Sources of inefficient power generation by coal-fired thermal power plants in China: A metafrontier DEA decomposition approach

江口, 昌伍
福岡大学経済学部

TAKAYABU, Hirotaka
Graduate School of Economics, Kyushu University

LIN, Chen
School of Applied Economics, Renmin University of China

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Sources of inefficient power generation by coal-fired thermal power plants in China: A metafrontier DEA decomposition approach

Shogo EGUCHI[1*], Hirotaka TAKAYABU[2], and Chen LIN[3]

[1] *Faculty of Economics, Fukuoka University, Fukuoka, Japan*

[2] *Graduate School of Economics, Kyushu University, Fukuoka, Japan*

[3] *School of Applied Economics, Renmin University of China, Beijing, China*

* Corresponding Author:

Address: 8-19-1, Nanakuma, Jonan-ku, Fukuoka, 8140180, Japan

Email: eguchi43@fukuoka-u.ac.jp

Abstract

China is the world's largest CO_2 emitting country and coal-fired thermal power generation accounted for over 50% of total electricity generation in China in 2015. This study reports the changes in power generation efficiency of coal-fired thermal power plants in China from 2009 to 2011 and how the differences in the production scale of the power plants and regional heterogeneity affect the power generation efficiency. We propose a metafrontier data envelopment analysis (DEA) decomposition framework to investigate the sources of inefficiency in power generation. The results suggest that on average, power generation efficiency of the large-scale power plants is 13% higher than that of the small-scale power plants. Although operational inefficiency is the main source of inefficiency in eastern and central China, the technology gap—the differences in the quality of coal consumed for electricity production and in the equipment of the power plants among the regions is the main source of inefficiency in western China. This study uses the results of the framework to discuss the scrapping policies for the coal-fired thermal power plants in China. For large-scale power plants in western China, the components of inefficiency vary and thus policymakers should consider scrapping the thermal power plants based not only on the level of inefficiency but also on its components.

Keywords: data envelopment analysis, slack-based measure, metafrontier, efficiency, coal-fired thermal power plant, scrapping

1. Introduction

In 2015, the Paris Agreement was adopted at the COP21, which was the first international and cooperative framework prepared to mitigate the effects of climate change since the Kyoto Protocol [1]. Since the Industrial Revolution, global CO_2 emissions have been consistently growing and they are estimated to be 32.3 Gt-CO_2 in 2015 [2]. China is the world's largest CO_2 emitting country and produced 9.2 Gt-CO_2 in 2015 [2]; the thermal power sector generated 80% of total electricity in China and coal-fired thermal power generation accounted for over 70% of total electricity generation of the thermal power sector in 2015 [3, 4].

In the Paris Agreement, the Chinese government set a CO_2 reduction target: to reduce per capita CO_2 emissions by 60–65% by 2030 relative to the emission levels in 2005. The government also agreed on the above CO_2 reduction targets in "The 13th five-year plan for energy development of the People's Republic of China" and declared that they would control the electricity generation by coal-fired thermal power plants to manage the growing electricity demand [5].

China's renewable energy installation capacity has been considerably growing in recent years, accounting for 26.7% of the total energy generation in 2018 [6]. Due to the rapid increase in energy generation from renewable energy sources, the operating rate of the coal-fired thermal power plants has dropped significantly and many coal-fired power plants have had a deficit problem in recent years. To address these problems, the government started to reduce the overcapacity of coal-fired power plants and suspended the construction of 104 coal-fired thermal power plants, which were either at the planning stage or and under construction, in 2017 [7].

To implement the environmental policies for mitigating the impacts of climate change, the Chinese government needs to solve the overcapacity problem of coal-fired thermal power plants (e.g., scrapping the existing power plants with outdated equipment) and improve their power generation efficiency. However, most previous studies have focused on the power generation efficiency of coal-fired power plants at the province level due to data limitations.

The study by Hu and Wang [8] is one of the seminal studies on the energy efficiency at the province level in China. They utilized the data envelopment analysis (DEA) and extended the traditional energy efficiency indicator, which is the ratio of GDP to electricity consumption, to an inclusive indicator (total-factor energy efficiency; TFEE), considering other input factors such as labor and capital. Hu and Wang [8] demonstrated that many provinces in central and eastern China showed improvements in TFEE from 1995 to 2002. Hu and Wang [8] also found the U-shaped relationship between TFEE and per capita income, which implies that energy efficiency can be improved depending on the economic growth.

In recent studies on the energy efficiency in China, metafrontier analysis has been widely used to estimate the energy efficiency based on regional heterogeneity [15-18]. A methodology for metafrontier analysis was developed by O'Donnell *et al*. [9]; the regional gap in efficiency can be estimated by measuring the distance between the metafrontier consisting of the pooled data and group frontiers, which are unique to each regional group.

Wang *et al*. [10] analyzed the changes in coal intensity using the data for 389 coal-fired thermal power plants from 2009 to 2012 in China. They found that power plants located in central China achieved the most significant improvement in coal intensity and smaller power plants experienced higher improvement in coal intensity during the study period. However, Wang *et al*. [10] analyzed the "average" changes in coal intensity for each group classified by production scale and region using a traditional DEA framework with an assumption of sole frontier technology. The impact of the difference in the production scale and regional heterogeneity on the power generation efficiency for individual power plants has not been studied to date to the best of our knowledge.

This study investigates not only the changes in the power generation efficiency of coal-fired thermal power plants, but also how the differences in the production scale of the power plants and regional heterogeneity would affect the power generation efficiency. We focus on individual power plants by using the plant-level data for electricity production from 2009 to 2011, which consist of the pooled 1643 Chinese coal-fired thermal power plants. In this study, we propose a metafrontier DEA decomposition framework to deepen the policy discussion about the efficiency improvement and scrapping strategy of the coal-fired thermal power plants in China.

The remainder of this paper is organized as follows. In Section 2, we survey the relevant literature. The proposed metafrontier DEA decomposition framework is described in Section 3, the data used in this study are explained in Section 4, the results and policy discussion are presented in Section 5, and concluding remarks are given in Section 6.

2. Literature Review

Since improving the energy efficiency is beneficial for both businesses and the environment, it is an important task for policymakers and business administrators. Many studies have evaluated the energy efficiency and its environmental impacts in China (Table 1). Table 1 consists of 14 and 13 representative preceding studies at the province and the plant level, respectively. Information on the decision-making unit (DMU), study period, production variables, and other notes are also provided in the table. Installed capacity, fixed capital stock, fuel consumption, and labor are mainly considered as input variables, and GDP and electricity production are used as output variables.

Many studies analyzed the environmental efficiency considering CO_2 and SO_2 emissions as undesirable outputs. Several studies (Du and Mao [11]; Du *et al*. [12]; Kaneko *et al*. [13]; Peng *et al*. [4]) estimated the pollution abatement cost by introducing the parametric frontier approach. Many studies computed the undesirable outputs such as CO_2 emissions following the Intergovernmental Panel on Climate Change (IPCC) guideline presented in Eq. (1) [14].

$$C = \sum_{i=1}^{I} \left(E_i \times NCV_i \times CC_i \times COF_i \times \frac{44}{12} \right), \tag{1}$$

where C represents the total CO_2 emissions from fuel combustion, E_i is the consumption of fuel i, NCV_i is the net calorific value of fuel i, CC_i is the carbon content of fuel i, COF_i is the carbon oxidation factor of fuel i, and $\frac{44}{12}$ is the ratio of the mass of one carbon atom combined with two oxygen atoms to the mass of an oxygen atom. Although all the coal-fired power plants analyzed in this study only use coal as fuel for electricity production, we cannot use the data for different types of coal (e.g., brown coal and black coal) in this study because of the data limitations. Therefore, we do not consider the production variables such as CO_2 emissions as undesirable outputs.

Table 1 also indicates whether each study considered the regional heterogeneity by using the metafrontier DEA model. According to Wang *et al*. [15], "conventional energy efficiency measurements presuppose that every province has similar and consistent production technology. However, due to significant differences in economic development, industrial structure, resource endowment and geographical environment, technological heterogeneity of energy utilization is something of inevitability. Ignoring this fact might lead to biased estimation."
Wang *et al*. [15] analyzed the energy efficiency considering regional heterogeneity by classifying 29 provinces in China into three groups: east, central, and west. They revealed that the level of energy efficiency and production technology is significantly different among these groups. Most provinces in the east had advanced production technology, achieving high energy efficiency, while energy efficiency in western provinces was the lowest.

Following Wang *et al*. [15], several studies including those by Du *et al*. [16], Zhang *et al*. [17], and Feng *et al*. [18] introduced the metafrontier DEA model by dividing Chinese provinces into three regions and estimated the energy and environmental efficiency by incorporating regional heterogeneity. Zhang *et al*. [17] applied the metafrontier analysis to the DEA framework and investigated the energy efficiency at the province level in China. They quantified that the improvement potential of energy efficiency of the provinces in the eastern region and found that 48% of the improvement potential was derived from the frontier technology between the regions (e.g., difference in the energy mix or population density between the regions) and the other 52% was from the operational management. Their findings could not be explained by the traditional DEA framework that assumes only the single frontier technology. Feng *et al*. [18] developed the three-hierarchy metafrontier DEA model where there are three industrial frontiers (i.e., primary, secondary, and tertiary industrial frontiers) under a metafrontier. Furthermore, three regions (i.e., east, central, and west) compose each industrial frontier. Similar to Feng *et al*. [18], Sun *et al*. [19] introduced the three-hierarchy metafrontier DEA model and evaluated the operational and environmental efficiency on fossil fuel power plants in China based on the province-level electricity statistics. The three-hierarchy metafrontier DEA model provided by Sun *et al*. [19] consists of a metafrontier for all periods, group frontiers for all periods (two groups: coastal and inland region), and sub-group frontiers in an analyzed period (11 sub-groups for each group: 11 periods between 2005 and 2015). They found that there are substantial group heterogeneity between coastal and inland provinces and coastal provinces experienced higher improvement rate of environmental efficiency than inland provinces.

Compared to the preceding studies at the province-level, fewer studies considered group heterogeneity in plant-level analyses. Zhang and Choi [20] analyzed the changes in power generation efficiency of coal-fired thermal power plants in China from 2005 to 2010 by using the metafrontier DEA model for only 93 power plants, which were divided into two regional groups (i.e., central and local areas). Long *et al*. [21] analyzed environmental efficiency of 192 thermal power plants in the Yangtze River Delta of China from 2009 to 2011 accounting for regional heterogeneity. They classified 192 thermal power plants into three regional groups: the Shanghai municipality, Jiangsu Province, and Zhejiang Province. Their results suggest the rate of coal use be decreased and the technology spillover of production technology and environmental technology among different provinces be expanded. Although Long *et al*. [21] has made a substantial contribution to the policy discussion on coal-fired power plants, the subject area was limited to the Yangtze River Delta.

In this study, we apply the multi-hierarchy metafrontier DEA model to the electricity production data of the pooled 1643 coal-fired thermal power plants all over China from 2009 to 2011. The proposed metafrontier DEA decomposition framework considers three layers: a metafrontier, group frontiers for production scale (i.e., three groups of large, medium, and small scale), and sub-group frontiers classified by region (i.e., three sub-groups for every group frontier: eastern, central, and western region). To the best of our knowledge, there are no other studies that evaluated the power generation efficiency incorporating the differences in the production scale of power plants and regional heterogeneity for the entire country. The proposed metafrontier DEA decomposition framework will be useful to understand the technology gap in power generation efficiency caused by the differences in the production scale and regional heterogeneity and to discuss the environmental policies for technology improvement toward the reduction of CO_2 emissions and the scrapping of coal-fired thermal power plants in China.

Table 1. Previous studies on energy and environmental efficiency of Chinese provinces and China's thermal power plants

Authors	Year	Journal	DMU	Study period	Inputs	Goods	Bads	Group heterogeneity
Lam, P.L. and Shiu, A.	2001	Utilities Policy	30 provinces	1995, 1996	Capacity (*1) Fuel Labor	Electricity generation	-	
Lam, P.L. and Shiu, A.	2004	Review of Industrial Organization	30 provinces	1995-2000	Capacity Fuel Labor	Electricity generation	-	
Hu, J. and Wang, S.	2006	Energy Policy	29 provinces	1995-2002	Capital (*2) Fuel Labor Land (*3)	GDP	-	
Kaneko, S., et al.	2010	Energy Policy	30 provinces	1998-2006	Capital Labor	GDP	SO2	
Wang, Q., et al.	2013	Economic Modelling	29 provinces	2000-2010	Capital Fuel Labor	GDP	-	✓
Zhou, Y., et al.	2013	Energy Policy	Power industry in 30 provinces	2005-2010	Capital Fuel Labor	Electricity generation	SO2 NOx CO2	
Du, K., et al.	2014	Applied Energy	30 provinces	2006-2010	Capital Fuel Labor	GDP	CO2	✓
Wu, F., et al.	2015	Computaional Economics	An industrial sector in 28 provinces	1997-2008	Capital Fuel Labor	GDP	-	
Zhang, N., et al.	2015	Ecological Indicators	30 provinces	2001-2010	Capital Fuel Labor	GDP	SO2 CO2 COD	✓
Meng, F., et al.	2016	Applied Energy	30 provinces	1995-2012	Capital Fuel Labor	GDP	CO2	
Zhang, Y-J., et al.	2016	Applied Energy	An industrial sector in 30 provinces	2005-2012	Capital Fuel Labor	GDP	CO2	
Feng, C., et al.	2017	Renewable and Sustainable Energy Reviews	Three industrial sector in 30 provinces	2013	Capital Fuel Labor	GDP	CO2	✓
Peng, J., et al.	2018	Journal of Cleaner Production	Thermal power sector in 30 provinces	2004-2013	Capacity Fuel Labor	Electricity generation	CO2	
Sun, C., et al.	2018	Energy Policy	Fossil fuel power plants in 30 provinces	2005-2015	Capacity Fuel Labor	Electricity generation	CO2	✓

(Continued)

Yang, H. and Pollitt, M.	2009	European Journal of Operational Research	221 coal-fired power plants	2002	Capacity Fuel Labor	Electricity generation	SO2	
Yang, H. and Pollitt, M.	2010	Energy Policy	582 coal-fired power plants	2002	Capacity Fuel Labor	Electricity generation	SOx NOx CO2	
Zhang, N. and Choi, Y.	2013	Energy Economics	93 fossil fuel power plants	2005-2010	Capacity Fuel Labor	Electricity generation	CO2	✓
Zhao, X. and Ma, C.	2013	Energy Economics	34 coal-fired power plants	1997-2010	Capacity Fuel Labor	Electricity generation	-	
Mou, D.	2014	Energy Policy	252 coal-fired power plants	2009-2011	Capacity Fuel	Electricity generation	-	
Zhang, N., et al.	2014	Energy Policy	252 fossil fuel power plants	2010	Capacity Fuel Labor	Electricity generation	CO2	
Du, L. and Mao, J.	2015	Energy Policy	518 coal-fired power plants in 2004 640 coal-fired power plants in 2008	2004 2008	Capital Fuel Labor	Electricity generation	CO2	
Song, C., et al.	2015	Energy Conversion and Management	34 coal-fired power plants	2012	Coal Oil Water Electricity	Electricity generation Capacity utilization	-	
Du, L., et al.	2016	Resource and Energy Economics	648 coal-fired power plants	2008	Capital Fuel Labor	Electricity generation	CO2	
Yu, Y., et al.	2017	Energy Policy	5048 coal-fired power plant (pool)	1999-2008	Capacity Fuel Labor	Electricity generation	CO2	
Liu, X, et al.	2018	Journal of Cleaner Production	84 thermal power plants	2005-2010	Capacity Fuel Labor	Capacity utilization	CO2 SO2	
Long, X., et al.	2018	Renewable and Sustainable Energy Reviews	192 thermal power plants	2009-2011	Capacity Fuel	Electricity generation	CO2	✓
Wang, C., et al.	2019	Energy Economics	389 coal-fired power plants	2009-2012	Capital (*4) Fuel Labor (*5)	Electricity generation	-	
Our study			1643 coal-fired power plants (pool)	2009-2011	Capital (*6) Fuel	Electricity generation	-	✓

(*1) Capacity refers to installed capacity measured by Watt.
(*2) Capital is measured by monetaly unit of fixed capital stock.
(*3) Hu and Wang (2006) used total sown area of farm crops as a proxy of biomass energy input.
(*4) Wang et al. (2019) used product of installed capacity of a plant and average utilization hours of a province as capacity.
(*5) Wang et al. (2019) used wage payment as labor input.
(*6) Following and Shanmugam and Kulshreshtha (2005) and Wang et al. (2019), our study used product of installed capacity and utilization hours of a plant as capital.

3. Methods

3.1 Slack-based measure (SBM)

DEA is a nonparametric method first developed by Charnes *et al*. [22] to evaluate the performance of decision-making units (DMUs) simultaneously considering multiple inputs and outputs without any assumption for the type of production function. The DEA model developed by Charnes *et al*. [22] is called "*radial*." This model evaluates the relative efficiency of the DMUs based on the proportional reduction of input (or proportional expansion of output) vectors toward the production possibility frontier [22, 23]. Although the radial DEA model can manage multiple inputs and outputs, it might overestimate the performance of DMUs because it ignores the slack variables for inputs and outputs in computing the efficiency score of DMUs [22, 24].

This study adopts the slack-based measure (SBM) model developed by Tone [23] to evaluate the power generation efficiency of coal-fired thermal power plants in China. SBM is a "*non-radial*" DEA model, which solves the problems associated with the radial DEA model by incorporating the slack variables in computing the efficiency score [23]. In this study, we use the input-oriented SBM model and estimate the efficiency score ρ^* of DMU_z using Eq. (2) [23-25].

$$
\begin{aligned}
&\rho^* = \min 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_{iz}^-}{x_{iz}} \\
&s.t. \\
&x_{iz} = \sum_{j=1}^{N} x_{ij}\lambda_j + s_{iz}^- \left(i = 1,...,m\right) \\
&y_{rz} = \sum_{j=1}^{N} y_{rj}\lambda_j - s_{rz}^+ \left(r = 1,...,s\right) \\
&\sum_{j=1}^{N}\lambda_j = 1 \\
&\lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0
\end{aligned}, \qquad (2)
$$

where x_{iz} and y_{rz} represent the input and output vectors, respectively. x_{ij} and y_{rj} represent the input and output matrices, respectively, consisting of all the DMUs. N denotes the sample size of the pooled DMUs during the entire study period. i and r denote the number of inputs and outputs, respectively. λ_j, s_i^-, and s_r^+ are the weight vector, and the slacks for inputs and outputs, respectively, and they are endogenously determined by solving Eq. (2). ρ^* is an efficiency score based on the input and output slacks and DMU_z is efficient when

$\rho^* = 1$. For inefficient DMUs, the efficiency scores are estimated based on the relative distance between the inefficient DMUs and the production possibility frontier consisting of the DMUs with $\rho^* = 1$. Efficiency score ρ^* ranges between 0 and 1 ($0 < \rho^* \leq 1$) and a higher value means higher efficiency. $\sum_{j=1}^{N} \lambda_j = 1$ is a constraint to allow for the variable returns to scale (VRS) assumption [26].

This study considers two inputs—coal consumption and *capital* (defined as the product of installed capacity and actual operational hours), and one output, *net* electricity production (defined as the difference in the electricity consumed for the operation of power plants from the gross electricity production) [27, 28]. Therefore, i =2 and r = 1 in this study conducted over 2009 through 2011.

3.2 Metafrontier DEA

Figure 1 shows the concept of the multi-hierarchy metafrontier DEA decomposition framework proposed in this study. In Figure 1, the metafrontier consists of all the technologies used during the study period of three years. Therefore, by using the efficiency score ρ^* obtained by Eq. (2), the meta inefficiency in Figure 1 is computed as follows:

$$\textit{Meta inefficiency} = 1 - \rho_z^* \qquad (3)$$

Based on Wang *et al*. [10][1], we decompose the meta inefficiency into three components: inefficiencies caused by the differences in the scale of the power plant, by inter-regional heterogeneity, and by the operational management of the power plant. As shown in Figure 1, technological inefficiency[2] represents the inefficiency due to the differences in the scale of the power plant. Inter-regional inefficiency represents the inefficiency due to the technology gap between the regions within the group of the power plants with the same production scale. Finally, managerial inefficiency represents the gap in the management of power plants with the same production scale and region. By using the metafrontier decomposition framework proposed in this study, we can identify the sources of inefficiency for electricity production, which cannot be revealed by the traditional DEA model that assumes sole frontier technology.

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[1] Wang *et al*. [10] pointed out that the power generation efficiency would be affected by the difference in scale of the plant and region where the plant is located.

[2] As a variable representing technology, we can also consider the vintage of the power plant. However, due to the data availability for the vintage of the power plant, we make use of the production scale (i.e., installed capacity) of the power plant as the variable representing technology.

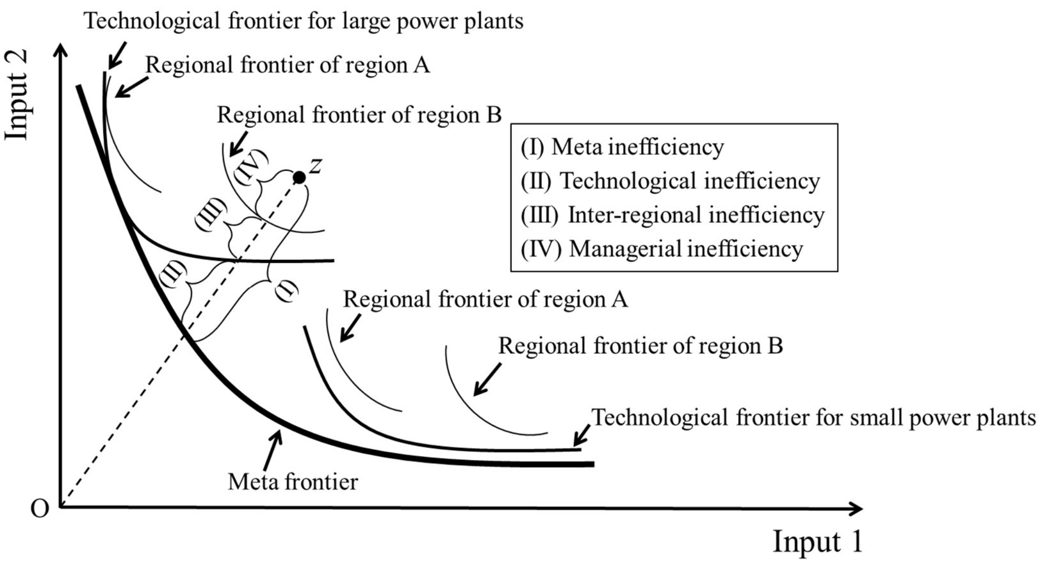


Figure 1. The metafrontier DEA decomposition framework proposed in this study

In order to estimate the technological inefficiency for DMU_z belonging to group t ($t = 1, \ldots, T$), we have to set up the technological frontier, which is unique to each group classified by the production scale of the power plants, and compute the efficiency score of DMU_z in group t as in Eq. (4).

$$
\begin{aligned}
&\rho^{t*} = \min 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_{iz}^{-}}{x_{iz}} \\
&s.t. \\
&x_{iz} = \sum_{j=1}^{N^t} x_{ij}\lambda_j + s_{iz}^{-}\left(i = 1,\ldots,m\right) \\
&y_{rz} = \sum_{j=1}^{N^t} y_{rj}\lambda_j - s_{rz}^{+}\left(r = 1,\ldots,s\right) \\
&\sum_{j=1}^{N^t}\lambda_j = 1 \\
&\lambda_j \geq 0, s_i^{-} \geq 0, s_r^{+} \geq 0
\end{aligned}
, \qquad (4)
$$

where t ($t = 1, \ldots, T$) represents the number of groups classified by the production scale and N_t represents the number of DMUs in group t. In this study, $T = 3$ because we classify all the power plants into three groups—large, medium, and small—based on the installed capacity. By using the results of Eqs. (2) and (4), technological inefficiency for DMU_z in group t can be estimated as follows [18]:

$$Technological\ inefficiency_z = \rho_z^{t*} - \rho_z^{*} \qquad (5)$$

We then estimate the inter-regional inefficiency of DMU$_z$ in group t. We classify the Chinese provinces into three groups: east, central, and west. We reveal the inter-regional technology gap in power generation efficiency (i.e., inter-regional inefficiency) by measuring the distance between the technological frontier and the frontier that is unique to each regional group (i.e., regional frontier) in group t [15, 17, 18]. The efficiency score of DMU$_z$ in group t of region p can be estimated as follows.

$$\begin{aligned} &\rho^{p,t*} = \min 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_{iz}^-}{x_{iz}} \\ &s.t. \\ &x_{iz} = \sum_{j=1}^{N^{p,t}} x_{ij}\lambda_j + s_{iz}^- \left(i = 1,\ldots,m\right) \\ &y_{rz} = \sum_{j=1}^{N^{p,t}} y_{rj}\lambda_j - s_{rz}^+ \left(r = 1,\ldots,s\right) \\ &\sum_{j=1}^{N^{p,t}} \lambda_j = 1 \\ &\lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0 \end{aligned}, \quad (6)$$

where $N^{p,t}$ represents the number of DMUs belonging to region p (p = 1,…, P) in group t, and P = 3 because the provinces are classified into three groups. By combining the results of Eqs. (4) and (6), the inter-regional inefficiency in group t of region p can be computed as follows [18]:

$$Inter\text{-}regional\ inefficiency_z = \rho_z^{p,t*} - \rho_z^{t*} \quad (7)$$

Note that the inequality $\rho_z^* \leq \rho_z^{t*} \leq \rho_z^{p,t*}$ holds because the technological frontier is a subset of the metafrontier and the regional frontier is a subset of the technological frontier [9, 18].

The managerial inefficiency of DMU$_z$ can be estimated as follows [18]:

$$Managerial\ inefficiency_z = 1 - \rho_z^{p,t*} \quad (8)$$

Managerial inefficiency means the inefficiency related to the operational management of the power plant within the same technological group and region. Finally, the meta inefficiency of DMU$_z$ can be decomposed as in Eq. (9).

$$Meta\ inefficiency_z = Technological\ inefficiency_z + Inter\text{-}regional\ inefficiency_z + Managerial\ inefficiecy_z \tag{9}$$

Table 2 shows the possible sources and possibility of improvement of three inefficiencies estimated by the metafrontier decomposition framework proposed in this study. Since technological inefficiency is caused by the differences in the scale of the power plant, we need to consider scrapping or rebuilding the power plants to improve technological inefficiency and thus the possibility for inefficiency improvement is considered low. Inter-regional inefficiency would result from the difference in the quality of the coal consumed for electricity production and the differences in the equipment of power plants among regions. Therefore, the possibility for improvement of inter-regional inefficiency is considered higher than that of technological inefficiency. Finally, since managerial inefficiency corresponds to the inefficiency in the operational management of the power plant, the possibility for improvement is considered the highest. By using the metafrontier decomposition framework, we can not only investigate how the difference in the production scale of the power plants and regional heterogeneity would affect the power generation efficiency, but also discuss the strategies for efficiency improvement and the scrapping policies for coal-fired thermal power plants.

Table 2. Possible sources and possibility of improvement of three inefficiencies estimated by metafrontier decomposition framework

	Sources of inefficiency	Possibility for improvement
Technological inefficiency	-Inefficiency in the scale of the plants	Low
Inter-regional inefficiency	-Difference in the quality of the coal between the regions -Difference in the equipment of the plant between the regions	Medium
Managerial inefficiency	-Inefficient management	High

4. Data

The framework proposed in this study uses two inputs, coal consumption and the capital and one output of the net electricity production. We chose these two inputs because the inefficiency in electricity production is caused by the utilization factor (defined as the ratio of the actual electricity production to the production capacity) and coal intensity (defined as the ratio of the coal consumption to the actual electricity production) [27, 28]. Although Wang *et al*. [10] uses the average operational hours for each province, we use the actual operational hours for each power plant and thus can estimate the power generation efficiency more precisely. As mentioned in Section 2, since we cannot identify the types of coal consumed for electricity production at the plant level, there would be a strong linear correlation between coal consumption and CO_2 emissions if we estimate the CO_2 emissions as per Eq. (1). Therefore, we do not consider CO_2 emissions as an undesirable output in this study. The data for the inputs and the output were obtained from China Electricity Council [29] over a period of 2009–2011.

We exclude the DMUs with abnormal values from the efficiency estimation. First, we remove the DMUs with operational hours over 8760 h (24 h × 365 d) and the DMUs whose net electricity production is over the capital value. We also exclude the DMUs whose coal intensity lies in more than 1.5 interquartile ranges below the first quartile or above the third quartile. To classify the coal-fired thermal power plants into three groups (large, medium, and small) based on the installed capacity, we divide all the DMUs during the entire study period into three equal parts following the method presented in Wang *et al*. [10] because there is no clear criterion for the production scale of the installed capacity.

Table 3 provides the descriptive statistics of the data used in this study. The average and maximum values for all the inputs and the output increased from 2009 to 2011, indicating an increase in the production scale of the coal-fired power plants in China during the study period. Moreover, the pooled sample size of the DMUs during the study period is 1643 and the sample size varies from year to year.

Table 3. Descriptive statistics of the data used in this study

		Input		Output	
Year	Statistics	Capital (million KWh)	Coal consumption (thousand ton)	Net electricity production (million KWh)	Sample size
2009	Avg.	3688.6	1759.4	3345.0	567
	Max.	26232.0	13658.9	25077.9	
	Min.	1.5	0.02	0.05	
2010	Avg.	4204.4	2041.2	3839.8	569
	Max.	26611.2	13649.9	25466.3	
	Min.	0.4	0.3	0.3	
2011	Avg.	4728.6	2358.5	4306.6	507
	Max.	29505.6	15653.1	28236.9	
	Min.	0.8	1.3	0.7	

5. Results and Discussion

5.1 Change in meta inefficiency from 2009 to 2011

Figure 2 shows the changes in the meta inefficiency during the study period. The average of meta inefficiency of all DMUs in 2009 is 0.233, which indicates that their electricity production in 2009 is inefficient by 23.3% compared to the metafrontier technology. In 2011, the average meta inefficiency of all DMUs is 0.228, which indicates that meta inefficiency improved by 0.5% from 2009 to 2011. The average meta inefficiency of the DMUs belonging to the small production scale group (SMALL) in 2009 is 0.297, whereas that of the DMUs belonging to the large production scale group (LARGE) is 0.167, indicating that there is an efficiency gap of 13% in electricity production between the two groups. Moreover, although the average meta inefficiency for MEDIUM and SMALL groups did not greatly change from 2009 to 2011, that for the LARGE group deteriorated by 1.1%.

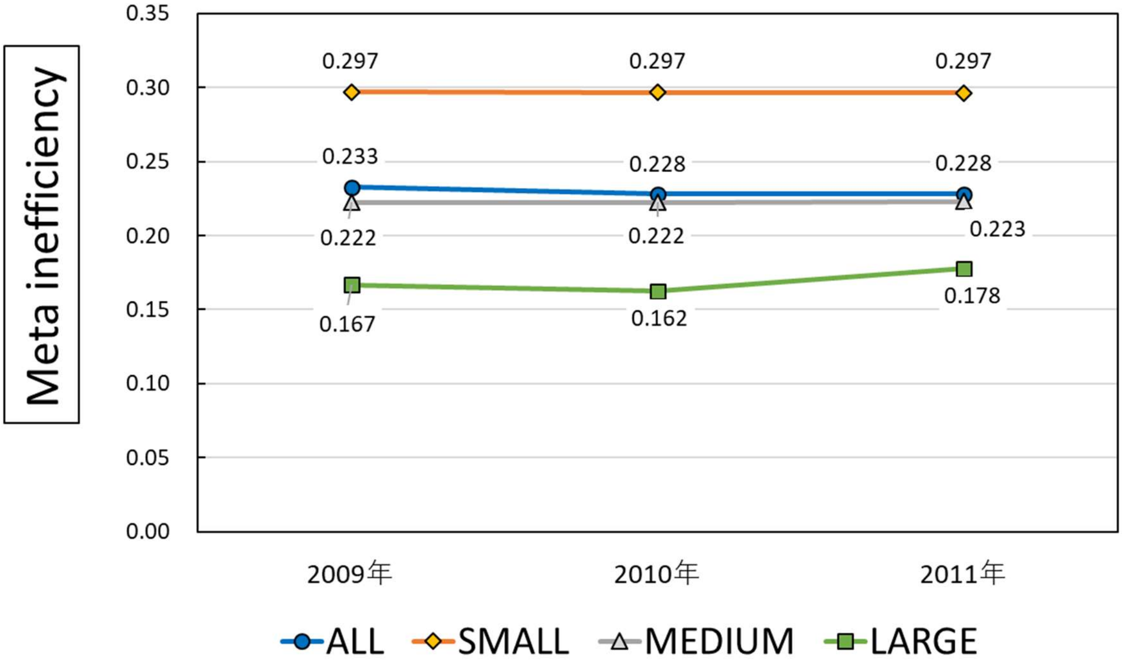


Figure 2. Change in meta inefficiency from 2009 to 2011

Figures 3 and 4 show the average of coal intensity and auxiliary power ratio aggregated by each production scale group during the study period, respectively. Here, coal intensity can be defined as the ratio of the coal consumption (ton) to the net electricity production (10 thousand kWh). Auxiliary power ratio is the ratio of the electricity consumed within the power plant to the gross electricity production; the data can be obtained from China Electricity Council [29]. The lower value shows higher performance for both indicators, and the factor affecting the changes in meta inefficiency can be analyzed by investigating these indicators. For the LARGE group, although the auxiliary power ratio improved from 7.56 to 7.35 from 2009 to 2011, the coal intensity deteriorated from 4.83 to 5.10. The expansion of meta inefficiency for the LARGE group was induced because the improvement in the auxiliary power ratio was offset by the deterioration of the coal intensity. However, since the changes in meta inefficiency were not substantial during the study period, the results of the metafrontier decomposition analysis focusing only on 2011 are presented in Section 5.2.

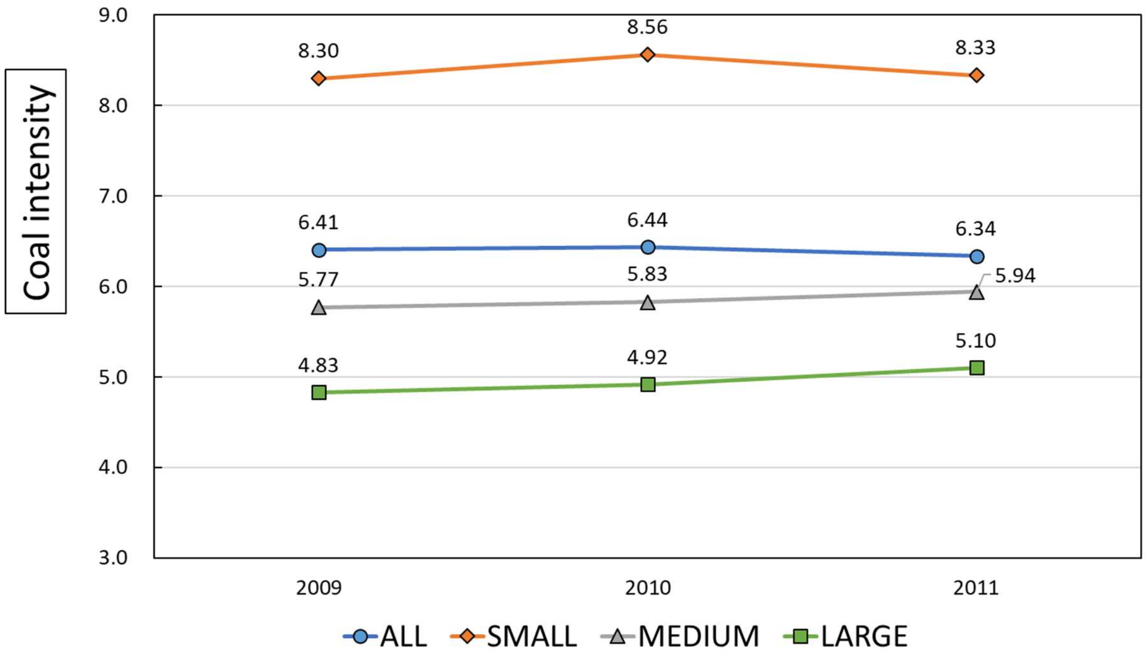


Figure 3. Change in coal intensity from 2009 to 2011

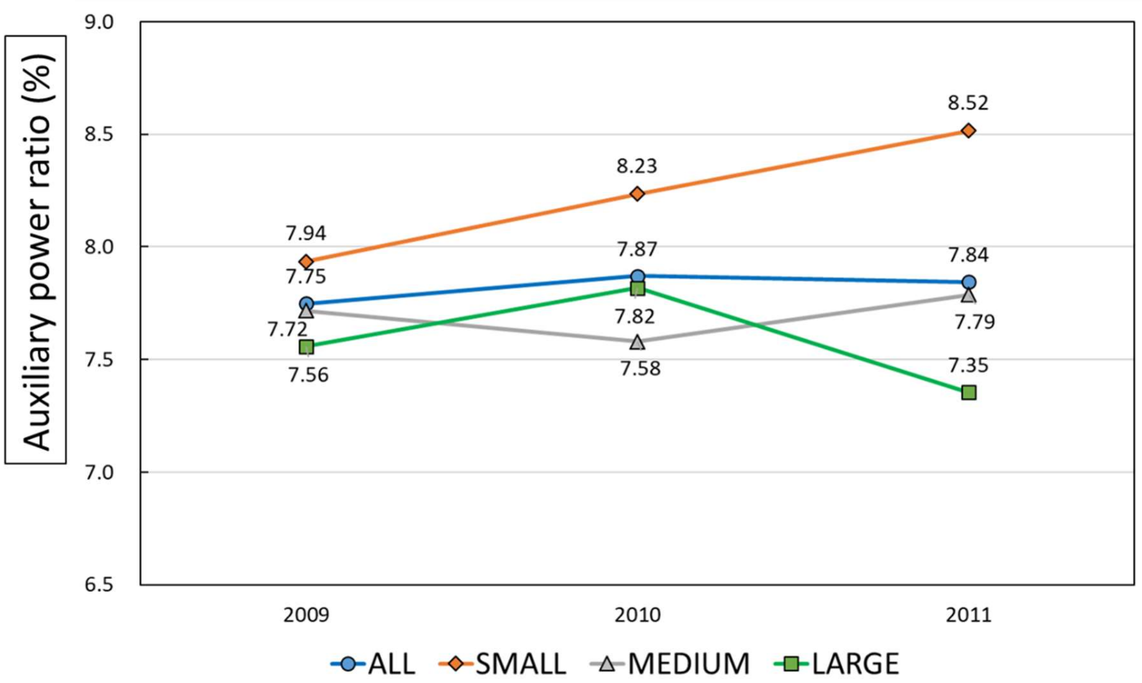


Figure 4. Change in auxiliary power ratio from 2009 to 2011

5.2 Results of metafrontier decomposition analysis in 2011

Figure 5 is the boxplot of the technological inefficiency of three groups aggregated by production scale in 2011. The average value of the LARGE group shows the highest value of 0.047, whereas that of the SMALL group shows the lowest value of 0.024, implying a technology gap of 2.3% between the technological frontiers of the two groups. However, the gap in the technological inefficiency among the three groups is marginal compared to the one regarding inter-regional and managerial inefficiencies.

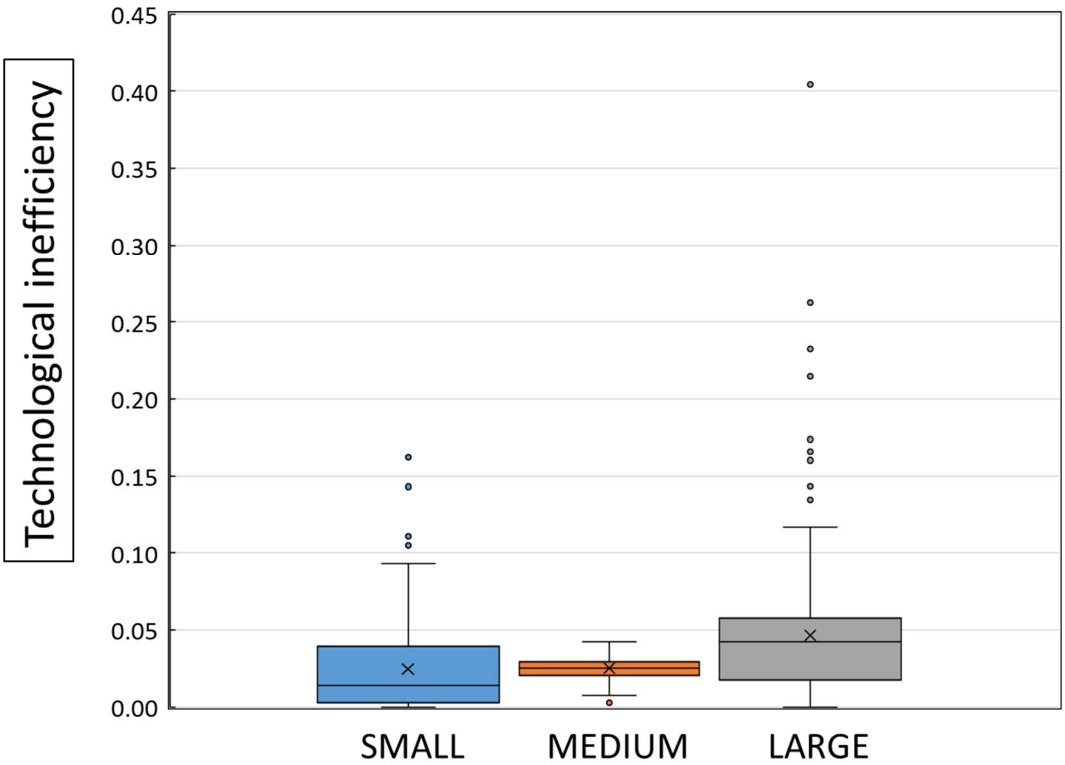


Figure 5. Boxplot of the technological inefficiency for each group in 2011

Figure 6 is the boxplot of the inter-regional inefficiency of the 3×3 groups aggregated by production scale and region in 2011. The inter-regional inefficiency in the LARGE group in the western region shows the highest average value (0.093). This result indicates that the frontier technology of large-scale power plants in the west is substantially low compared to the technological frontier consisting of all power plants belonging to the LARGE group. The inter-regional inefficiency in the LARGE group in the east shows the lowest average value (0.002), which suggests that coal-fired thermal power plants with cutting-edge technology are mostly located in the east. In contrast to the results of the LARGE group, the average inter-regional inefficiency values for the plants in the SMALL group in the east show the highest value (0.037), which suggests that the tendency of inter-regional inefficiency is different from that of the production scale. The gap in the inter-regional inefficiency is smaller in the SMALL group than that in the MEDIUM and LARGE groups.

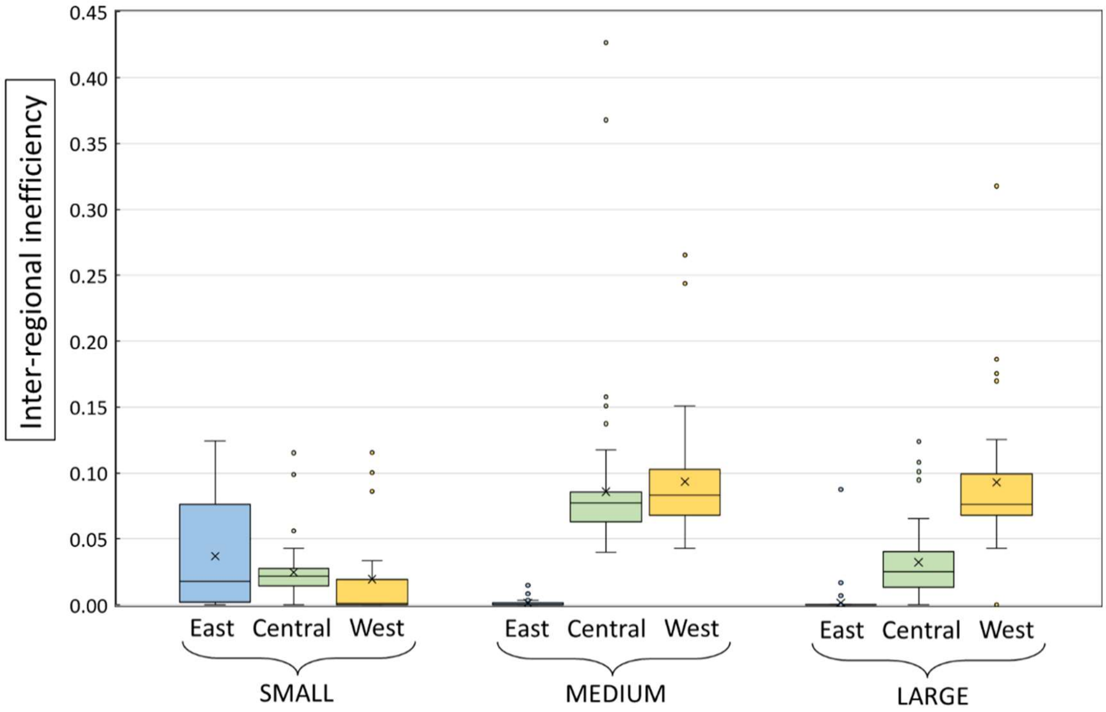


Figure 6. Boxplot of inter-regional inefficiency for each group in 2011

The reason behind the differences in the inter-regional inefficiency values among the regions could be the economic level of the regions. Xie *et al*. [30] stated that economic growth is one of the driving factors of new construction of coal-fired thermal power plants in China. Since the eastern region is the most developed area in China, the growing electricity demand in the east induced the new construction of large power plants with advanced technology in that region, which may contribute to lowering the inter-regional inefficiency of the LARGE group in that region. On the contrary, since the western region is associated with slow economic growth and low electricity demand, new construction of large coal-fired thermal power plants is limited and many power plants with outdated technology may still exist in that region, leading to significant levels of inter-regional inefficiency.

Inter-regional inefficiency could be also affected by the differences in the quality of coal consumed for electricity production. According to Miura [31], raw coal mined in China is mostly low-quality coal with high ash content, whereas the one mined in Australia and Indonesia is high-quality coal with low ash content. In 2010, China imported 56,296 and 15,158 thousand tons of coal from Indonesia and Australia, respectively, and the sum of the coal imported from these two countries accounts for 52% of total coal imports in China [3]. Therefore, the imported high-quality coal distributed in the eastern coastal areas such as Guangdong and Fujian is likely consumed within the eastern region owing to small transportation costs, contributing to lowering the inter-regional inefficiency of the MEDIUM and LARGE groups in the eastern region.

Figure 7 is the boxplot of the managerial inefficiency values for 3×3 groups aggregated by production scale and region in 2011. The average managerial inefficiency of the SMALL group is substantially higher than that of the MEDIUM and LARGE groups. Therefore, for the SMALL group, although the technological and inter-regional inefficiencies are relatively small, there is a substantial gap in managerial inefficiency and it is the main source of the large meta inefficiency. In the LARGE group, managerial inefficiency values in the eastern and central regions are relatively higher than those in the western region.

To lower managerial inefficiency, coal intensity and auxiliary power ratio should be improved. Although the quality of coal varies from region to region, by using the "coal washing" technology, the coal quality can be greatly improved at the low cost of 2–3 USD per ton of coal [31]. To improve the auxiliary power ratio, plant managers need to reconsider the use of boilers, turbines, and lighting equipment in power plants.

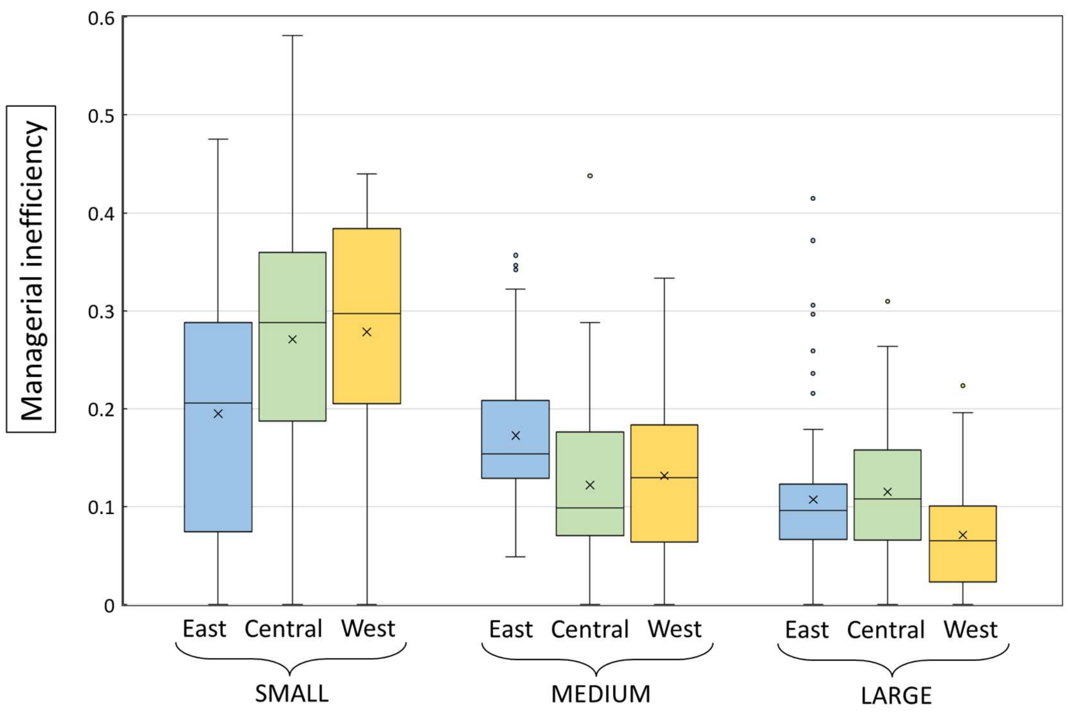


Figure 7. Boxplot of managerial inefficiency values for each group in 2011

Figure 8 is the cumulative bar chart indicating the average of three inefficiencies of the 3×3 groups aggregated by production scale and region in 2011. In Figure 8, the sum of the average of three inefficiencies corresponds to the meta inefficiency for each group. Meta inefficiencies of the SMALL group are relatively higher than those of the MEDIUM and LARGE groups. Large inefficiency values, which correspond to the managerial inefficiency, are observed in the central region of the SMALL group. For the LARGE group, the most substantial meta inefficiency values are observed in the western region and the main source is the inter-regional inefficiency. Furthermore, for the LARGE group, the second largest meta inefficiency is observed in the central region and mainly caused by managerial inefficiency. Therefore, the main source of meta efficiency is different for each region even within the same production scale group.

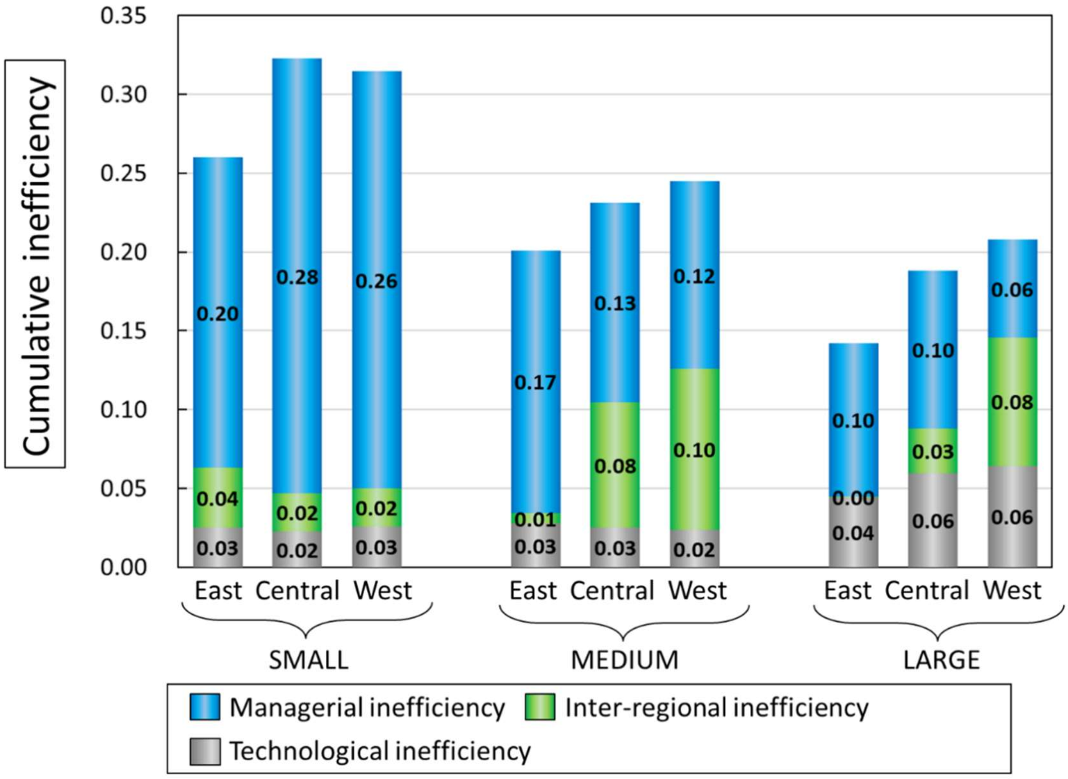


Figure 8. Cumulative bar chart of three inefficiencies for each group in 2011

Although the results of this study revealed that electricity production by small coal-fired power plants is inefficient compared to that by medium and large plants, it is crucial to improve the inefficiency of the large power plants with the substantial coal consumption. For this purpose, we should discuss the policies that support scrapping the large power plants if their electricity production is significantly inefficient.

5.3 Policies for scrapping large-scale power plants

In this section, we discuss the scrapping policies for coal-fired thermal power plants with large production scale (i.e., power plants whose installed capacity is in top 33%) based on the results provided by the metafrontier DEA decomposition framework of this study, which quantifies the meta inefficiency of each power plant and decomposes it into three sources (technological inefficiency, inter-regional inefficiency, and managerial inefficiency).

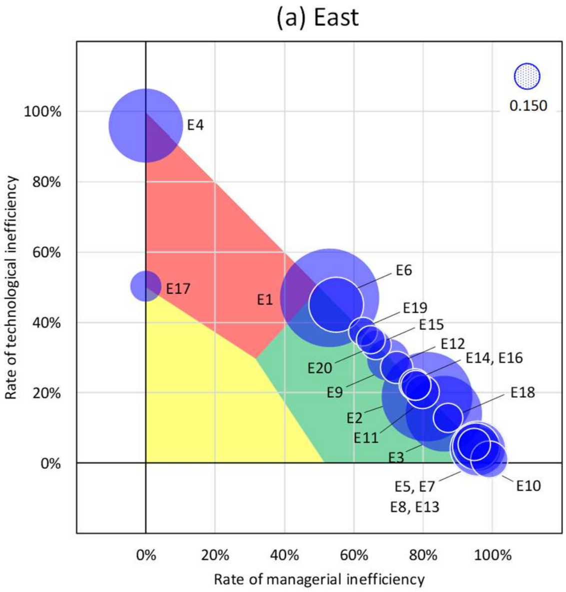
In order to improve the technological inefficiency, plant managers need to change the production scale of the plant by scrapping or rebuilding them and thus the possibility for improvement is considered quite low. Improving the inter-regional efficiency is a little hard but easier than the improvement of technological inefficiency. The possibility of improving the managerial inefficiency is the highest.

As a scrapping policy, we propose that power plants with high meta inefficiency values should be scrapped. If several power plants have the same level of meta inefficiency, scrapping priority should be decided based on the ratios of technological, inter-regional, and managerial inefficiencies to meta inefficiency. In other words, we assign the highest scrap priority to power plants with a large proportion of technological inefficiency, whereas we do not place priority on power plants with a large proportion of managerial inefficiency.

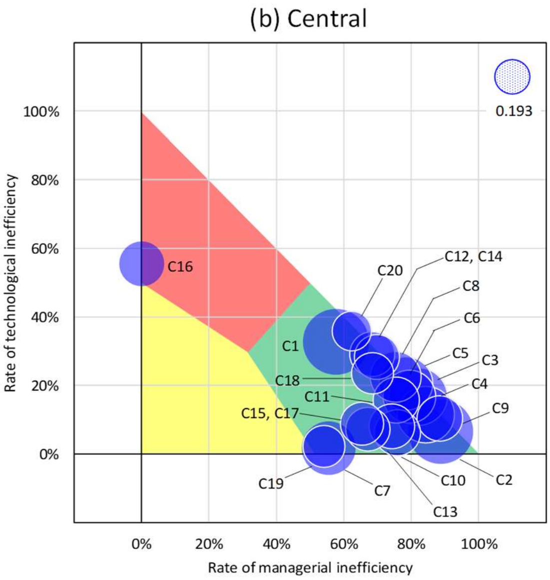
Table 4 shows the meta inefficiency (MTI) of the top 20 power plants in the LARGE group in each region in 2011. Table 4 also provides the ratio of technological inefficiency (TC), inter-regional inefficiency (RG), and managerial inefficiency (MG) to meta inefficiency. The components of the meta inefficiency vary considerably from plant to plant. In order to visualize the data presented in Table 4, we provide a bubble chart in Figure 9. In Figure 9, the size of each circle represents the meta inefficiency value, and vertical and horizontal axes represent the ratio of technological and managerial inefficiency values to meta inefficiency, respectively. The circle and the value placed on the upper right portion of each figure show the average meta inefficiency for all power plants in each group.

Table 4. Top 20 large power plants by meta inefficiency and component for each region

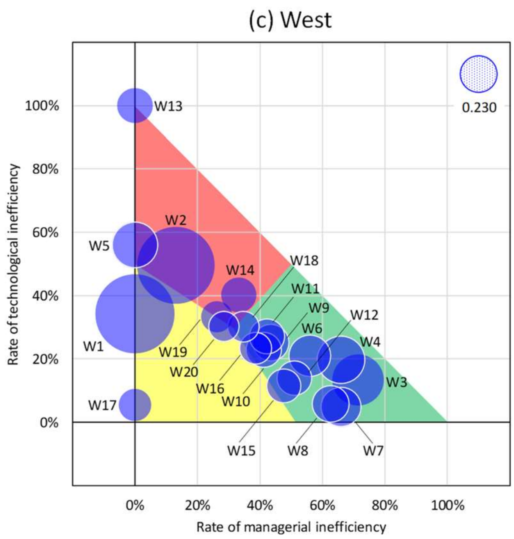
East						Central						West					
Plant	Province	MTI	TC	RG	MG	Plant	Province	MTI	TC	RG	MG	Plant	Province	MTI	TC	RG	MG
#13	Hubei	0.559	47%	0%	53%	#126	Anhui	0.356	33%	10%	58%	#25	Guizhou	0.484	34%	66%	0%
#108	Jiangsu	0.512	19%	0%	81%	#61	Inner Mongolia	0.349	7%	5%	89%	#63	Shaanxi	0.470	50%	37%	13%
#36	Liaoning	0.432	14%	0%	86%	#64	Inner Mongolia	0.320	17%	1%	82%	#36	Yunnan	0.313	13%	15%	71%
#228	Guangdong	0.421	96%	4%	0%	#78	Heilongjiang	0.313	11%	4%	84%	#33	Yunnan	0.297	20%	14%	66%
#217	Guangdong	0.319	4%	0%	96%	#41	Inner Mongolia	0.297	21%	1%	78%	#7	Sichuan	0.286	56%	44%	0%
#199	Shandong	0.317	45%	0%	55%	#70	Inner Mongolia	0.292	17%	4%	79%	#24	Guizhou	0.261	21%	23%	56%
#41	Liaoning	0.272	5%	0%	95%	#157	Henan	0.289	2%	43%	55%	#16	Guizhou	0.250	5%	29%	66%
#77	Jiangsu	0.246	4%	0%	96%	#54	Inner Mongolia	0.282	23%	2%	75%	#13	Guizhou	0.231	6%	31%	63%
#29	Liaoning	0.237	29%	1%	70%	#73	Inner Mongolia	0.255	10%	1%	88%	#59	Shaanxi	0.229	25%	31%	43%
#141	Zhejiang	0.218	1%	0%	99%	#40	Shanxi	0.254	6%	18%	76%	#56	Shaanxi	0.222	23%	36%	41%
#95	Jiangsu	0.197	20%	0%	80%	#67	Inner Mongolia	0.254	16%	9%	76%	#50	Shaanxi	0.221	27%	31%	42%
#32	Liaoning	0.190	27%	0%	72%	#75	Jilin	0.250	29%	2%	68%	#10	Guizhou	0.217	14%	35%	51%
#198	Shandong	0.189	5%	0%	95%	#171	Henan	0.250	8%	18%	74%	#53	Shaanxi	0.215	100%	0%	0%
#47	Shanghai	0.186	22%	0%	78%	#85	Heilongjiang	0.247	28%	2%	70%	#6	Sichuan	0.214	40%	27%	33%
#195	Shandong	0.178	34%	0%	66%	#28	Shanxi	0.245	7%	26%	67%	#21	Guizhou	0.212	11%	41%	48%
#202	Guangxi	0.176	22%	0%	78%	#173	Henan	0.243	55%	45%	0%	#74	Gansu	0.200	23%	38%	39%
#26	Liaoning	0.176	50%	50%	0%	#18	Shanxi	0.239	9%	26%	65%	#19	Guizhou	0.197	5%	95%	0%
#192	Shandong	0.175	13%	0%	87%	#154	Henan	0.232	24%	8%	69%	#62	Shaanxi	0.197	30%	35%	35%
#172	Shandong	0.171	37%	0%	63%	#44	Inner Mongolia	0.232	2%	44%	54%	#30	Yunnan	0.191	33%	40%	26%
#71	Jiangsu	0.169	35%	0%	65%	#84	Heilongjiang	0.219	36%	2%	62%	#66	Shaanxi	0.191	30%	41%	28%



(a) East		
Plant	Province	Plant name
E1	Hubei	Hebei Hanfeng Power Plant
E2	Jiangsu	Xuzhou power plant
E3	Liaoning	Liaoning Qinghe power generation co., LTD
E4	Guangdong	Guangdong Sanshui Hengyi power plant
E5	Guangdong	Guangdong Honghaiwan power plant
E6	Shandong	Shandong Huarun power (heze) co., LTD
E7	Liaoning	Liaoning Tieling power plant
E8	Jiangsu	Guodian Jianbi power plant
E9	Liaoning	Liaoning Guodian Kangping power generation co., LTD
E10	Zhejiang	Zhejiang Jiahua power generation co., LTD
E11	Jiangsu	Jiangyin Sulong electric generation co., LTD
E12	Liaoning	Liaoning Huaneng Dalian power plant
E13	Shandong	Shandong Zoucheng power plant
E14	Shanghai	Shidongkou power generation company
E15	Shandong	Shandong Yunhe Power Plant
E16	Guangxi	Guangxi Fangchenggang electric power co., LTD
E17	Liaoning	Liaoning Guodian power Zhuanghe power generation company
E18	Shandong	Shandong Weifang power plant
E19	Shandong	Shandong Guodian Shiheng power plant
E20	Jiangsu	Datang Xutang power generation co., LTD



(b) Central		
Plant	Province	Plant name
C1	Anhui	Anhui Wuhu Tianmenshan power plant
C2	Inner Mongolia	Inner Mongolia Huolinhe Hong jun aluminum electric company
C3	Inner Mongolia	Inner Mongolia Huolinhe Pithead power generation company
C4	Heilongjiang	Heilongjiang Fulaerji plant
C5	Inner Mongolia	Inner Mongolia Baiyin Huajinshan power generation co., LTD
C6	Inner Mongolia	Inner Mongolia Xiwang aluminum group Xiwang power plant
C7	Henan	Henan Qinbei power plant
C8	Inner Mongolia	Inner Mongolia Guohua Hulun Buir power generation co., LTD
C9	Inner Mongolia	Inner Mongolia Yuanbaoshan power generation company
C10	Shanxi	Shanxi Zhaoguang power generation co., LTD
C11	Inner Mongolia	Inner Mongolia Jinglong power generation co., LTD
C12	Jilin	Jilin Huaneng Jiutai plants
C13	Henan	Henan YiAn electric power co., LTD
C14	Heilongjiang	Heilongjiang Mudanjiang second power plants
C15	Shanxi	Shanxi Xingneng power generation co., LTD
C16	Henan	Henan Mengjin power plant
C17	Shanxi	Shanxi Luneng Hequ power plant
C18	Henan	Henan Pingdingshan Yaomeng power generation co., LTD
C19	Inner Mongolia	Inner Mongolia Dalate power company (north)
C20	Heilongjiang	Heilongjiang Hegang power plants



(c) West		
Plant	Province	Plant name
W1	Guizhou	Guizhou Xingyi electric power development co., LTD
W2	Shaanxi	Shaanxi Qinling power generation co., LTD
W3	Yunnan	Guodian Qujing power generation co., LTD
W4	Yunnan	Guodian Xuanmie power generation co., LTD
W5	Sichuan	Xinping thermal power plant
W6	Guizhou	Guizhou Yaxi power plant
W7	Guizhou	Guizhou Nayong thermal power plant
W8	Guizhou	Guizhou Faer power plant
W9	Shaanxi	Shaanxi Huadian Pucheng power co., LTD
W10	Shaanxi	Shaanxi Huadian Pucheng power plant phase iii
W11	Shaanxi	Shaanxi Hancheng second power co., LTD
W12	Guizhou	Guizhou Dafang power plant
W13	Shaanxi	Shaanxi Hancheng second power co., LTD
W14	Sichuan	Luzhou Chuannan power generation co., LTD
W15	Guizhou	Guizhou Qianbei power plant
W16	Gansu	Gansu Jingyuan second power co., LTD
W17	Guizhou	Guizhou Pannan power plant
W18	Shaanxi	Shaanxi Huaneng international power development company Tongchuan power plant
W19	Yunnan	Diandong Yuwang energy co., LTD. (phase ii)
W20	Shaanxi	Shaanxi Weihe power generation co., LTD

Figure 9. Top 20 large power plants by meta inefficiency and component for each region

In Figure 9, since power plants with larger circles have higher meta inefficiency values, policymakers should scrap these power plants first. Moreover, power plants located in Area R (painted in red) have a large proportion of technological inefficiency and thus the scrap priority should be the highest. Since the power plants located in Area G (painted in green) have a large proportion of managerial inefficiency, the potential for improvement is relatively high and policymakers do not have to place high priority on those plants for scrapping. For power plants located in Area Y (painted in yellow), however, the proportion of both the technological and managerial inefficiencies is small (i.e., the proportion of inter-regional inefficiency is large) and thus the scrapping priority for those plants is medium.

Figure 9 (a) shows the results for the large-scale power plants in the eastern region. Most plants are located in Area G, meaning that they have a large proportion of managerial inefficiency. Focusing on the size of the circles, meta inefficiency of plants E1, E2, E3, and E4 is especially large. Since plant E4 has a large proportion of technological inefficiency as well as large meta inefficiency, policymakers should assign high priority to scrap this power plant. Figure 9 (b) shows the results for the large-scale power plants in the central region. All the power plants are located in Area G except for plant C16. Figure 9 (c) shows the results for the large power plants in the west. The components of meta inefficiency vary in this group. Since power plants W1 and W2 have large meta inefficiency values and are located in areas Y and R, respectively, scrapping priority for those plants is considered high. Although power plants W4 and W5 have almost the same level of meta inefficiency, power plant W4 is located in Area G and plant W5 is located in Area R. For this reason, policymakers should place higher priority to scrap plant W5. Appendix 1 provides the bubble chart for all coal-fired power plants in nine groups.

In this section, we discussed the scrapping policies for coal-fired power plants based on the results provided by the metafrontier DEA decomposition framework developed in this study, focusing on the level and components of meta inefficiency. If the traditional DEA framework that assumes sole frontier technology was used, the scrapping policy based on the components of inefficiency could not have been discussed. To the best of our knowledge, there are no preceding studies that presented a policy discussion based on the components of inefficiency and this is one of the main contributions of this study.

6. Conclusion

In this study, we quantitatively analyzed the changes in the power generation efficiency of the coal-fired thermal power plants in China from 2009 to 2011. We also developed the metafrontier DEA decomposition framework to investigate how power generation efficiency is affected by production scale, regional heterogeneity, and operational management. The improvement rate of meta inefficiency during the study period was found to be 0.5% and power generation efficiency only slightly increased from 2009 to 2011. We also investigated the meta inefficiency for groups classified by production scale and demonstrated that the average power generation efficiency of the LARGE group was 13% higher than that of the SMALL group in

2009.

Then, we focused on the year 2011 and classified all the power plants by production scale and region, decomposing the meta inefficiency into three groups: technological, inter-regional, and managerial inefficiency. The average technological inefficiency was the highest in the LARGE group. Since there is a large proportion of managerial inefficiency in the eastern and central regions for the LARGE group, plant managers of the power plants are encouraged to utilize clean coal technologies such as coal washing and reconsider the utilization of the boilers, turbines, and lighting equipment in power plants to effectively improve the power generation efficiency. In western region, there is a large proportion of inter-regional inefficiency and thus plant managers are advised to introduce advanced equipment and use high-quality imported coal, which is already used in the eastern coastal area. Therefore, improving the power generation efficiency is more challenging in the western region than in the eastern and central regions. The effective strategy for improving power generation efficiency varies greatly by region and production scale and thus these findings will provide important basis for plant managers and policymakers.

This study has certain limitations. Managerial inefficiency can be further decomposed into other terms such as the vintage or the ownership of the power plants. We could not pursue these classifications due to data limitations. Note that the number of DMUs would decrease if we assumed more layers in the multi-hierarchy metafrontier DEA model and we would suffer from mathematical problems due to the weakened discriminatory power of DEA caused by the small number of DMUs [32].

In this study, we fully utilized the results of the metafrontier DEA decomposition framework and discussed the policies that support the scrapping of the coal-fired thermal power plants in China. Since there are no preceding studies that discuss such policies based on the components of inefficiency, the policy discussion in Section 5 can be considered one of the main contributions of this study. Furthermore, the metafrontier DEA decomposition framework proposed in this study is applicable to the efficiency and productivity analyses in the fields of economics, energy, and environment and provide a basis for decision-makers and policymakers.

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