# Performance Analysis of Power Plants under Heterogeneous Technologies with Meta Frontier Framework

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***Abstract*-There have been numerous studies measuring efficiency and productivity in the electricity industry worldwide but little research focusing on the comparisons of generation technologies. This study provides a better direction for the proper analysis of the electricity generation sector by examining the performance changes and comparing efficiencies among different types of electric power plants. To account for technology heterogeneity, we apply a meta frontier framework, which is composed of technology specific frontiers. This method allows analyses of the existing gap between generation technologies in the generation part of the electricity industry. The inter- and intra-efficiency variations of the technology groups are investigated using determinant analysis. The overall process is composed of two parts: efficiency measurement by deterministic meta frontier framework and regression analysis for determinant analysis. In the determinant analysis of efficiency differences, we exploit several common and time invariant characteristics of the plants. The results based on panel data of power plants indicate that there are significant technological gaps among different types of plants and several external factors affect performance of the plants.**

***Keywords-Meta Frontier; Panel Data; Efficiency; Electricity Industry; Heterogeneous Technologies***

## I. INTRODUCTION

In efficiency analysis, there have been general presuppositions related to the characteristics of production units and the production set. One is that a unit with a given technology can be compared with other units using the same technology. Thus, homogeneity of underlying technology has been one of the common assumptions in efficiency and productivity estimation. It is possible to lessen the constraints if we expand the application by considering various technological or operational features that are common factors in production.

Various technologies in the production set have been handled in different ways in previous studies. The production units with different technologies in a specific area are considered as members of the same technological group in a broader sense. In recent years, some studies characterize units in respect of their technological heterogeneity by separating them into different production sub-groups. As a first stream, few empirical studies on the efficiency comparison of electricity industry use data from a specific group of plants such as fossil-fuelled power plants (e.g.,[1], [2]). Lam and Shiu[3] and [4]analyse performance of China's thermal power plants. Lam and Shiu[3] used cross sectional data to estimate technical efficiency, while Lam and Shiu[4]analysed total factor productivity using panel data of power generation. Heshmati [5] analysed efficiency of Korean generator plants with different characteristics.

A second stream of studies used a production set that is composed of a very different type of plants. For example, Kamerschen and Thompson [6] applied a cost model to compare costs and efficiency of nuclear and fossil-fuelled steam generation plants. In a different case, Chang et al. [7] examined cost efficiency and scale economies of the plants of Taiwan Power Company including various types of fuel. In their subsequent factor analysis, they found that older plants with higher installed capacity show lower cost performance.Liu et al. [8] also used various types of plants to evaluate the efficiency of major thermal power plants in Taiwan. The combined cycle power plants show the highest performance. The heating value of total fuels was the most important factor in the high performance of thermal power plants.

A third stream of studies focused on a specific type of plants such as coal-fired and hydro power plants.Fare et al. [9] selected 100 steam electric utility plants to investigate the effect of environmental restrictions, while Sueyoshi et al. [10] focused on the evaluation of environmental performance of US coal-fired power plants.Hiebert[11] regarded coal and gas plants as different groups with separately estimated cost frontier models. Meanwhile,Barros [12] used only data of hydroelectric plants to evaluate productivity and efficiency changes over time.

In the case of the third stream, usually the focus is on a specific purpose like the environmental performance of heavy polluting plants. Here the search is for the best practice among a restricted part of the industry.In the second stream case, the plants using different fuels are regarded as members of the same production set in spite of their technological heterogeneity. Since there are various types of plants, the latter approach has inevitable limitations in comprehending the overall performance of industry. Although there is an on-going debate on the problem of comparison between heterogeneous plants, a generic approach including different technologies is required to consider their technology heterogeneity.

The most up-to-date and representative model for considering group heterogeneity in technology and production is meta frontier analysis. Since conceptual introduction of the meta production function suggested by Hayami[13], more extensive meta frontier estimation model and framework have been presented by Battese and Rao[14], Battese et al. [15], and O'Donnell et al. [16]. They enabled the comparison of efficiency among units with different technologies. Meta frontier methodology utilizes a two level frontier: one for individual technology groups and the other for the whole set. The inter-group difference is expressed by a technology gap between the groups, while the intra-group difference is displayed by the rate of technical efficiency within a group.

Most previous studies using meta frontier focus on intra- or inter-group differences in efficiency of the same industry but across regions in technology adoption. As an early empirical study using meta frontier framework, Battese et al. [15] showed the technological gap of the garment industry in different regions of Indonesia. The authors introduced two measurement approaches to estimate the meta frontier. One is by solving the linear programming problem using a minimum sum of absolute deviations, and the other is to solve the quadratic programming problem using a minimum sum of squares of deviations. O'Donnell et al. [16] illustrated regional distinctions of agricultural efficiency with parametric and nonparametric methodologies.

Kounetas et al. [17] focused on the analysis of firms operating under different technologies. In the empirical application, they used two different manufacturing industries: chemicals and textiles. They also examined commercial banks of different nations in the second empirical analysis. Kounetas et al. [17] expanded the concept of heterogeneity to the different levels of access and acceptance of general purpose technologies, while O'Donnell et al. [16] regarded the source of difference attributed to the different opportunities in production. The environmental differences may come from the characteristics of production conditions such as resource endowments, economic infrastructure, and physical and social background. They mentioned that the technical efficiency can be managed from different aspects. The changes in the managerial activity and structure of the firm discussed in Kounetas et al.[17] can be related to internal aspects, while the reaction to the environmental changes can be interpreted as external aspects.

In this study, we extend the application of meta frontier framework to analysis of technological differences in the same industry sector. This approach differs from the previous studies, which mainly focused on the variations across industries and regions. By employing the deterministic meta frontier production approach, we conduct empirical analysis of fossil-fuelled power plants. These plants are compared under the concept of meta frontier because they produce the same output, electricity, and they use the same inputs but with different processes. The technology heterogeneity can be interpreted as original differences in production technologies and operational characteristics. In order to identify the determinants of inefficiency, we apply a second step determinant analysis.

The efficiency scores indicate only how firms or plants are performing compared to best firms in the same industry. Recently, some literature suggested a second stage regression to verify the determinants of efficiency [18] or analysis of variance(ANOVA)[19]. Lam and Shiu[3] found that capacity factor and fuel efficiency are significant factors affecting technical efficiency in their second stage with Tobit regression analysis. However, Simar and Wilson [20] illustrated that an approach based on a truncated regression with a bootstrap provides a more satisfactory performance.

Some important implications could be derived from efficiency estimation and determinant analysis to measure the performance of generation plants. In order to compare the production technology of the distinct groups, we distinguished the groups based on their generation type .By application to different types of electric power generation, this paper avoids the limitation of previous regional heterogeneity studies. Thus, our approach not only helps to plan a more efficient supply of electricity, but also to provide appropriate prospects of selection and combination among different electricity generation techniques available in the market.

The remainder of this paper is organized as follows. In the next section, we briefly explain the Korean electricity industry and electricity generation mix. We describe the data in Section III and specification of the model used in Section IV. Section V presents the empirical result, including the comparison of production efficiency between two groups. Finally, concluding remarks and policy implications are summarized in the last section.

## II. HETEROGENEOUS ELECTRICITY GENERATION TECHNOLOGIES IN KOREA

In response to the rapidly growing demand for electricity, generation capacity has also increased with consideration for an optimized mix of generation resources and environmental regulations to reduce pollution and carbon emissions. For example, the dependence of Korea Electric Power Corp. (KEPCO) on oil for generation is now about 7%, whereas the level amounted to almost 90% in the 1970s. Power generation mix and cost mix are changing on the basis of the objective to reduce the proportion of oil in the primary sources. As a result the oil input decreased to 2% in resource mix and 7% in cost mix of primary energy use in 2008. This policy of reduction in oil dependency has resulted in increased dependency on coal and nuclear energy, and the proportion of combined cycle power plants has also increased.

In 2008 the generation systems of Korea had an aggregate generating capacity of 77,652 megawatts (MW) of electricity in common use. The information on the share of different components of the total generation capacity is shown in Figure 1 for the period from 2002 to 2008. Steam, nuclear, and combined cycle generation types are the main contributors to the total energy generation capacity. The capacity share of coal power plants gradually increases over time, whereas that of nuclear is slowly decreasing. In recent years, the share of renewable energy is also growing due to the green energy paradigm, and a new energy strategy has been established with the increase of nuclear power plants due to the instability in the oil price and the scarcity of fossil fuels.

As mentioned above, the power industry in Korea usually operates by utilizing thermal and nuclear power plants as its base load and others including combined cycle plants as its peak load sources. Generation companies have constructed thermal and internal combustion units in order to meet the increasing power demand. Subject to market conditions, the generation subsidiaries have continuously added additional thermal and combined cycle plants. Such units are constructed more quickly than other units.

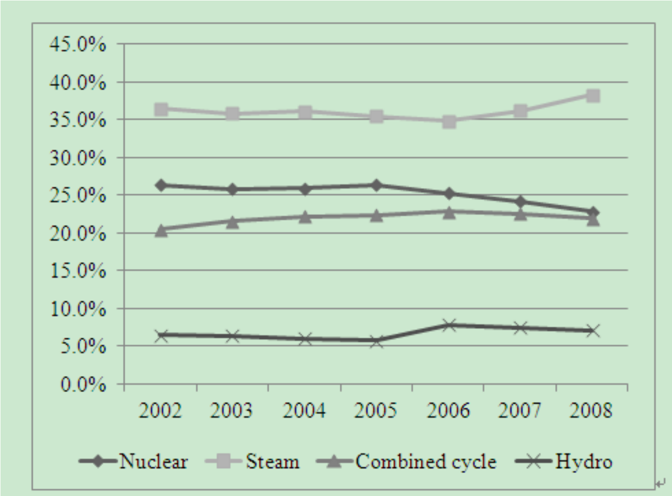


Fig. 1 Changes in the Share of Installed Capacity by Generation Type, 2002-2008

After the restructuring of the generation sector in 2001, the Korean electricity exchange market has used the cost-based pool (CBP) system as its pricing system. In the beginning, CBP was composed of two sub-prices, which are system marginal price (SMP) and capacity price (CP). SMP is the price that compensates producers for their variable costs and can be classified into base load marginal price(BLMP) and SMP. CP is the price that is aimed to compensate producers for their fixed costs. The price system differs, depending on the type of generator and the inclusion or exclusion of unconstrained supply schedules. The generators are sorted into base generators or general generators depending on the load type. And the price level differs, depending on the type of generator employed in the production of electricity.

The pricing rule was changed to deal with fuel cost changes and the companies' unfair profits. As the price of coal went up, the BLMP rule revealed a problem in that the profit of base generators decreased rapidly. Therefore, the pricing rule was changed to follow the regulated market price (RMP) rule in 2007. The BLMP was changed into a RMP to guarantee the profit of base load. The pricing rule was unified with the common rule; this means that the compensation of fixed cost was reduced while the compensation of variable cost was enlarged. The RMP rule also met a problem in that the profit of liquefied natural gas (LNP) generators increased rapidly, but the coal generator had a low profit due to the high price of coal. This caused an unbalanced result of profits among companies depending on their share of base load generators.

A new system with a marginal price rule was substituted to adjust the distorted price structure in May 2008. The price of base and general generators is determined by the same pricing interval rule designed to stimulate the investment of base generation facilities from private companies. With the changes of fuel price and pricing rule, the share of power trading by fossil fuel type has changed as shown in Figure 2. The amount of generation by bituminous and LNG have increased, while the share of oil and anthracite have decreased. The share of LNG, 2007-2008 excepted, increased.

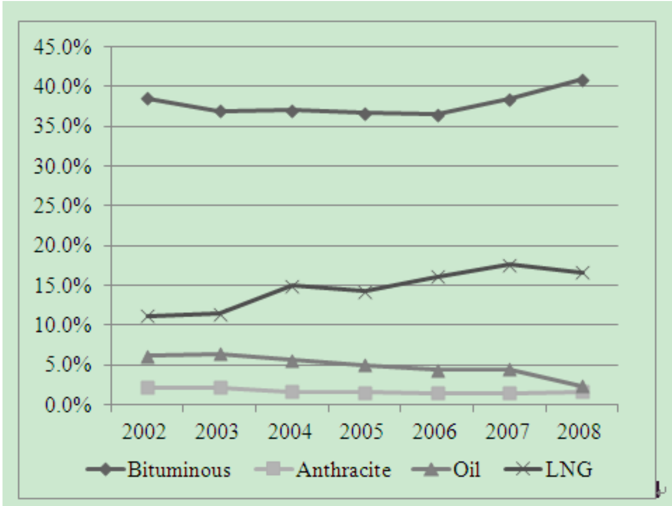


Fig. 2 Generation Quantity by Fuel Type, 2002-2008

## III. THE DATA

In this study, we use Korean electricity panel data to compare the difference in performance among technological sub-groups. The time periods studied is 2002-2008. The period covers post separation of the generation part from the integrated system.

The electricity generating plants that have either single or multiple generation units are considered as a decision making unit (DMU). The total number of plants covered in the study is 28 fossil-fuelled power plants. We separated the plants into two sub-groups based on the generation technologies, such as steam generation plants and combined cycle generation, which account for about 60% of the total generation .The plants use various fuels including anthracite and bituminous coal, oil, and LNG. The total number of analysed observations is 189. The sub-samples separated by generation technology are 123 and66, respectively.

In order to analyse the data by using a meta frontier methodology, we used one output and three inputs. The yearly average electric power generated by power plants is used as the output, while capital, fuel, and labour are inputs. The yearly average electric power generated is obtained by total generation in gig watt hours divided by the total hours of operation. We use capacity installed in M was representative value for the capital, while thermal consumption caloric value is used to measure the total fuel use and the number of employees is used to measure the labour input.

We use additional characteristic of plants and external variables to analyse the determinants of inefficiency in the second step. The extra variables include the age of plants, the number of units operating under a plant, fuel type and pricing policy in the electricity market. Three dummy variables are included in the second step. Dummy for fuel type includes oil and gas (LNG) and type of load such as peak load. The pricing rule changed twice in 2007 and 2008. Dummy for pricing rule is used as an external factor. Table 1 shows a full list of the main variables used and their summary statistics.

TABLE 1 SUMMARY STATISTICS OF THE VARIABLES, 2002-2008

| Variables | Unit | Obs. | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Electricity Generation | kW | 189 | 844,021 | 989,697 | 2,764 | 3,737,939 |
| Nameplate Capacity | kW | 189 | 1,272,908 | 1,034,996 | 20,000 | 4,000,000 |
| Fuel consumption | $10^9$kcal | 189 | 15,794 | 18,530 | 62 | 70,938 |
| Labour | Number | 189 | 330 | 206 | 30 | 934 |
| Number of units | Number | 189 | 3.5 | 2.0 | 1.0 | 8.0 |
| Age of plant | Number | 189 | 14.6 | 10.4 | 0.0 | 38.3 |

Detailed information of power generation of the Korean power plants, such as total electricity output, generating facility capacity, fuel consumption, and number of units, are obtained from statistics of electric power in Korea published yearly by KEPCO. The information on specific operating data, like number of employees, is acquired directly from the six main generation companies in the market.

## IV. MODEL SPECIFICATION AND ESTIMATION

We estimate the efficiency of power plants based on two different types of data sets, which correspond to the individual sub-groups and pooled data. The groups are separated by generation technology into steam turbine and combined cycle. There are several applications of the meta frontier methodology. Huang et al. [21] applied meta frontier to estimate cost efficiency and to analyze the scale of electricity distribution in Taiwan by dividing distribution units into two groups. Yang and Chen[22] compared small and medium-sized enterprises with large enterprises while investigating the existence of size effect by applying a meta frontier model. Our study has similarity with the above studies in the use of methodology, but the application differs in respect with segment of the industry.

Since the introduction of the stochastic meta frontier model by Battese and Rao[14]), a number of studies have developed the framework more precisely with practical applications. There are two parametric approaches to obtain the parameters of the meta frontier function to construct the outer feature of group frontiers: minimum sum of absolute deviations and minimum sum of squares of deviations between group-frontiers and meta frontier. A more detailed description of the methodology and the differences between these two approaches is found in Battese, Rao, and O'Donnell [16]. Non-parametric model is another approach to obtain the technology gap ratio and efficiency of meta frontier. The description of the data envelopment analysis (DEA) methodology can be found in O'Donnell, Rao, and Battese[16].Kounetas et al. [17] decomposed the efficiency into input-invariant and output-invariant components using generalized directional distance functions.

The meta frontier and technology group-frontiers in the production frontier analysis are expressed as follows. A *k* frontier model of K technology groups can be expressed as (1) if the exponent of production function is linear in the parameter vector $\beta_k$ :

$$y_k = f(x, \beta_k)e^{V_k - U_k} \equiv e^{x_k \beta_k + V_k - U_k} \quad (1)$$

Where $x_k$ is a vector of inputs and $y_k$ is a vector of outputs. For the reasons of simplicity of notations, the plant and time subscripts (*i* and *t*) are left out. The technical efficiency under group *k* frontier can be obtained by:

$$TE_k = e^{-U_k} \quad (2)$$

A deterministic meta frontier production function that envelops all technology group-frontiers can be defined as:

$$y_k^* \equiv f(x_k, \beta^*) = e^{x_k \beta^*} \quad (3)$$

Where $\beta^*$ represents the vector of parameters of the meta frontier function. Meta frontier has linear constraints $x_k \beta^* \geq x_k \beta_k$ in the deterministic estimates for all the groups (*k*=1, 2, …, K).

With the definitions of meta frontier and technology group-frontiers, the total efficiency incorporating the feature of meta frontier can be calculated and decomposed into technical efficiency in the technology group and the technological gap between the meta frontier and group-frontiers ,shown below:

$$TE^* = TGR_k \times TE_k \quad (4)$$

The meta frontier technical efficiency ($TE^*$) can be calculated by the product of the technical efficiency ($TE_k$) based on the technology group-frontier and the technology gap ratio ($TGR_k$). Because the range of both $TE_k$ and $TGR_k$ values is between zero and one, $TE^*$ also has values in the range between zero and one. $TE^*$ is always lower than $TE_k$ due to the gap ratio being less than one.

In using the parametric approaches, data on the inputs and outputs of units can be used to obtain either least squares or maximum-likelihood (ML) estimates of the unknown parameters of the technology group-frontier, as indicated in Coelli[23]. In case of DEA-based programming, the procedures in DEA and Malmquist productivity index (MPI) analysis can be utilized to obtain the technology gap ratio with the convex model. Linear models are used for every unit in every time period to obtain annual frontiers. The method of minimum sum of absolute deviation is used to get the parameters of the meta frontier function.

In order to investigate the factors that affect the two inefficient components, efficiency from technology group-frontier, we apply the technical efficiency effect model suggested by Battese and Coelli[24]. The model specified for panel data written as (5) is applied when we estimate efficiency based on technology group-frontiers used as a component in the meta frontier analysis:

$$\mathbf{y}_{it} = \mathrm{e}^{\mathbf{x}_{it}\boldsymbol{\beta} + V_{it} - U_{it}} \tag{5}$$

Where $\mathbf{y}_{it}$ denotes the output for the $i$-th plant ($i = 1, 2, ..., N$) at the $t$-th period observation ($t = 1, 2, ..., T$); $\mathbf{x}_{it}$ is a vector including inputs and other explanatory variables of the $i$-th plant at the $t$-th period; $\boldsymbol{\beta}$ is a vector of parameters to be estimated; the $V_{it}$ s are assumed to be i.i.d. $N(0, \sigma_v^2)$ random errors, independently distributed of the $U_{it}$ s; the $U_{it}$ s are non-negative random variables, associated with technical inefficiency in production, which are assumed to have truncated normal distribution with mean, $\mathbf{z}_{it}\boldsymbol{\delta}$, and variance, $\sigma_v^2$; $\mathbf{z}_{it}$ is a vector of explanatory variables associated with the technical inefficiency of plants over time; and $\boldsymbol{\delta}$ is a vector of coefficients to be estimated.

Therefore, in the technical efficiency effect model, $U_{it}$ could be specified as a function of determinants of inefficiency as follows:

$$U_{it} = \mathbf{z}_{it}\boldsymbol{\delta} + W_{it} \tag{6}$$

Where $W_{it}$ is defined as a random variable that has a truncated normal distribution with zero mean and variance, $\sigma_v^2$. $U_{it}$ is assumed to be a non-negative truncation of the $N(\mathbf{z}_{it}\boldsymbol{\delta}, \sigma^2)$ distribution. The technical efficiency effects are specified as:

$$m_{it} = \mathbf{z}_{it}\boldsymbol{\delta} = \delta_0 + \delta_1 time + \delta_2 units + \delta_3 age + \delta_4 oil + \delta_5 LNG \tag{7}$$

Where $m_{it}$ is inefficiency score and $\mathbf{z}_{it}$ is potential inefficiency determinants such as yearly time trend, the number of generator units within a plant, the age of plant, and fuel types, like oil and LNG used for electric power generation.

After estimating the model and efficiency level, in a second step an attempt is made to extract factors that affect the level of efficiency. In this stage, we employ truncated regression analysis with bootstrapped DEA. The main goal of the analysis is to identify the determinants of efficiency and estimate the influence of potential determinants on the technology gap ratio (TGR). The relationship between TGR scores and their potential determinants can be described as:

$$TGR_{it} = \alpha + \mathbf{z}_{it}\boldsymbol{\gamma} + \varepsilon_{it} \tag{8}$$

Where $\alpha$ is intercept and $\varepsilon_{it}$ is defined as a random variable with distribution of $N(0, \sigma_\varepsilon{}^2)$ by unity bounded condition. The specification of the technical efficiency effects differs by data level and is specified for different units.TGR, which has values in [0, 1] interval, is regressed on internal and external factors in power generation written as:

$$TGR_{it} = \mathbf{z}_{it}\boldsymbol{\gamma} = \gamma_0 + \gamma_1 time + \gamma_2 units + \gamma_3 age + \gamma_4 load + \gamma_5 policy1 + \gamma_6 policy2 \tag{9}$$

Where $\mathbf{z}_{it}$ is a vector of various factors including time trend, the number of generator units, the age of plants, load type, pricing policy of electricity in the market, which could influence TGR. The vector $\boldsymbol{\gamma}$ is the estimated coefficients corresponding to each factor. Our empirical result shows how these general factors change TGR, even though there could be other potential factors.

Simar and Wilson [20] showed the validity of the bootstrapping truncated regression model to obtain confidence intervals for the estimated coefficients by removing bias from correlation between efficiency scores and explanatory factors. We also use Tobit regression for the comparison of the results. Tobit regression model is developed by Pitt and Lee [25] and Olatubi and Dismukes[26]. Barros and Peypoch (2008) showed an application in the electric generating sector using bootstrapped truncated regression to analyze determinants of efficiency of thermoelectric power plants with explanatory variables such as yearly trend, age of the plant, fuel, and pollution.

Several pieces of research applied similar methods in order to identify the principal factors related to technological or environmental differences in the second stage. Lam and Shiu[3] applied the Tobit model for the same purpose ,identifying determinants in technical efficiencies, while Lam and Shiu[4]analysed technical efficiency sources of total factor productivity. Dadzie and Dasmani[27]examined determinants of meta frontier technical efficiencies of food crop farmers. However, there have not been many studies analysing determinant factors based on the meta frontier approach.

## V. ANALYSIS OF THE RESULT

This section is divided into two subsections. In subsection A, we show technical efficiency and its variation over time and by groups based on the stochastic frontier and meta frontier analysis. In subsection B, we analyse determinants affecting group inefficiency and TGR. It is notable that the empirical result implies that each group isusing different technology ,has a different production function, and is also influenced by various factors to different degrees.

*A. Efficiency Measurement within A Technology Group*

In the formation of groups and meta production function, we partition the sample into two groups by power generation technology ,namely, steam turbine based plants (Group1) and combined cycle power plants (Group2). The inter-group difference is expressed by TGR, while the intra-difference is displayed by technology group-frontier technical efficiency (TE). Table 2 shows the summary statistics of the estimated TE, TGR, and their product, the meta frontier technical efficiency (TE*)for each group. TE values are obtained by technical efficiency effect model for each group, while TGRs are calculated by deterministic meta frontier framework. For a matter of comparison ,we also estimate the model with technical efficiency effects model (pooled) including both groups and computed average efficiency values of each group reported in Table 2.

Before using the meta frontier method, we should determine whether a pooled technical efficiency effects model is sufficient or whether meta frontier analysis is necessary due to the heterogeneity in the plant's production technologies. Using the generalized likelihood ratio (LR) test ([15], a test value of the null hypothesis that production technologies of each group are similar is 89.74. Compared to the critical value of 18.47, which is at 99% confidence level from chi-squared distribution, the LR statistic is statistically significant. The test result suggests that the two groups use different production technologies and that meta frontier estimation is the preferred method for efficiency analysis.

Group1 demonstrates a higher mean efficiency than Group2 in the case of TE. The TE of Group2 ranges widely from 0.5069 to 0.9979. This means that the average performance level of Group1 is higher than Group2, and the room for efficiency improvement among the units in Group2 is larger than those in Group1. In other words, the large variations in efficiency among combined cycle power plants suggest that it is possible to increase the overall performance in the electricity industry by improving these plants' management and performance. Group1 shows smaller standard deviation in efficiency, suggesting steam plants have been operated in relatively uniform conditions.

A high TGR is interpreted as meaning that there has not been much technological difference compared with the most advanced technology in the industry. If some samples show a large variation in the TE rather than in the TGR component, it means that the corresponding group has a similar technological level compared with other groups, but it has a large variation within the group itself. The numbers for groups with a large gap ratio have the opposite interpretation.

The averages of TGR varies from 0.8523 (Group1) to 0.9490 (Group2) as shown in Table 2. This result implies that plants using a combined cycle on average reach only about 90% of the best performing units in the industry ,while Group1 shows higher value in TE. Even though some units operating combined cycle generators have lower TEs within the group, it can be said that they use more innovative technology than those operating steam generators in terms of TGR. The efficiency values are lowered from 0.9616 to 0.8195 in Group1 and from 0.8925 to 0.8464 in Group2, reflecting the distance from the meta frontier.

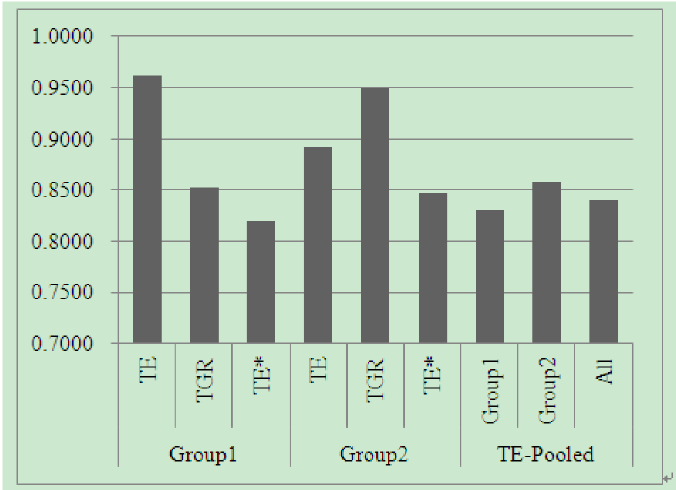


Fig. 3 The Decomposition of Meta Frontier and Technical Efficiency Effects Based Efficiencies

TABLE 2

EFFICIENCIES BY META FRONTIER ANALYSIS AND TECHNICAL EFFICIENCY EFFECTS MODEL

| Group | Efficiency | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|---|
| Meta frontier Models: | | | | | |
| Group1 | TE | 0.9616 | 0.0459 | 0.7954 | 0.9971 |
| | TGR | 0.8523 | 0.0695 | 0.6349 | 1.0000 |
| | TE* | 0.8195 | 0.0765 | 0.6283 | 0.9852 |
| Group2 | TE | 0.8925 | 0.1322 | 0.5069 | 0.9979 |
| | TGR | 0.9490 | 0.0460 | 0.8049 | 1.0000 |
| | TE* | 0.8464 | 0.1299 | 0.4826 | 0.9871 |
| Technical Efficiency Effects Models: | | | | | |
| TE-pooled | All units | 0.8402 | 0.1050 | 0.5056 | 0.9999 |
| | Group1 | 0.8302 | 0.0867 | 0.6055 | 0.9959 |
| | Group2 | 0.8587 | 0.1312 | 0.5056 | 0.9999 |

TABLE 3
THE DEVELOPMENT OF TE, TGR, TE* OVER TIME

| Year | TE | TGR | TE* | TE-pooled |
|---|---|---|---|---|
| 2002 | 0.9404 | 0.8871 | 0.8391 | 0.8298 |
| 2003 | 0.9417 | 0.8608 | 0.8140 | 0.8362 |
| 2004 | 0.9296 | 0.8292 | 0.7764 | 0.8283 |
| 2005 | 0.9377 | 0.8926 | 0.8441 | 0.8361 |
| 2006 | 0.9365 | 0.8801 | 0.8311 | 0.8449 |
| 2007 | 0.9389 | 0.8724 | 0.8237 | 0.8545 |
| 2008 | 0.9377 | 0.8415 | 0.7933 | 0.8492 |

Decomposition of the TE into TGR and TE*components for the study period is reported in Figure 3. The efficiency levels from the meta frontier show a different picture compared with the pooled technical efficiency effects model (TE-pooled). Steam turbine plants have lower meta-efficiency (0.8195) than combined cycle (0.8464) under meta frontier, while the gap between the two groups and variations of efficiencies becomes bigger when pooled analysis is applied. This shows that there can be large difference between efficiency obtained from meta frontier analysis and those from pooled technical efficiency effects model. In the latter case, by pooling the two groups in the same frontier, one ignores the technological gap between the groups. Figure 3 displays the efficiency results and their underlying components from the two models. We can easily see the shape of TE and TGR components from Figure 3,which enable us to distinguish the key determinant of TE* for each technology group.

Table 3 shows the development of average efficiencies of all DMU sover time ,while Figure 4.A and 4.B show the development of efficiency components by groups during the same period. As shown in Table 3, the TEs, which imply efficiency in a group, slowly decrease, while TGRs are changed with large variation. The TE* values under meta frontier fluctuate around 0.77-0.84. When applying the pooled technical efficiency effects, TE-pooled efficiencies change from 0.8298 in 2002 to 0.8492 in 2008 with a stable increasing trend. TE* values are mainly influenced by variation in the TGR component. While the value of TE, TGR, and TE* in 2008 are lower than in 2002, the average efficiency based on the pooled model increased over time.

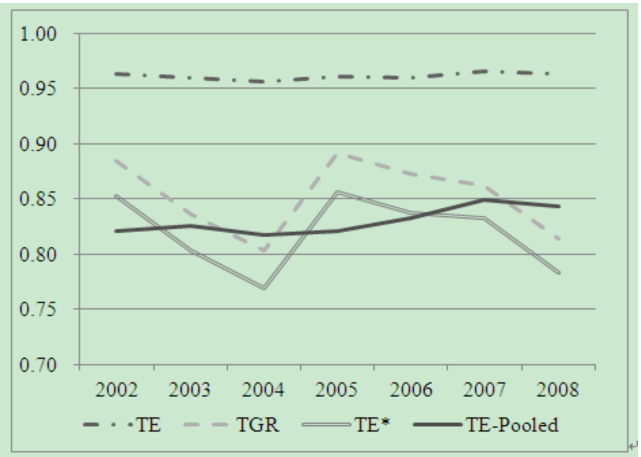


Fig. 4.A The development of TE, TGR, and TE* (Group1 Steam plants)

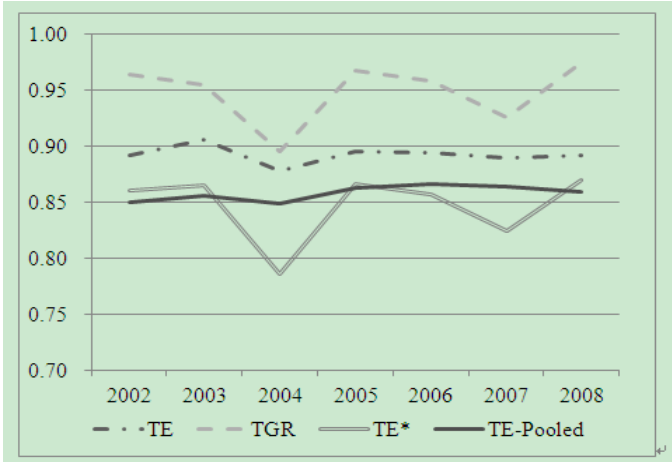


Fig. 4.B The development of TE, TGR, and TE* (Group2 Combined cycle plants)

## B. *The Determinant Analysis of TE and TGR*

In this section, we analyse the determinants of efficiency components TE and TGR. The main part of our second stage analysis is to use technical efficiency effects and regression methods for examining the relationships between the efficiency values, TE and TGR, and their assumed explanatory variables.

Table 4.A depicts the result of the technical efficiency effects frontier analysis. Here, the technical efficiency effects model is estimated at the plant level grouped by generation type.This helps us to understand the heterogeneity in results and their implications based on the use of different sub-samples classified by generation type. The estimated coefficient of facility capacity in the pooled model (TE-pooled)is 0.1790, which means that the facility capacity has a positive effect on average power generation. The fuel elasticity of output, measured as caloric consumption is directly proportionate to the generated power quantity in the pooled data as well as in each of the two sub-samples. The labour elasticity is significant but its effect differs, depending on the generation type. In Group1, the labour factor is positively related to output measured as average generation quantity, while in Group2 and the pooled data modelslabour hasnegative effects. We can guess thatthis is the result of inefficient management of workers or improper operating structure in the industry. In addition to sign differences, the effectiveness of factors also differs across the group.

The various delta coefficients are determinants of potential technical inefficiency. A variable with negative coefficients reduces the inefficiency level, while a positive effect increases inefficiency. Time trend, which is included to represent the trend in variation in efficiency, shows a positive effect on efficiency .As expected, the obsolescence of the power plants increases the production inefficiency. In combined cycle generation, the numbers of units in the same plant decreases the inefficiency, and this means that there is economy of scale in combined cycle generation.

From the empirical result, we can see that production efficiency in same generation type is hardly influenced by the fuel type. The dummy variable associated with fuel type labelled as 'Oil 'has a negative coefficient, equal to -0.1288 and -0.8023 in each of the two group models. This means that the plants using oil show higher efficiency, while for the pooled model it is insignificant.

The estimation results from the three models in Table 4.B show which factors influence the TGR. In this step, TGR data of all units are used in order to examine the determinants of the technology group's gaps without a formal technology group separation. We include time trend, number of units, and age variable as group characteristics in Model1. It includes an additional dummy variable of the load type, which captures the operating characteristic of the plant. The peak load indicates the plant is a peak load operating plant, which is compared with a base load plant. Model2 has additional variable associated with the pricing policy of the trading market to solve the unbalanced revenues of utilities by applying different electricity prices according to the type of load. The policy changed twice in 2007 and 2008. Since a high TGR means a high efficiency level in the meta frontier, a factor with a negative sign has a negative effect on the level of efficiency.

In the models, a large number of units within a plant show commonly lower values of TGR, while the age of plants also shows negative effectiveness on TGR but with different significance levels. This may reflect the fact that the combined cycle group, which has higher TGR scores, usually has a small number of units and has been constructed recently. In Model1 and Model2, the load type shows that peak load plants show a higher value than base load plants. On the other hand, the peak load variable shows a considerable positive effect on TGR, which is matched with the characteristic of combined cycle plants. The policy dummy variables in Model2 show that TGR has decreased a little bit after changing the market rule in spite of low significance. This could mean that the change in the pricing rule has no positive effect on the performance gap reduction in the fossil-fuelled generation sector. The results from Tobit regression in Model3arealso reported in Table 4.B. The Tobit results are similar to those of the truncated regression model, considering the sign and significance of the parameters.

TABLE 4 A

TECHNICAL EFFICIENCY EFFECTS MODEL ESTIMATION RESULTS, WITH ELECTRIC POWER GENERATIONS DEPENDENT VARIABLE

| Variable | Parameter | Group1 | Group2 | Pooled |
|---|---|---|---|---|
| Constant | $\beta_0$ | -3.3003***<br>( 0.0594) | -3.7420***<br>(0.0400) | -3.6386***<br>(0.0786) |
| Ln(capacity) | $\beta_1$ | 0.0045<br>(0.0160) | 0.0555***<br>(0.0130) | 0.1790***<br>(0.0106) |
| Ln(fuel) | $\beta_2$ | 0.9980***<br>(0.0123) | 1.0595***<br>(0.0072) | 0.9916***<br>(0.0133) |
| Ln(labour) | $\beta_3$ | 0.0836***<br>(0.0215) | -0.1311***<br>(0.0116) | -0.2608 ***<br>(0.0210) |
| Constant | $\delta_0$ | -0.1011<br>(0.0647) | -0.8287***<br>(0.1139) | 0.0961*<br>(0.0583) |
| Time trend | $\delta_1$ | -0.0102*<br>(0.0053) | -0.1622***<br>(0.0164) | -0.0150*<br>(0.0083) |
| No. of units | $\delta_2$ | -0.0102<br>(0.0208) | -0.1377***<br>(0.0297) | -0.0335***<br>(0.0137) |
| Age of plant | $\delta_3$ | 0.0099***<br>(0.0019) | 0.1773***<br>(0.0152) | 0.0101***<br>(0.0017) |
| Oil | $\delta_4$ | -0.1288***<br>(0.0278) | -0.8023***<br>(0.1816) | -0.0055<br>(0.0485) |
| LNG | $\delta_5$ | -0.0009<br>(0.0331) | - | 0.1141**<br>(0.0530) |
| $\sigma^2$ | | 0.0024 | 0.0421 | 0.0202 |
| $\Gamma$ | | 0.5680 | 0.9995 | 1.0000 |
| Observations | | 123 | 66 | 189 |

* p<0.1, ** p<0.05, *** p<0.01, ( ) std dev

TABLE 4 B
DETERMINANTS OF TGR

| | | Truncated regression | | Tobit regression |
|---|---|---|---|---|
| Variable | Parameter | Model1 | Model2 | Model3 |
| Constant | $\gamma_0$ | 0.8805*** (0.0174) | 0.8667*** (0.0191) | 0.8585*** (0.0148) |
| Time trend | $\gamma_1$ | -0.0022 (0.0025) | 0.0030 (0.0042) | 0.0028 (0.0032) |
| No. of units | $\gamma_2$ | -0.0051*** (0.0026) | -0.0050** (0.0025) | -0.0037** (0.0019) |
| Age of plant | $\gamma_4$ | -0.0005 (0.0005) | -0.0005 (0.0005) | -0.0004 (0.0004) |
| Peak load | $\gamma_5$ | 0.1840*** (0.0203) | 0.1826*** (0.0199) | 0.1184*** (0.0090) |
| Policy1 | $\gamma_6$ | - | -0.0150 (0.0188) | -0.0142 (0.0141) |
| Policy2 | $\gamma_7$ | - | -0.0373* (0.0216) | -0.0291* (0.0164) |
| $\sigma_\varepsilon^{2}$ | | 0.0589 (0.0039) | 0.0583 (0.0038) | 0.0512 (0.0027) |
| Obs. | | 186 | 186 | 189 |

Note: * p<0.1, ** p<0.05, *** p<0.01, ( ) std. dev

The exercise here not only shows the determinants of efficiency but also the fact that the TGR can be affected by group characteristics. These results show that a consideration of technological heterogeneity among groups is necessary to account for different features in efficiency and group performance gap measurements.

## VI. CONCLUDING REMARKS

The measurements of performance of some industries always raise questions on how to handle the units with different technologies that are included in the industrial boundary. Using a performance comparison between two groups of plants across different generation technologies based on the same input and output factors, we applied the meta frontier framework in order to account for technology heterogeneity. We showed an empirical analysis of efficiency of electricity power plants operating with two different generation technologies using fossil-fuels.

With this methodology we decomposed the efficiency into two components: TE and TGR. Under the new frontier, the overall efficiencies and their variations were changed somewhat. The result illustrates the different distribution of inter-group and intra-group differences in the overall efficiency. One group showed a small variation in the TGR, while the other group displayed a low technological level in the meta frontier with higher values in the case of an internal comparison with the same technological units. In the results, the TE under meta frontiers generally decided by the TGR, which is measured by comparison with the most effective technology group as reference.

The temporal development of inefficiency also supplies evidence of different patterns in changes over time. The influence of inherent determinants such as type of technology and external factors such as government policy in the market can give different and group-dependent effectiveness. This result can give different implications by separating the internal and external inefficiency determinants of the technology group. This is in line with the findings of O'Donnell et al. [16]that there are two aspects, management and structure of the firm and production environment which must be taken into account. However, in this case we apply the concept of meta frontier differently.

Meta frontier functions have in a few cases been applied to compare the performance of units with different backgrounds such as regional differences or sectoral differences in technology levels. The framework has not previously been applied to the different technological groups in an industry due to different views on the boundary of the production set. In our study, we tried to apply this concept to unique plant level data from the electricity generation industry in Korea.

Knowledge about which factors affect the efficiency of units and the technology gap within and between groups of plants can help managers and policy makers to set more proper strategies for advancement of the whole industry. This is also related to the two different aspects—namely, internal and external—of efficiency enhancement activities in the production part, because it can come from internal manageable factors or group characteristics affected by external changes due to the fundamental technological distinction.

To draw more implications and a proper methodological structure for the determinant analysis of different technologies, the analysis of determinants can be strengthened by incorporating factors like innovative activities, the impact from environmental regulatory changes ,new competing technologies, etc. Cost efficiency and multi-factor analysis considering this kind of technological heterogeneity will also give more implications from different perspectives. Although we tried to expand the determinants of technology differences with group characteristics, further studies are needed to explore additional multidimensional factors that can potentially affect the technology differences by groups.

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