, management and development and key regulatory functions such as price regulation, are conducted by the National Energy Policy Council (NEPC). NEPC employs a cost of service form of control to regulate retail electricity tariff together with combination of rate of return (ROR) and revenue cap regulation on base electricity tariff.

To determine the base electricity tariff, the revenue requirement of each state owned enterprise (SOE) in the electricity supply industry (ESI), which are the Electricity Generating Authority of Thailand (EGAT), the Metropolitan Electricity Authority (MEA) and the Provincial Electricity Authority (PEA), is estimated based upon investment plans for the relative power utilities, a set of financial performance targets and efficiency improvement target.¹ A set of financial performance targets is employed to ensure that these SOEs will have the appropriate level of earnings, which is the principal idea of ROR regulation, whereas an efficiency improvement target is employed to encourage them to improve their operating efficiency, which is the aim of incentive regulation.

Apart from revenue requirement, the marginal cost of each SOE are estimated. Then the base electricity tariff is calculated. In addition to the base electricity tariff, any change of preset value will be passed through to the customer via Automatic Adjustment Mechanism (F_t).² The retail electricity tariff is derived from base electricity tariff and F_t .

From now on only the efficiency improvement target employed to determine revenue requirement will be discussed as it is the central idea of this paper.

¹ The detail of revenue requirement determination is not publicly available.

² The detail of Automatic Adjustment Mechanism is provided by Energy Policy and Planning (2004).

For the efficiency improvement criteria, only their controllable variable costs³ are regulated by efficiency improvement target or the X factor. Controllable variable costs are estimated to increase by $(1+CPI-X)$ each year. The X factor was taken from London Economics (1997) which are 5.8, 2.6 and 5.1 per cent for generation, transmission, and distribution and supply, respectively.⁴

London Economics (1997) estimated the efficiency improvement target of Thai electricity companies. For those in Thai electricity generation activity, the simple ratio analysis was conducted followed Data Envelopment Analysis to measure efficiency level and productivity growth of 11 power plants of EGAT, two independent power producers: Rayong Electricity Generating Co. Ltd. and Khanom Electricity Generating Co. Ltd., and one small power producer: COCO, during the period 1991–96.

In London Economics's study, output is electricity generated whereas the inputs are capital, which is proxied by the capacity of the plant measured in MW of nameplate, and labour and nonlabour operating inputs, which is proxied by operating expenditures. It does not include fuel, which is the most important input in electricity generation, into the model.

The result shows that only Mae Moh thermal power plant of EGAT is on the frontier, with the other power plants facing the low or negative productivity growth. The average productivity growth was 5.8 per cent which is straightforwardly employed as the X factor.

³ Total operating cost of three SOEs in ESI in Thailand is separated into three portions: 20, 40 and 40 per cent of fixed costs, uncontrollable costs and controllable variable costs respectively.

⁴ It should be noted that when this form of regulation was imposed, ESI restructuring in Thailand had not been fully undertaken. The government decided to impose this regulation on the three SOEs by classified caps according to different characteristic of activities: natural monopoly (transmission and distribution) and competitive activities (generation).

This efficiency improvement target has not been reviewed and revised since then. Although the efficiency improvement target is very important to determine revenue requirement, which subsequently affect the base and retail electricity tariff, there is no formal and up-to-date study using the modern efficiency measurement for regulatory purposes in the electricity generation sector in Thailand. This study aims to fill the gap.

The objective of this study is to measure the efficiency improvement level of the electricity generation sector in Thailand for regulatory purposes in electricity generating activity, using modern, comparative efficiency measurement techniques, namely parametric (Stochastic Frontier Analysis) and nonparametric (Data Envelopment Analysis) approaches, and employing new power plant data set covering period of 1992–2000.

For comparison between techniques, this study uses three consistency conditions: consistency in efficiency level, ranking and the identification of the best and worst performers as criteria.

This study also examines the technical inefficiency model by using power plant specific variables to capture the effect of different characteristics of power plants on inefficiency levels.

This study is divided into 6 sections. In Section 2, the concept of efficiency measurement are presented together with the parametric and nonparametric techniques of efficiency measurement. The data and variables of Thai power plants are explained in Section 3.

In Section 4, the empirical results of technical efficiency estimation from both parametric and nonparametric approaches and the consistency conditions are reported. Section 5 explores choice of efficiency measure for regulatory purpose. In Section 6, the conclusion and policy implications will be drawn.

2 Efficiency measurement methods

The choice of efficiency measurement methods for regulatory purpose relies on various factors. Rossi and Ruzzier (2000) summarised the major decisions that has to be made before conducting efficiency measurement are: the relevant efficiency concept (economic, technical or allocative efficiency); the relationship that is going to be estimated (cost or production function); measurement methods (parametric or nonparametric methods); and variables. Making decisions on these issues rely on the objective of regulation, the characteristics of regulated industry to be regulated, rules and regulation in a particular country and the availability of data.

This section will discuss the regulatory choices of efficiency concept, the relationship that is going to be estimated and the measurement methods that should be adopted in the electricity generation sector in Thailand. The choice of variables will be discussed in the next section.

The economic or overall efficiency of the firm has two components: technical efficiency, which refers to the ability of a firm to minimise inputs proportionally to produce a given set of output⁵; and allocative or price efficiency, which refers to the ability to combine inputs and outputs in optimal proportions, given the prices of inputs and outputs and the production technology. With one output, in this study electricity, the allocative efficiency can be achieved through the least-cost input mix, sometimes called input mix allocative efficiency.

⁵ This is the concept of input-oriented technical efficiency. Alternatively, the output-oriented technical efficiency refers to the ability of a firm to maximise output from a given set of inputs. In this study the concept of input-oriented measure is selected because as the SOE, each plant in EGAT is required to generate and dispatch electricity following the merit order in order to satisfy a certain level of demand and therefore the quantities of input are the major decision variables. Nevertheless, it should be noted that the output and input technical efficiency measures will result in the same set of efficient firms but the measures of technical efficiency of inefficient firms may be different (Coelli et al., 1998, p. 59). Both measures provide the same values only under the constant return to scale assumption.

The measurement of the allocative efficiency of state own enterprises is not fruitful for the management of SOE; because the allocative inefficiency mostly comes from the factor market distortions which are not under their control. Strong labour union limited access to capital market and subsidised input prices such as fuel are major sources of allocative inefficiency in the state owned enterprises.

In addition the input prices are not available, hence only the technical efficiency of a firm is employed to estimate the efficiency improvement target for regulating the performance of EGAT, the electricity generating SOE.

To measure the technical efficiency, a production frontier must be constructed. With the given data of inputs and outputs, a frontier is fitted and the technical efficiency is measured as the distance between each data point and the estimated production frontier. There are two major approaches used to construct the production frontier: the parametric and nonparametric approach.

The parametric approach uses econometric methodology to estimate the production function and measure technical efficiency scores from the residual term. It can distinguish the effects of noise from the effects of the technical inefficiency, however the estimated technical inefficiency is influenced by the structure of the error term and the validity of the assumption about its distribution. In addition, since this approach is parametric, it confounds the effect of misspecification of the functional form of production technology and inefficiency.

The nonparametric approach uses mathematical programming to construct the production frontier and measure efficiency relative to the constructed frontier. The advantage of this approach is that a specific functional form is not required, hence this approach is less prone to model specification error. However, this approach is nonstochastic, therefore it cannot distinguish the noise from the effects of technical inefficiency.

Essentially, the two approaches use different techniques to construct the production frontier. Lovell (1993) concluded that neither approach strictly dominates the other. Employing both methods with the same set of data to estimate the production frontier under the same assumption of return to scale should produce similar results (Coelli et al., 2003, p.20). Both methods will be employed in this study.

2.1 Stochastic Frontier Analysis

The traditional econometric production model to estimate the production frontier, often called the ‘deterministic production frontier’, is defined as

$$y_{it} = f(x_{it}, \beta) e^{(-u_{it})} \quad (1)$$

$i = 1, 2, \dots, N$, and $t = 1, 2, \dots, T$, where

y_{it} is the output of the firm i at time t ;

x_{it} denotes a $(1 \times K)$ vector of inputs;

$f(\cdot)$ is a suitable functional form (such as Cobb Douglas or translog functional form);

β is a vector of unknown parameters to be estimated; and

u_{it} is an error term in which all deviations from the frontier are assumed to be the result of technical inefficiency. It neglects the possible effects of measurement errors and other noise such as the effects of weather, strikes and luck.

To take into account these effects, random error is included into the deterministic production frontier to create ‘stochastic production frontier’ which is defined as

$$y_{it} = f(x_{it}, \beta) e^{(v_{it} - u_{it})}, \quad (2)$$

where v_{it} is random error, accounting for measurement error and other random noise, which is assumed to be identically, independently distributed, to have $N(0, \sigma_v^2)$ -distribution, to be independent of the u_{it} ; and u_{it} is the technical inefficiency effect⁶.

The technical efficiencies of each firm in each year can be predicted using the conditional expectation of $e^{(-u_{it})}$, given the value of $\varepsilon_{it} = v_{it} - u_{it}$. Since u_{it} is a non-negative random variable, these technical efficiency predictions are between 0 and 1. A value of 1 indicates full technical efficiency.

The technical efficiency measures are obtained as

$$TE_{it} = E(e^{-u_{it}} / \varepsilon_{it}), \quad (3)$$

where $\varepsilon_{it} = v_{it} - u_{it}$.

The above production frontier analysis and technical efficient measurement rest on the major assumption that all the units share the same production technology and encounter the same environmental variables. For electricity generating activity, the environmental or firm specific factors which are beyond control of units such as ownership, regulatory environment, different characteristics and age of production units may have an influence on technical inefficiency scores.

To estimate the effects of environmental factors on technical inefficiency, this study adopts the Battese and Coelli (1995) model to construct the single stage estimation of technical inefficiency scores and models of its determinants.⁷ It assumes that technical inefficiency

⁶ The statistical properties of u_{it} varies by the type of data such as cross section or panel data and assumptions imposed. Greene (1993) and Kalirajan and Shand (1999) review the literature on this issue extensively.

⁷ Coelli et al. (1999) explains that there are two views to accommodate the firm-specific environmental variables in the model. The first approach assumes that the environmental variables influence the production frontier and should be included directly into the production function as the independent variables. This approach is somehow comparable to the all-in-one approach for DEA. The resulting technical efficiency terms are net of influences of environmental variables.

The second approach assumes that the environmental factors have influence only on the degree of technical inefficiency and these factors should be modelled in the technical inefficiency regression. Most of the early works use the two-stage estimation approach, in which the technical inefficiency scores are estimated in the first stage and are regressed upon environmental factors in the second stage. It is argued that there is a problem of inconsistency in this approach. Since the error term, representing the inefficiency score, is assumed to be

effects, u_{it} , are independently but not identically distributed non-negative random variables. From Equation 2, for the i -th firm in the t -th period, the distribution of u_{it} , is obtained by truncation at zero of $N(m_{it}, \sigma_u^2)$; where

$$m_{it} = z_{it}\delta, \quad (4)$$

where z_{it} is a $p \times 1$ vector of variables affecting the technical efficiency of a firm and δ is an $1 \times p$ vector of parameters to be estimated.

FRONTIER Version 4.1 is employed (Coelli, 1996b). This program is designed specifically to estimate Battese and Coelli (1995) by simultaneous maximum likelihood estimation of the stochastic frontier and the model of technical inefficiency effects. This program utilises the parameterization by replacing σ_v^2 and σ_u^2 with $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)$. After obtaining the estimates, this software package also provides the estimated technical efficiency levels of each plant in each year. Following Battese and Coelli (1988), these levels are calculated by using

$$TE_{it} = \frac{1 - \Phi(\sigma_A - \gamma \varepsilon_{it} / \sigma_A)}{1 - \Phi(\gamma \varepsilon_{it} / \sigma_A)} \exp(\gamma \varepsilon_{it} + \sigma_A^2 / 2) \quad (5)$$

where $\Phi(\cdot)$ is the distribution function of the standard normal random variable, $\gamma = \sigma^2 / \sigma_s^2$,

$$\sigma_s^2 = \sigma^2 + \sigma_v^2 \text{ and } \sigma_A = [\gamma(1-\gamma)\sigma_s^2]^{1/2}.$$

Before estimating the technical inefficiency, the various hypotheses will be tested to find the most appropriate functional form of the production structure. A likelihood ratio test is employed to simultaneously test the significance of groups of coefficients. The likelihood ratio test is based on the statistic:

$$\lambda = -2[L(H_0) - L(H_A)], \quad (6)$$

identically distributed in the first stage, regressing it in the second stage suggests that it is not identically distributed. Therefore, a single stage approach is proposed. The specification of a model in which both inefficiency scores and its regression are estimated in a single model such as the Battese and Coelli (1995) model.

where $L(H_A)$ and $L(H_0)$ are the maximized values of the log-likelihood function under H_A and H_0 , respectively. This λ statistic has asymptotic chi-square distribution, with degrees of freedom equal to the number of restrictions imposed under the null hypothesis. H_0 is rejected when $\lambda > \chi^2_c$ where χ^2_c is a critical value from the $\chi^2_{(j)}$ distribution where j is number of restrictions.

2.2 Data Envelopment Analysis

The method of production frontier construction by mathematical programming is called Data Envelopment Analysis (DEA).⁸ DEA uses mathematical programming to build a non-parametric piece-wise frontier over the data. Technical efficiencies are estimated relative to this frontier.

To conduct a DEA analysis, assumptions regarding returns to scale have to be considered carefully. Charnes et al. (1978) proposed an input-oriented measure of technical efficiency with an assumption of constant return to scale (CRS).⁹ To estimate the technical efficiency of a firm i , the following linear programming problem¹⁰ is conducted.

$$\begin{aligned}
 & \min_{\theta, \lambda} \theta \\
 & \text{subject to} \\
 & -y_i + Y\lambda \geq 0 \\
 & \theta x_i - X\lambda \geq 0 \\
 & \lambda \geq 0
 \end{aligned} \tag{7}$$

where

⁸ The details of the method at the introductory level are presented by Coelli et al. (1998), Cooper et al. (1999) and Thanassoulis (2001). More technical and comprehensive reviews of this methodology are given by Ali and Seiford (1993) and Charnes et al. (1994).

⁹ In some DEA books, this model is referred as the CCR model in which CCR stands for Charnes, Cooper and Rhodes.

¹⁰ Originally the mathematical programming problems to estimate the production frontier are introduced in the multiplier form. Employing the duality in linear programming, the problems in envelopment form can be derived. The technical derivation, particularly regarding the efficiency analysis, is shown in Ali and Seiford (1993). One benefit of solving the problems in the envelopment form is that it requires fewer constraints than in the multiplier form (Coelli et al., 1998, p.141). Also, to be consistent with the DEA software, which will be mentioned later on, the linear programming problem will be stated in the envelopment form.

y_i represents the output of firm i ;

x_i is a vector of firm i 's inputs with elements x_{ij} ($j = 1, 2, \dots, M$);

Y is a $(1 \times N)$ vector of the outputs of all firms with elements y_i ($i = 1, 2, \dots, N$);

X is a $(M \times N)$ matrix of the inputs of all firms with element x_{ij} ;

λ is a $(N \times 1)$ vector of weight λ_i to be determined; and

θ is a scalar value denoting the technical efficiency score.

The linear programming problem must be solved N times, once for each firm i . If θ takes a value of 1, indicating a point on the frontier which means a technically efficient firm or a best-practice firm, this means that a particular firm has zero technical inefficiency. If θ is less than unity, a firm is operating off the production frontier which means that the particular firm is technically inefficient and can potentially reduce inputs by a factor of $(1-\theta)$ while holding output constant by adopting the behaviours of best-practice firms.

The CRS assumption is restricted to the case where firms are operating at an optimal scale. This assumption is not appropriate to the firms operating in an imperfectly competitive market or SOEs, which is a common characteristic in power generation activity. There are some firms that do not operate at the optimal scale or are smaller than the other firms due to factors out of their control which are usually determined by historical factors or government policies.

The model with an assumption of variable return to scale (VRS) should be considered in order to eliminate the scale effect from the technical efficiency measurement. Banker et al. (1984) extended the model by Charnes et al. (1978) by imposing the assumption of VRS into a model.¹¹

To modify the CRS linear programming problem into VRS specification, they add the

¹¹ In some DEA books, this model is referred as BCC model in which BCC stands for Banker, Charnes and Cooper.

convexity constraint: $N1'\lambda = 1$ to Equation 7 as follows

$$\begin{aligned} & \min_{\theta, \lambda} \theta \\ & \text{subject to} \\ & -y_i + Y\lambda \geq 0 \\ & \theta x_i - X\lambda \geq 0 \\ & N1'\lambda = 1 \\ & \lambda \geq 0 \end{aligned} \tag{8}$$

where

$N1$ is an $N \times 1$ vector of ones.

This model envelopes the data points more tightly than the CRS model, therefore the obtained technical efficiency scores are greater than or equal to those in the CRS model.

The convexity constraint also ensures that an inefficient firm is only benchmarked against firms of a similar size whereas in a CRS specification, a firm may be benchmarked against firms which are substantially larger or smaller than it.

Technical efficiency scores obtained from the CRS model are called global technical efficiency, since the implied comparison is with firms operating at the optimal scale whereas those obtained from the VRS model are called local pure technical efficiency.

If a firm is fully efficient in both CRS and VRS specifications, it is operating in the most productive scale.

If a firm has a full score in VRS model but a low score in CRS model, it is operating locally efficiently but not globally efficiently due to the scale of the firm. The difference between the CRS and VRS technical efficiency scores indicates that the firm has scale inefficiency.

The computer software package, DEAP Version 2.1, is employed to measure the technical efficiency under both constant and variable return to scale (Coelli, 1996a). In DEAP Version 2.1, the technical efficiency scores can be estimated by three DEA models, which vary by the treatment of slacks, namely one-stage, two-stage and multi-stage DEA.

One-stage DEA is the model explained above. To estimate the technical efficiency, the

treatment of slacks is not necessary because the slacks are considered as the allocative efficiency. Coelli et al. (1998) argues convincingly that solving DEA linear programming above can achieve satisfactory measurement of technical efficiency.¹²

In this study the panel data are employed. To deal with the role of time, the intertemporal model which merges the data for all the years into one set and calculates efficiency scores for the whole data set is chosen.¹³

This model is based on the assumption that no technological change occurs during the period of study. This assumption is consistent with the fact that the Thai power plants generate electricity by using the same generation techniques throughout the period of study.

This is not surprising because the electricity power plants have a long life and the establishment of new power plants, new units or a change in generation techniques is costly and time consuming, therefore the evidence of technical change in this industry is somewhat limited.

As explained about the significance of firm-specific variables in the technical inefficiency model, to estimate the effects of environmental factors on technical inefficiency, the technical inefficiency estimated from the first-stage DEA is used as the dependent variable in a second stage regression in which the independent variables are the environmental variables.¹⁴

¹² The two-stage and multi-stage DEA models were estimated. The results of technical efficiency scores of these two models are the same as those of the one-stage model. The only difference among them is the values of slacks.

¹³ Tulkens and Eeckaut (1995) provided the definition and derivation of three methods of non-parametric frontier to deal with the role of time: contemporaneous, sequential and intertemporal model. The choice of model depends on the characteristics of sample and application of model (Linna, 1998, pp.417–418).

¹⁴ The method employed here is called the two-stage approach. By this approach the effects of environmental variables can be statistically tested. According to Fried et al. (1999), there are three broad classifications of methods to accommodate the environment variables in DEA analysis: the frontier separation approach, the all-in-one approach and the two-stage approach. The frontier separation approach disaggregates the data set into a sub group according to a categorical variable which is the environmental variable, such as ownership structure. The frontiers are estimated for each sub group and for the pooled data set. The effect of environmental variables is estimated by the comparing sub-group and pooled technical efficiency scores. This method is limited to the case of one categorical variable. The all-in-one approach is to include the environmental variables directly into the linear programming formulation as either input(s) or output(s). This approach is not limited to one environmental variable. However the choice of putting it as either input or output has to be made carefully. As input it implies that the environmental variable is favourable whereas as output it implies that it is an unfavourable operating

Since inefficiency scores computed from the DEA model are bounded between 0 and 1, ordinary least square regression would produce biased and inconsistent estimators in the second stage regression. Therefore, to avoid this problem, the tobit model of inefficiency scores using maximum likelihood estimation is adopted. The specification of the tobit model will be discussed in following sections.

2.3 *Consistency conditions*

Due to the strength and weakness of each approach, this study employs both DEA and SFA to estimate and compare technical efficiency scores. It is likely that there are some inconsistencies in scores from different approaches. Hence the question of comparing and identifying the most and least efficient power plants arises.

To answer this question, Bauer et al. (1998) proposed a set of consistency conditions for the different efficiency models for the regulatory purposes. Owing to the different purpose, this study adopts a subset of consistency conditions requiring efficiency scores obtained from the different models should be consistent in their efficiency levels, rankings and identification of the best and worst power plants.

Note that for the comparison between approaches to make sense, this study ensure that the empirical studies by different approaches refer to the same sample and variables and makes use of the same efficiency concept.

3 Data and variables

Before explaining data and variables used for the estimation, it is worth mentioning that data limitation exists. Coelli et al. (2003) stated clearly that limited access to the data of public enterprises is the conventional problem for developing countries, therefore good proxies of

environment. The operating environment has been judged before including in the model. This method is not appropriate if a test on how the operating environments affect the efficiency will be conducted.

variables for frontier models are always rarely obtained. Even in the developed countries in which data is easier to access and more organised, they also face a data constraint due to the nature of public enterprises.¹⁵ Therefore, with data limitation, it should be noted that the results obtained are suboptimal.

EGAT's electricity generation consists of two major types of power plants: thermal and hydro power plants. EGAT's thermal power plants generate electricity by converting the heat from fuel combustion into mechanical energy and then electricity via several types of generation system: conventional thermal or steam turbine, gas turbine, combined cycle and diesel engine system.

The conventional thermal and combined cycle thermal power plants generally serve as base load plants,¹⁶ whereas gas turbine, diesel thermal and hydro power plants supply electricity for the peak load and reserve capacity.

In this study, the data covers all of the thermal power plants excluding the diesel power plants. The reason for this is that the diesel power plants are of a small size and capacity, being not more than 5 MW which is very small when compared with the other types of power plants. Given that diesel oil is the most expensive fuel EGAT seldom operates them and often retains them as the last resort.

The data is provided by EGAT. For reasons of confidentiality, data is provided in units of power plants rather than the data of each power plant. It should be noted that there are a number of power plants which consists of different types of electricity generation techniques. The data in each unit level allows comparison of the performance of different production techniques.

The data set consists of annual measures of output and three inputs: labour, capital and fuel in

¹⁵ Lovell (2002) summarised the data problem of assessing the public enterprise performance into three respects: definition of service provided, price of service and service quality.

¹⁶ Base load plant is the electricity generating plant operating to meet requirement for energy on a round-the-clock basis.

the period 1992 to 2001. In the obtained sample data set, some observations are not available in certain years because some units had started operations in later years, or closed down due to the high cost of operation, lower electricity demand and service life expiration.

Owing to these data omissions, the final unbalanced panel data set includes 170 observations. To reduce the data set to the balanced panel data, the units with incomplete annual data and the missing data of some of the units in 2001 are eliminated.

Most of units eliminated are those of gas turbine power plants, which is not surprising because almost all of the gas turbine power plants serve to meet peak demand.

Eventually the final balanced panel data set consists of 12 units and covers period of 1992 to 2000. For the reason of simplicity from now on the units will be regarded as power plants.

Table 1 shows the summary statistics of each variable in the balanced panel data. A description of each variable in the whole unbalanced panel data set is briefly explained as follows.

The output is the electricity generated by each plant with the average output in this sample being 3,481.95 GWh. The largest plant, which is the lignite-type conventional thermal power plant, can generate 12,146.77 GWh whereas the smallest gas turbine plant can produce only 0.29 GWh to serve the peak demand. The capital measure¹⁷ used is the capacity of each plant in MW.¹⁸ The average capacity of plants in the sample is 657.18 MW, with largest combined cycle plant having a total of 2,031 MW of generating capacity and the smallest gas turbine plant having 14 MW.

The most troublesome variable is the employment number. According to EGAT officials, the

¹⁷ Coelli (2002) pointed out that as a proxy of capital, a measure of the overall capital investment adjusted for depreciation and embodied technical change is more preferable. Due to the data limitation, this measure cannot be constructed.

¹⁸ In this study, capacity is not depreciated. To the author's knowledge, depreciating the nameplate capacity cannot be done. This is proven by various frontier studies on electricity generating activities using the non-depreciating capacity as proxy of capital. Age of power plants will be included as the environmental variable in the technical inefficiency model. Inclusion of the age will represent depreciation of power plants. Technical efficiency scores obtained will net out the effect of depreciation of capital.

data of employment in some plants is not recorded at all and for some only in some years, therefore the fragmented employment data cannot fit in the data set of the other variables.

To avoid the problem of missing data, indexing the employment number from the labour expenditures is the only option, however the labour expenditures are not recorded separately. They are recorded as the portion of operating, maintenance, administrative and general expenses because in the electricity generation activity most labour is employed to do these tasks. Therefore the summation of these expenditures can be a proxy of labour expenditures.

The period of study covers the period of financial crisis in which EGAT suffered from the loss of foreign exchange. The administrative and general expenses are very high, particularly in 1999 as it includes of the expenditures from the headquarters in which loss from foreign exchange is a major component. Moreover the labour component in this expenditure is not related to electricity generation but is related to administrative jobs in the headquarters. Therefore these expenses do not reflect the true cost of electricity operation.

To avoid overestimation of labour expenditures, only the summation of operating and maintenance expenditures will be employed for the calculation of labour input. These aggregates will be deflated by the wage bill and then adjusted by the conversion factors¹⁹ to obtain the estimated labour input.²⁰

The last variable is fuel. Each type of power plant has a particular combination of fuel used due to the different electricity generation systems.

The conventional thermal power plants use either lignite or fuel oil and natural gas as their main fuel, whereas the combined cycle power plants employ natural gas.

¹⁹ EGAT provided the true employment numbers of two units in the conventional thermal and combined cycle power plants throughout the period of study. These numbers are employed to calculate two average conversion factors, one of which is to convert the wage deflated labour expenditure into the proxy of number of employment of units in the conventional thermal power plants and another is for units in combined cycle and gas turbine power plants. Using the same conversion factor for the combined cycle and gas turbine power plants is based on the fact that their production techniques are similar.

²⁰ Due to data limitation, an estimation of employment numbers is required, however the best way is to directly obtain the data of labour. Further study should be conducted by updating and obtaining the true employment number, however with better exposure to the data, the quality adjusted labours are more satisfactory.

The gas turbine power plants use diesel oil.

Apart from their main fuel, some of power plants use other additional fuel such as diesel oil to start up or to test the operation of plant. Therefore, it is difficult to choose a single measure of fuel input.

To avoid difficulties in comparing different physical plants using different fuels, it is ideal to convert volumetric measures of fuels into “joule” measurements of the actual heat energy content. The converted number can then be aggregated into a fuel figure for each plant. The average fuel used is 34,880.43 terajoules. The largest plant uses 129,725.95 terajoules whereas the smallest plant uses 5.45 terajoules.

For measurement of technical efficiency in Thai power plants, the balanced panel data is employed. To capture the variation in technical inefficiency across Thai power plants, two firm-specific variables, the age of the power plant and power plant dummy variable, are included in the technical inefficiency model.²¹

The age of plant could affect its technical inefficiency a number of ways.

On the one hand the older plants reflect the older production technology and equipment which may increase plant inefficiency as the power plant ages.

On the other hand the better adaptation of production conditions in the older plants may lead to higher efficiency levels. In the balanced panel data, the age of plants varies between 11 and 360 months with an average of 165 months. The power plant dummy variable, which takes the value 1 for the j -th power plant and 0 otherwise, is included to capture each plant specific characteristics.

²¹ There are more environmental variables determining technical inefficiency. Joskow and Schmalensee (1987), Khanna et al. (1999) and Knittel (2002) provide a detailed explanation and justification of various determinants of technical inefficiency. Due to the data limitation, all of the possible determinants in the model are not covered.

4 Empirical results

In this section, the efficiency measurements of the Thai power plants are conducted by the methods of DEA and SFA and the use of the balanced panel data of Thai power plants. The mean value of technical efficiency scores estimated by DEA and SFA are reported in Table 2 and the details of estimation of each model will be discussed as follows.

4.1 Stochastic Frontier Analysis

To find the most appropriate production structure, the translog production function with the technical change represented by time trend and squared time trend is selected as the unrestricted model. The hypotheses regarding the form of technical change and Cobb Douglas production function are then tested against it by the likelihood ratio test.

Table 3 reports the results from the testing production structure hypotheses.

The Cobb Douglas functional form is rejected in any form of technical change, therefore the translog production function is selected. The two translog functions with technical change in the form of only time trend and both time trend and squared time trend are rejected, hence the most favourable model is translog production function with no technical change.

This result is consistent with the fact that the electricity generating techniques of the plants do not change over the period of study, and it confirms that the intertemporal model for DEA is appropriate.

Equation 2 is thus specified by the translog production function as follows:

$$\begin{aligned} \ln(Q_{it}) = & \beta_0 + \beta_K \ln(K_{it}) + \beta_L \ln(L_{it}) + \beta_F \ln(F_{it}) + \beta_{KK} [\ln(K_{it})]^2 + \beta_{LL} [\ln(L_{it})]^2 \\ & + \beta_{FF} [\ln(F_{it})]^2 + 2[\beta_{KL} \ln(K_{it}) \ln(L_{it}) + \beta_{KF} \ln(K_{it}) \ln(F_{it}) \\ & + \beta_{LF} \ln(L_{it}) \ln(F_{it})] + v_{it} - u_{it} \end{aligned} \quad (9)$$

$$i = 1, 2, \dots, N, \text{ and } t = 1, 2, \dots, T,$$

where Q_{it} is electricity output (GWh) by the i -th plant in the t -th year; K_{it} , L_{it} and F_{it} represent capital (MW), labour (persons) and fuel inputs (terajoules), respectively. The model is written in natural logarithmic form, denoted by ln . To investigate the influence of firm-specific variables on the technical inefficiency, this study follows Battese and Coelli (1995) as already explained above. Equation 4 will be specified below:

$$m_{it} = \delta_0 + \sum_{j=1}^{11} \delta_j p_j + \delta_a AGE_{it} + \xi_{it} \quad (10)$$

where $\xi_{it} \sim N(0, \sigma_\xi^2)$.

Equation 9 and 10 (SFAA) are simultaneously estimated by the maximum likelihood method the estimates shown in Table 4.

To ensure that the inefficiency effects are stochastic, the null hypothesis that the inefficiency effects are not present; $H_0 : \gamma = \delta_0 = \dots = \delta_{11} = \delta_a = 0$; and the inefficiency effects are not stochastic; $H_0 : \gamma = 0$ and the coefficients of the variables in the technical inefficiency model are zero; $H_0 : \delta_0 = \dots = \delta_{11} = \delta_a = 0$ and $H_0 : \delta_1 = \dots = \delta_{11} = \delta_a = 0$ are tested.

In Table 5 the results show that all of null hypotheses are rejected and indicate that the technical inefficiency effect is stochastic and related to plant dummy variables and the age of power plants. However, the estimate of γ is not significantly different from 1 at 5 per cent level of significance which indicates that the stochastic frontier model is not significantly different from the deterministic frontier. All the deviation from the frontier results from the technical inefficiency.

The results of the inefficiency model show that age is statistically significant from zero, at 1 per cent significance level, and has a positive effect on technical inefficiency as expected. Also, the results of the plant dummy variables show that the plant characteristics have a particular effect on the technical inefficiency in both negative and positive ways.

From the estimates in Table 4, the output elasticities with respect to capital, labour and fuel and return to scale elasticity are calculated around mean and reported in Table 6.

All of them have the expected positive signs. The output elasticities of capital, labour and fuel are 0.55, 0.12 and 0.75 respectively. The production elasticities are dominated by the fuel elasticity because in electricity generation the fuel is the most important input.

The labour elasticity is smallest, which matches with labour being the least important input in electricity generation.

The return to scale elasticity, 1.42, indicates that Thai power plants operate at an increasing return to scale.

The mean technical efficiency scores of each plant are reported in Table 2.

4.2 Data Envelopment Analysis

The plant-level global (DEA CRS) and pure (DEA VRS) technical efficiency scores of Thai power plants are calculated. The mean values of both technical efficiency scores of each plant over the period of study are shown in Table 2.

To examine the effects of plant-specific variables on the technical inefficiency, the tobit model is specified by the same variables as those in the SFA as below:

$$(1 - \theta_s)_i = \psi_0 + \sum_{j=1}^{11} \psi_j p_j + \psi_a AGE_i + \omega_i, \quad (11)$$

where θ_s is the technical efficiency score of s , representing CRS (global) and VRS (pure) efficiency; p_j is a plant dummy variable, which takes the value 1 for the j -th plant and 0 otherwise; AGE is the age of each plant in months; and ψ s are unknown parameters to be estimated. $\omega_i \sim N(0, \sigma_\omega^2)$.

The estimates of tobit regressions on the global and pure technical inefficiency scores are shown in Table 7. Age is statistically significantly different from zero at 1 per cent significance level and has an expected positive effect on the technical inefficiency, therefore it

can be concluded that technical efficiency deteriorates as the plant ages which is consistent with the conclusion drawn by Khanna et al. (1999) in the case of thermal power plants in India. The results of plant dummy variables of both regressions indicate that the plants with different characteristics have different levels of technical inefficiencies. These results are useful for ranking the most and least efficient plants which will be discussed below.

4.3 Consistency of results from Data Envelopment Analysis and Stochastic Frontier Analysis

The technical efficiency scores from DEA with both CRS (DEA CRS) and VRS (DEA VRS) assumptions and SFAA are reported in Table 2.

The most striking result is that the mean technical efficiency score from SFAA, 0.77, is somewhat lower than those from DEA CRS and DEA VRS which are 0.82 and 0.88, respectively.

This result is contrary to the fact that technical efficiency estimates from DEA should be lower than those from SFA because DEA does not separate the technical inefficiency effect from the error term, and the efficiency levels of each plant are hugely different between DEA and SFA. Possible reasons of higher DEA scores and differences of efficiency mean and level can be the inclusion of age in the estimation of technical efficiency scores by SFAA, as the older plants are less efficient and can result in the lower technical efficiency scores.

Therefore Equation 10, remodelled by eliminating age as the plant-specific variables (SFANA), is estimated and presented in Table 8.²²

Results of tests on the inefficiency model are shown in Table 9.²³

²² The production structure strictly follows Equation 9 for reason of consistency, therefore the detail of tests of production structure is not needed and not provided here. However it should be mentioned that the author attempted all of the tests and found no serious problem regarding this model.

²³ By using λ statistics (-16.94), the null hypothesis of $H_0: \gamma=0$ is not rejected. Coelli (1995) used the Monte Carlo experimentation to investigate the properties of the maximum likelihood estimator of γ and found that

The value of γ , 0.03, is statistically different from zero at 5 per cent confidence level, therefore the production function with no technical efficiency effect is not an adequate representation of the data. Also the value of γ is statistically different from one at 1 per cent level of significance so the model is different from the deterministic model.

When comparing results from SFANA and SFAA, it is obvious that the value of γ obtained from SFANA is much smaller than the one in SFAA and almost close to zero. When considering the statistical significance of each individual coefficient of power-plant dummy variables in technical inefficiency effect, the SFAA model has more favourable results.

The technical efficiency scores after eliminating the age variable increase dramatically.

The mean score of SFANA, 0.97, is the largest and higher than those of DEA. It results from low value of γ .

It is clear that dropping age of plant does impact the scores, therefore the choice of modelling approach does affect the results.

This study does not aim to choose the best model but to observe the effect of age on technical efficiency scores, therefore both SFAA and SFANA model will be discussed together with the DEA model later on.

To be comparable with SFANA, the tobit regressions of both CRS and VRS technical inefficiency scores in Equation 11, excluding age as explanatory variable, are also estimated and reported in Table 10.

The mean technical efficiency scores from DEA CRS and VRS, 0.82 and 0.88 respectively, are high. Undoubtedly the global technical efficiency which does not take the scale effect into account results in the lower score. Eliminating the scale effect pushes the plants to the frontier as scale effect does matter in the power plant efficiency.

Due to some inconsistency in scores from different approaches, the question of comparing

when γ^* is small, maximum likelihood estimator is biased. Therefore the λ statistics have incorrect size and its test is invalid. Coelli suggested that t test of γ is sufficient.

and identifying the most and least efficient power plants arises.

Following a set of consistency conditions, the obtained results show that the first condition, consistency in efficiency levels is not met. It can conclude that the levels of efficiency scores for both DEA and SFA methods vary across power plants and at mean values, however it is possible that the ranking of power plants from different methods are similar.

In Table 11 Spearman rank-order correlations between scores from different techniques are positive but most of them are very low. Only the correlation between nonparametric models (DEA CRS and DEA VRS), 0.78, is statistically different from zero at the 5 per cent level of confidence. The result suggests that DEA and SFA give an inconsistent ranking in comparison with each other. Again this condition is not met. Although the different models do not rank the power plants in a similar way, they may be consistent in identifying the most and least efficient power plants. In Table 12, the upper triangle shows the proportion of power plants that both simultaneously classified in the upper quartile (three power plants) by the two techniques, whereas the lower triangle shows the same for the lower quartile (three power plants).

For consistency in identifying the best power plants, there is a good consistency among and across both DEA and SFA techniques, but no consistency between DEA CRS and SFNA.

Consistency in identifying the worst power plants is relatively low among and across techniques.

Even though the consistency conditions of efficiency level and ranking of both DEA and SFAA are not met, consistency in identifying the best and worst plants is met. The ranking obtained from the tobit regression with the age of both CRS and VRS technical inefficiency scores (TA CRS and TA VRS) when compared with ranking from SFAA are particularly

consistent, as shown in Table 13.²⁴ When comparing ranking obtained from the tobit regression without the age of both CRS and VRS (T CRS and T VRS) and SFANA, the result is not highly consistent.

The age of power plants does affect negatively the technical efficiency scores. Dropping it from the regression yields the improvement of scores, however ignoring it affects the consistency of identifying the best and worst power plants negatively. Therefore, ranking obtained from regression with age has net out the effect of age on technical efficiency scores and results in consistency in identifying the most and least efficient power plants across the models.

It can be concluded that a gas turbine power plant (number 12), a conventional thermal power plant using fuel oil and natural gas (number 8) and the combined cycle power plant (number 10), are considered the top three of the most efficient power plants. Conventional thermal power plants using lignite (number 1) and using fuel oil and natural gas (number 4) are the worst performers.

Efficiency of power plants can be assessed using the measures of productivity. The partial factor productivities, which are the ratio of output to input: capital, labour and fuel, represented by Y/K , Y/L and Y/F respectively, are commonly used. As shown in Table 3, for the best performer, plant number 12 has the highest partial productivity of capital, 7.22, whereas plant number 10 has the highest partial productivity of labour and fuel, 26.15 and 0.12 respectively.

As for the worst performers, plants number 1 and 4 have the lowest partial productivity of capital.

Therefore it can be concluded that the results from frontier analysis are consistent with the simple partial productivity measures. It should be noted that the partial productivities of

²⁴ It is noted that in this study in case that power plants' mean technical efficiency scores are equal, those power plants are ranked among themselves by power plant numbers.

power plants fuel do not vary much, from 0.07 to 0.12, because the amount of fuel used to generate a certain level of electricity is fixed whereas the wide range of partial productivities of labour results from the different electricity generation techniques.

5 Regulatory choice of efficiency measures

In the previous sections, efficiency measurement for regulatory purpose was proposed and demonstrated. Assuming that the regulator agrees on the empirical results, the next step is to use these results to set the regulatory tool, the X factor. It should be noted that this section aims to provide a demonstration on how to choose regulatory tool but not to finalise the exact value of the X factor which should be set based on the discretion of regulators and discussion with the regulated entity

Following Coelli et al. (2003), the X factors can be set at power plant-specific level or a single X factor can be set for all power plants or for an enterprise, depending on the regulatory objectives.

For illustration, the technical efficiency scores from DEA VRS and SFANA will be employed for calculation of the X factor because their results are the most comparable, reliable and consistent with each other as discussed in the previous section.

The objective of setting the power plant-specific X factors is to ensure that by the end of the regulatory period, each firm has full technical efficiency score. For power plants that are technically inefficient, plants may be asked to reduce a whole or a half of the inefficiency gap. For example, according to results from SFANA power plant 9 has a TE score of 0.91 and is the most inefficient firm in the sample. The regulator could ask it to achieve the efficiency improvement level of 9 (a whole of the inefficiency gap or EI1) or 5 (a half of the inefficiency gap or EI2) per cent over the regulatory period. The power plant-specific efficiency targets are calculated for each plant in the sample from both SFANA and DEA VRS and shown in Table

14. For the power plant on the frontier, the efficiency improvement target is zero. It is obvious that EI1 and EI2 from DEA VRS are higher than those from SFANA because of the lower technical efficiency scores.

For the single efficiency improvement target for all power plants or for an enterprise, the average of the power plants' efficiency improvement target can be employed. The average of EI1 and EI2 from SFANA are 3 and 1 per cent respectively whereas those from DEA VRS are 13 and 6 per cent respectively over the regulatory period.

It is recommended that the efficiency improvement target should be calculated on an annual basis. The percentage of annual efficiency improvement target depends on how long the regulatory period is. For example if the regulatory period is four years, the power-plant specific efficiency improvement target of power plant 9 from SFANA EI1 is 2.18 per cent per year.²⁵ This measure allows power plants to gradually and smoothly improve their performance to achieve their targets. The jump from inside to be on frontier without setting a timeframe is unlikely to achieve. As for an enterprise, the annual single efficiency improvement target is derived from the average of EI1 of 0.74 per cent per year from SFANA and 3.1 per cent per year from DEA VRS.

Review and revision of efficiency improvement target should be undertaken both during and at the end of the regulatory period to continually evaluate their performance and to ensure that power plants and/or enterprise are given with the right incentive to improve their efficiency.

In this study, from the results of SFA there is no evidence of technical change in this sample group, hence percentage of frontier shift is zero per cent in this study. However, Coelli et al. (2003) recommends the inclusion of a level of technical change into the efficiency improvement target to encourage the firms on the frontier to improve their performance. With the new dataset, the evidence of technical change may appear.

²⁵ It is calculating by $(1.09)^{1/4}$.

Choices of efficiency measures, including power-plant specific or single efficiency improvement target; and annual targets or single target for whole regulatory period, rely on regulatory discretion. Once the efficiency measurements are conducted and completed, the regulated firms have to be invited to be involved with the final determination process of the X factor (Rossi and Ruzzier, 2000, p.90).

6 Conclusion

The efficiency improvement target, or the X factor, is an important regulatory tool to encourage the electricity generation SOE, EGAT, to improve its operating efficiency. This regulatory variable was taken from London Economics (1997) and has been employed without any review and revision since then. The revision of the X factor is needed to evaluate the enterprise performance and to provide new and improved incentives for efficiency improvement.

This study has estimated the technical efficiency of EGAT at power plant level by DEA and SFA and demonstrated choices in setting the X factor for regulatory purpose.

As for the power-plant specific efficiency improvement target, the empirical results from evaluating the Thai power plants are beneficial to the internal management, enabling the EGAT executives to improve the performance of the less efficient power plants. EGAT can also use these measures as the criteria for the future IPP and SPP bids.

As for the single X factor for an enterprise, the results can be adopted for the next estimation of revenue requirement.

It is important to note that the final value of the X factor depends on regulatory discretion and decisions.

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Table 1 Summary statistics of variables of Thai power plants in balanced panel data

Variable	Mean	Standard deviation	Minimum	Maximum
Output (GWh)	4,146.53	3,076.33	40.03	12,146.77
Capacity (MW)	700.05	493.53	25	1,800
Labour (persons)	462.07	394.71	59.3	1,907.27
Lignite (million tonnes)	1.16	2.74	-	12.06
Fuel oil (million litres)	348.46	597.91	-	2,172.94
Diesel oil (million litres)	14.57	47.39	-	273.85
Natural gas (million cubic feet)	14,309.43	16,070.67	-	53,182.18
Fuel (terajoule)	41,379.35	30,694.55	518.87	129,725.95
Age (months)	165.33	84.67	11	360

- zero

Table 2 Technical efficiency scores^a and descriptive statistics

Types	Plant	Age ^b	SFAA	SFANA	DEA CRS	DEA VRS	Y/K	Y/L	Y/F
Conventional thermal - lignite	1	272	0.91	1	0.76	0.82	5.34	2.74	0.1
	2	200	0.69	0.98	0.81	0.81	5.98	4.81	0.1
	3	140	0.47	0.99	0.82	0.91	6.08	7.51	0.1
Conventional thermal – fuel oil and natural gas	4	236	0.84	0.94	0.73	0.75	5.44	2.88	0.09
	5	360	0.5	0.96	0.79	0.83	5.77	7.6	0.1
	6	209	0.65	0.99	0.85	0.88	6.13	15.05	0.11
	7	107	0.63	0.93	0.82	0.9	5.95	19.56	0.1
	8	334	0.99	1	0.81	0.99	6.1	0.92	0.08
Combined cycle	9	242	0.72	0.91	0.81	0.84	5.65	19.21	0.1
	10	127	0.96	1	0.91	0.95	6.29	26.15	0.12
	11	121	0.85	1	0.79	0.86	5.46	17.55	0.11
Gas turbine	12	212	0.97	0.99	0.93	0.96	7.22	13.52	0.07
	Mean		0.77	0.97	0.82	0.88	5.95	11.46	0.1
	Median		0.78	0.99	0.81	0.87	5.97	10.56	0.1
	Minimum		0.47	0.91	0.73	0.75	5.34	0.92	0.07
	Maximum		0.99	1	0.93	0.99	7.22	26.15	0.12
	Standard deviation		0.18	0.03	0.06	0.07	0.50	8.15	0.01

^a The mean technical efficiency scores over the period of study.

^b The reported age is in months and is the age at the end of period of study.

Table 3 Results from testing production structure hypotheses

Model Description (Restrictions)	Log- Likelihood Function	λ	$\chi^2_{0.95,(j)}$	j	Decision
Translog (No Technical Change) ($\beta_t = \beta_{tt} = 0$)	140.25	-2.7	5.99	2	Do not reject H_0
Translog (Technical Change with t and t ²)	138.91				
Translog (Technical Change with t) ($\beta_{tt} = 0$)	134.67	8.46	3.84	1	Reject H_0
Cobb Douglas (No Technical Change) ($\beta_{KK} = \beta_{LL} = \beta_{FF} = \beta_{KL} = \beta_{KF} = \beta_{LF} = \beta_t = \beta_{tt} = 0$)	119.79	38.24	15.51	8	Reject H_0
Cobb Douglas (Technical Change with t and t ²) ($\beta_{KK} = \beta_{LL} = \beta_{FF} = \beta_{KL} = \beta_{KF} = \beta_{LF} = 0$)	117.69	42.44	12.59	6	Reject H_0
Cobb Douglas (Technical Change with t) ($\beta_{KK} = \beta_{LL} = \beta_{FF} = \beta_{KL} = \beta_{KF} = \beta_{LF} = \beta_{tt} = 0$)	118.49	40.84	14.07	7	Reject H_0

Table 4 **Maximum-likelihood estimates of translog stochastic frontier model**

Coefficient	Estimate	Standard Error	t-Statistics
β_0	-6.89	1.03	-6.66
β_K	-1.44	0.42	-3.43
β_L	0.97	0.31	2.92
β_F	2.14	0.27	7.94
β_{KK}	0.06	0.03	1.86
β_{LL}	0.01	0.03	0.18
β_{FF}	-0.04	0.03	-1.25
β_{KL}	0.07	0.03	2.18
β_{KF}	0.02	0.03	0.9
β_{LF}	-0.08	0.03	-2.5
δ_0	-0.51	0.12	-4.2
δ_1	0.07	0.08	0.84
δ_2	0.54	0.11	4.86
δ_3	1.05	2.02	5.2
δ_4	0.25	0.08	3.22
δ_5	0.52	0.14	3.76
δ_6	0.6	0.12	4.8
δ_7	0.84	0.15	5.59
δ_8	-0.44	1.19	-3.74
δ_9	0.41	0.1	4.28
δ_{10}	0.18	0.12	1.54
δ_{11}	0.49	0.12	3.95
δ_a	0.002	0.001	4.82
σ^2	0.01	0.001	5.4
γ	0.92	0.18	4.96
Log-likelihood	140.25		

Table 5 Results from testing the technical inefficiency model

Null hypothesis	Log-Likelihood Function	λ	$\chi^2_{0.95,(j)}$	j	Decision
$H_0: \gamma = \delta_0 = \dots = \delta_{1l} = \delta_a = 0$	97.83	84.84	24.38 ^a	15	Reject H ₀
$H_0: \gamma = 0^b$	130.07	20.36	5.14	2	Reject H ₀
$H_0: \delta_0 = \dots = \delta_{1l} = \delta_a = 0$	100.02	80.46	22.36	13	Reject H ₀
$H_0: \delta_l = \dots = \delta_{1l} = \delta_a = 0$	97.83	84.84	21.03	12	Reject H ₀

^a If the test involving $\gamma=0$, then λ has a mixed Chi-square distribution. The critical values for this test are obtained from Table 1 of Kodde and Palm (1986).

^b Coelli (1995) argued that testing γ by the two-sided likelihood ratio is invalid because λ has the incorrect size. He suggested that the test of γ by t-statistics is sufficient. The t-statistics of γ indicates that γ is statistically different from zero at 1 per cent confidence level.

Table 6 Estimates derived from the translog stochastic frontier model

Description	Estimate
Capital Elasticity of Output	0.55
Labour Elasticity of Output	0.12
Fuel Elasticity of Output	0.75
Return to Scale Elasticity	1.42

Table 7 **Tobit regression of technical inefficiency scores**

Variables	Constant return to scale		Variable return to scale	
	Estimate	Marginal effect	Estimate	Marginal effect
Constant	-0.16* (0.07)		-0.16** (0.06)	
p_1	0.09 (0.06)	0.09	0.09 (0.05)	0.08
p_2	0.14** (0.05)	0.13	0.18** (0.05)	0.16
p_3	0.21** (0.06)	0.2	0.14** (0.05)	0.13
p_4	0.17** (0.06)	0.16	0.21** (0.05)	0.18
p_5	-0.06 (0.08)	-0.06	-0.02 (0.06)	-0.02
p_6	0.08 (0.06)	0.07	0.09* (0.05)	0.08
p_7	0.26** (0.07)	0.24	0.2** (0.06)	0.17
p_8	-0.04 (0.07)	-0.04	-0.26** (0.07)	-0.23
p_9	0.07 (0.06)	0.07	0.11* (0.05)	0.09
p_{10}	0.12* (0.06)	0.12	0.11* (0.05)	0.09
p_{11}	0.27** (0.06)	0.25	0.22** (0.05)	0.2
AGE	0.001** (0.0003)	0.001	0.001** (0.0003)	0.001
Log-Likelihood Value	73.9		72.05	
R^2	0.28		0.47	
σ	0.12		0.09	

The numbers in parentheses are standard error.

* and ** indicates the statistically significant estimates at 5% and 1% significance level, respectively.

Table 8 **Maximum-likelihood estimates of translog stochastic frontier model without age variable**

Coefficient	Estimate	Standard error	t-Statistics
β_0	-6.6	0.99	-6.68
β_K	-0.3	0.87	-0.35
β_L	0.51	0.87	0.58
β_F	1.77	0.68	2.6
β_{KK}	0.02	0.15	0.1
β_{LL}	-0.02	0.19	-0.13
β_{FF}	-0.07	0.08	-0.84
β_{KL}	-0.03	0.09	-0.29
β_{KF}	0.04	0.1	0.33
β_{LF}	0.004	0.09	0.04
δ_0	-0.004	0.35	-0.01
δ_1	-0.1	0.77	-0.13
δ_2	0.03	0.37	0.07
δ_3	0.001	0.85	0.001
δ_4	0.07	0.44	0.15
δ_5	0.05	0.39	0.12
δ_6	-0.01	0.97	-0.01
δ_7	0.08	0.71	0.11
δ_8	-0.03	0.85	-0.04
δ_9	0.1	0.75	0.14
δ_{10}	-0.15	0.47	-0.32
δ_{11}	-0.11	0.33	-0.34
σ^2	0.01	0.004	1.94
γ	0.03	0.01	2.11
Log-likelihood	111.82		

Table 9 Results from testing the technical inefficiency model without age variable

Null hypothesis	Log-Likelihood Function	λ	$\chi^2_{0.95,(j)}$	j	Decision
$H_0: \gamma = \delta_0 = \dots = \delta_{11} = 0$	97.83	27.98	23.07 ^a	14	Reject H ₀
$H_0: \delta_0 = \dots = \delta_{11} = 0$	100.02	23.6	21.03	12	Reject H ₀
$H_0: \delta_1 = \dots = \delta_{11} = 0$	97.83	27.98	19.68	11	Reject H ₀

^a If the test involving $\gamma=0$, then λ has mixed Chi-square distribution. The critical values for this test are obtained from Table 1 of Kodde and Palm (1986).

Table 10 **Tobit regression without age variable of technical inefficiency scores**

Variables	Constant return to scale		Variable return to scale	
	Estimate	Marginal effect	Estimate	Marginal effect
Constant	0.07 (0.04)		0.02 (0.04)	
p_1	0.18* (0.06)	0.16	0.16** (0.05)	0.14
p_2	0.13* (0.06)	0.12	0.17** (0.05)	0.15
p_3	0.11 (0.06)	0.1	0.06 (0.05)	0.05
p_4	0.2** (0.06)	0.19	0.24** (0.05)	0.2
p_5	0.15** (0.06)	0.14	0.15** (0.05)	0.13
p_6	0.08 (0.06)	0.07	0.1 (0.05)	0.08
p_7	0.11 (0.06)	0.1	0.08 (0.05)	0.07
p_8	0.13* (0.06)	0.12	-0.13* (0.06)	-0.11
p_9	0.12* (0.06)	0.11	0.14** (0.05)	0.12
p_{10}	0.01 (0.06)	0.01	0.02 (0.05)	0.01
p_{11}	0.14* (0.06)	0.13	0.12* (0.05)	0.11
Log-Likelihood Value	66.83		65.64	
R^2	0.17		0.36	
σ	0.12		0.1	

The numbers in parentheses are standard error.

* and ** indicates the statistically significant estimates at 5% and 1% significance level, respectively.

Table 11 **Spearman rank-order correlations between efficiency scores obtained from different models**

	DEA CRS	DEA VRS	SFAA	SFANA
DEA CRS	1	0.78**	0.43**	0.25**
DEA VRS		1	0.45**	0.33**
SFAA			1	0.51**
SFANA				1

** 1 % level of significance (two sided)

Table 12 **Consistency in identifying the best and worst plants across models**

	DEA CRS	DEA VRS	SFAA	SFANA
DEA CRS		0.67	0.67	0.33
DEA VRS	0.67		1	0.67
SFAA	0.33	1		0.67
SFANA	0.33	0.33	0.33	

Note: The upper triangle represents the best plants. Each number is the proportion of plants that were identified by one model as the most efficient three plants were also identified as the most efficient three plants by the other model. The lower triangle shows the worst plants. Each number is the proportion of plants that were identified by one model as the least efficient three plants were also identified as the least efficient three plants by other model.

Table 13 Comparison of ranking of plants across models

Rank	DEA CRS	DEA VRS	Age			No age		
			TA CRS	TA VRS	SFAA	T CRS	T VRS	SFANA
1	12	8	5	8	8	12	8	11
2	10	12	8	5	12	10	12	10
3	6	10	12	12	10	6	10	8
4	3	3	6	1	1	3	3	1
5	7	7	9	6	11	7	7	12
6	2	6	1	9	4	9	6	6
7	8	11	10	10	9	2	11	3
8	9	9	2	3	2	8	9	2
9	5	5	4	2	6	11	5	5
10	11	1	3	7	7	5	1	4
11	1	2	7	4	5	1	2	7
12	4	4	11	11	3	4	4	9

Note: The numbers in the table represent the plant number.

Table 14 Estimation of efficiency improvement target

Plant	SFANA			DEA VRS		
	TE	EI1	EI2	TE	EI1	EI2
1	1	-	-	0.82	0.18	0.09
2	0.98	0.02	0.01	0.81	0.19	0.1
3	0.99	0.01	0.01	0.91	0.09	0.05
4	0.94	0.06	0.03	0.75	0.25	0.13
5	0.96	0.04	0.02	0.83	0.17	0.09
6	0.99	0.01	0.01	0.88	0.12	0.06
7	0.93	0.07	0.04	0.9	0.1	0.05
8	1	-	-	0.99	0.01	0.01
9	0.91	0.09	0.05	0.84	0.16	0.08
10	1	-	-	0.95	0.05	0.03
11	1	-	-	0.86	0.14	0.07
12	0.99	0.01	0.01	0.96	0.04	0.02
Mean		0.03	0.01		0.13	0.06

- zero

Note: TE stands for technical efficiency score whereas EI1 and EI2 stand for efficiency improvement target from a whole and a half of the inefficiency gap, respectively.