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Efficiency evaluation of thermal power plants in China based on the weighted Russell directional distance method

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ABSTRACT

China has the largest thermal power installed capacity worldwide, which has caused severe greenhouse gas emissions. To reduce the emissions and facilitate the development of energy savings and emission abatement, it is imperative to improve power-generating efficiency. In this paper, the nonparametric weighted Russell directional distance method (WRDDM) was used to evaluate the overall efficiency of thermal power plants in 30 provinces in China. The results show that the efficiency of East and North China is higher than that of Northeast and Southwest China. Furthermore, the correlations between scale, ownership and efficiency are discussed. The nonstate-owned plants with large generation capacity have a higher efficiency than the small and state-owned plants.

1. Introduction

Energy savings and emission abatement of the power sector play essential roles in sustainable development. China has the largest installed capacity of thermal power in the world, and the massive use of thermal power has led to excessive greenhouse gas emissions (IEA, 2018).

In addition, China's national Emission Trading Scheme (ETS) was officially established at the end of 2017, and the electric power industry was the first industry to be included. Based on this, improving the overall efficiency of the power sector is the best alternative for achieving emission abatement before any technological breakthroughs become operational (e.g., carbon capture and storage, CCS). Therefore, the efficiency evaluation of thermal power plants becomes significant, and such analysis can present instructions on efficiency improvement for stakeholders and policymakers.

In this paper, a nonparametric approach of data envelope analysis (DEA), called the weighted Russell directional distance function model (WRDDM), was adopted to evaluate the overall efficiency of thermal power plants in 30 provinces in China from 2012 to 2014. Nonparametric methods refer to those that do not require a specific equation related to the inputs and outputs (Wei et al., 2013), and a key advantage of the WRDDM over other DEA models is that it can increase the expected outputs and decrease the inputs as well as the unexpected outputs simultaneously and nonproportionally. Additionally, it can estimate the efficiency of each input and output and obtain the weighted overall efficiency. By using this method, decisionmakers can know specifically which part has been fully utilized or controlled and which part has potential for further improvement. Essentially, the overall efficiency of each plant varies due to differences in the region, technology, the management level, the year of operation, etc. By comparing the overall efficiency of different plants among different years and regions, the main factors that cause efficiency distinction can be determined. With the nonparametric test, we explored the determinants that may influence efficiency, such as the scale of plants and the difference of ownership. The results can generate more comprehensive suggestions on domestic plant efficiency improvement.

This article is organized as follows: Section 2 presents a literature review of previous studies. Section 3 introduces the methodology and data. In section 4, we illustrate the empirical results. Finally, we show the conclusions of our work and draw some policy implications.

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2. Literature review

DEA is a nonparametric method for efficiency evaluation. This method can estimate the effective production frontier based on a set of observations and obtain the production inefficiency of each decision-making unit. Zhou et al. (2008) collated nearly 100 representative papers on DEA used in energy and environment fields. Zhang and Choi (2014) summarized the directional distance function method from 1997 to 2013. Färe et al. (2007) used DEA to study the energy efficiency of American power plants. Zhang and Choi (2013) used DEA to evaluate the production and emission efficiency of Korean fossil fuel power plants. Sueyoshi et al. (2011) used the nonradial DEA method to evaluate the energy efficiency of Japan's fossil fuel power plants from 2005 to 2008 and compared their environmental benefits with those of the manufacturing industry in 2012 (Sueyoshi and Goto, 2011).

In studies on the power generation efficiency of China, Teng (2003) obtained the technical efficiency based on data from China's coal-fired power plants in 1991. Li and Zou (2012) selected the panel data of the power sector in 27 provinces from 2000 to 2009 and evaluated the technical efficiency and further discussed the influence of the economic level, the utility rate of electricity and incentive regulation on power generation efficiency. Choi et al. (2012) used the DEA model to estimate the CO_2 emission abatement cost, the potential and the energy utilization efficiency of thermal power plants based on data from 30 provinces from 2001 to 2010. Zhang and Xia (2011) combined DEA with the stochastic frontier approach (SFA) to analyze the technical efficiency of the power generation industry based on the panel data of 30 provinces from 2003 to 2009. They found that the technical efficiency was considerably low, and the state-owned plants performed worse than the nonstate-owned plants. Xie et al. (2012) used a two-stage DEA model to study the relation between generation methods and the environmental performance of the power industry and found that the correlation was significant. Yang and Michael (2009) used a three-multiplication DEA model to evaluate the environmental benefits of 582 thermal power plants in China in 2002. Niu (2017) used a three-stage super-DEA model that took unexpected outputs into consideration to calculate the carbon emission and intensity per capita with the data of fossil fuel consumption from 2003 to 2013.

Apart from the power industry, DEA has also been used in other energy-intensive industries. Jerry et al. (2012) estimated the efficiency of the Swiss paper industry in 1995, 2000 and 2005, they found that technological progress and an increase in funds could improve efficiency. Mandal (2010) used DEA to explore the impact of an unexpected output and environmental policies on the energy utilization efficiency of the India cement industry from 2001 to 2004, and he proposed that it would lead to great deviation without concerning the unexpected output. Liu and Wang (2015) improved the two-stage network DEA model and obtained an efficiency decomposition DEA model to evaluate the industrial sector efficiency of all the provinces in China in 2008 and compared the results with those of traditional DEA and the original two-stage network DEA model.

In this paper, the WRDDM was applied to obtain the overall efficiency of each power plant. The difference between the WRDDM and other DEA models is that it takes unexpected outputs into consideration and can measure the efficiency of each input and output. Using WRDDM, we can not only evaluate the efficiency but also show plants specifically how to improve their efficiency, for example, by decreasing the number of employees or investing less on equipment. This approach is more comprehensive than the traditional DEA model, which is why WRDDM is more useful for overall efficiency evaluation.

To the best of our knowledge, only a few scholars have applied the WRDDM to evaluate efficiency at the microlevel. Chen et al. (2011) first proposed this method on the basis of Chung et al. (1997) and Fukuyama and Weber (2009); then, Chen et al. (2015) improved this model using the data of 99 countries from 1991 to 2003 and evaluated the efficiency of each input and output. Wei et al. (2015) used this method to calculate the emission abatement potential of 68 and 124 power plants in 2004 and 2008 in Zhejiang Province, respectively, and constructed an energy-saving index and emission-abatement index. María et al. (2016) used this method to evaluate the environmental efficiency of wastewater treatment plants. Our work is the first to apply this method with recent data (2012 and after) in the power-generating industry in China. Therefore, the results of this paper could be a useful reference.

3. Data and methodology

3.1. Construction of the output set

The outputs of electricity generation are often divided into expected outputs and unexpected outputs (Chung et al. (1997), Zhou et al. (2012), Wei et al., (2015), Yang and Michael (2010). In this paper, vector $x = \{x_1, x_2, x_3\ x \in R_+\}$ was used to denote three inputs: labor, assets and energy consumption, $y \in R_+$ denotes expected outputs and $b \in R_+$ denotes unexpected outputs. P(x) represents the possible output set, and $P(x) = \{(y, b), x \text{ can produce } y, b\}$.

Meanwhile, P(x) satisfies the following assumptions (Wei et al., 2015).

(1) P(x) is a standard convex and compact set. That is, limited inputs can only produce limited outputs.
(2) The input is freely disposable, which indicates that the output set will not contract when the input increases. That is: If $x' > x$, then $P(x') \supseteq P(x)$.
(3) The null-jointness axiom is satisfied, which implies that unexpected outputs are jointly produced with expected outputs. That is: If $(y, b) \in P(x)$ and $b = 0$, $y = 0$.
(4) The expected and unexpected outputs satisfy joint weak disposability, which means two kinds of outputs can be reduced proportionally by θ. That is: If $(y,b) \in P(x)$ and $0 \le \theta \le 1$, then $(\theta y, \theta b) \in P(x)$.
(5) The expected output is strongly disposed, which implies that it is possible to dispose the expected products without reducing the unexpected outputs. That is: If $(y,b) \in P(x)$, and $(y', b) \le (y,b)$, then $(y', b) \in P(x)$.

3.2. Directional distance function

The traditional directional distance function (DDF) can be defined as follows:

$$\overrightarrow{D_0}\left(x,\ y,\ b,\ g_x,\ g_y,\ g_b\right) = \sup\left\{\beta : \left(y + \beta g_y, b + \beta g_b\right) \in P(x + \beta g_x)\right\}$$

g is a direction vector, and $g = (-g_x, g_y, -g_b)$ $(g \in R_+^N \times R_+^M \times R_+^J)$. This indicates that it is possible to both increase expected outputs and reduce unexpected outputs and inputs. The direction for input and the expected and unexpected outputs are g_x, g_y and g_b, respectively. Based on the direction vector g and output set P(x), we can derive the distance between the observations and the frontier, or the inefficiency level β. When $\beta = 0$, the output of this observation lies on the frontier, and the efficiency has reached the best outcome compared with all the other observations. The higher β is, the lower the overall efficiency and the higher the potential for efficiency improvement.

We applied the WRDDM to evaluate the inefficiency of each specific factor and obtained the weighted overall inefficiency. Some modifications were made based on the traditional DDF, and the new model is as follows:

$$\overrightarrow{D_0}(x,y,b,g) = \max\left(\omega_1^{k'}\beta_1^{k'} + \omega_2^{k'}\beta_2^{k'} + \omega_3^{k'}\beta_3^{k'} + \omega_4^{k'}\beta_4^{k'} + \omega_5^{k'}\beta_5^{k'}\right)$$

s.t.

$$\sum_{k=1}^{K} z^k y^k \geq \left(y^{k'} + \beta_4^{k'} \cdot g_y\right) \quad (1)$$

$$\sum_{k=1}^{K} z^k b^k = \left(b^{k'} - \beta_5^{k'} \cdot g_b\right) \quad (2)$$

$$\sum_{k=1}^{K} z^k x_n^k \leq \left(x_n^{k'} - \beta_n^{k'} \cdot g_{x_n}\right),\ n = 1,2,3 \quad (3)$$

$$\sum_{k=1}^{K} z^k = 1 \quad (4)$$

$$z^k \geq 0, k = 1, 2, \&, K \quad (5)$$

where z^k denotes the weight given to each input and output to construct the possible output set. The two sides for the constraints, (i), (ii) and (iii), indicate the optimally performed plant and the actual observation. The normalized weight assigned for each input and output is $\omega=(\omega_1,\omega_2,\omega_3,\omega_4,\omega_5)$. The inefficiency for the three inputs, the good output and the bad output, respectively, are denoted by $\beta_n(n = 1,2,3,4,5)$. An inequality sign in (i) and (iii) indicate strong disposability in assumptions (2) and (5). The constraint (ii) presents the weak disposability of the unexpected outputs and the assumption of null-jointness. Constraint (iv) represents that the model is under the assumption of various returns to scale (VRS). In recent years, some studies have been conducted under a constant return to scale (Wang et al., 2016; Han et al., 2018) and have been comparatively appropriate in terms of only generating efficiency. In this paper, we aimed to obtain the efficiency for each specific input and output, and it is reasonable to assume that the outputs would be enhanced by more than the proportional change in the inputs, such as labor, assets and energy consumption (Picazo. et al., 2005). Constraint (v) is used to ensure that all the intensity variables are nonnegative.

In this paper, CO_2 emissions were the only unexpected output included because greenhouse gas emissions are the primary concern. Meanwhile, we assumed that there were no priorities for the different inputs or outputs, and thus, they had the same weight. Following the previous study, ω can be set as (1/9,1/9,1/9,1/3,1/3) (Zhang and Choi, 2013) and $g=(g_x, g_y, g_b)=(-x_n, y, -b)$ (Wei et al., 2015), which means that the plants can scale the input/output in the direction of g.

3.3. Data

In this paper, the annual average number of employees, the total year-end assets, the total energy consumption (coal equivalence), the generating capacity and the CO_2 emissions were applied to the model. All the data were acquired from the China Electricity Council (CEC). Due to data limitation, CO_2 emissions were calculated by multiplying the energy consumption by the emission factor released by IPCC in 2006. Considering the technique differences, we separated the samples into two groups: coal-fired power plants and gas-fired power plants. Table 1 and Table 2 show the relevant variables used in this model.

Fig. 1 shows the number of coal-fired plants in each province. The number of gas-fired plants is comparatively small (30, 35 and 31). Provinces such as Hebei, Shanxi, Inner Mongolia, Jiangsu, Shandong, Henan, and Guangdong have a considerable number of plants, but the samples in Jiangxi, Hainan, and Qinghai are not sufficient, which makes the efficiency evaluated less supportive.

4. Empirical results

The linear programming method and MATLAB® were used to solve the WRDDM model, and the results were compared both among the years and the different regions.

4.1. Efficiency difference among years

4.1.1. Coal-fired power plants

Table 3 shows the notations used in this model. As mentioned above, the CO_2 emissions were derived from the energy consumption and caused the same value of β_3 and β_5.

The value of β for each province is displayed in Fig. 2. The inefficiency among the provinces varies significantly. In addition, the average β each year was 0.473, 0.392, and 0.272, which implies that the differences among the provinces was narrowing over time. For provinces such as Liaoning, Jilin, Heilongjiang, Henan, Guangxi, Sichuan, Yunnan, Shanxi and Xinjiang, the β was higher than the average all three years. In contrast, provinces such as Hebei, Shanghai and Zhejiang outperformed the average in three years. For Hainan and Jiangxi, the sample size is considerably small (1 and 2, respectively), and the β derived cannot be of great reference.

It should be noted that the comparison among years is not precise since the samples for three years are not exactly the same. To make the β comparable in these years and to explore how efficiency has changed over time, we further screened a total of 261 power plants with data for all the years as a new sample and measured the inefficiency of each input and output. The results are shown in Table 4.

Table 4 shows that the average β has dropped over the years. Specifically, approximately 62.45% of all the plants showed a descending trend in β, and 23.47% of them showed the opposite trend. This indicates that most of the plants have improved their overall efficiency and that the gap among the plants was narrowing. It is interesting to find that in 2014, the β_1 and β_3 were much higher than those in 2012 and 2013, which shows that the plants performed much worse in 2014 than in the last two years in terms of labor and energy utilization. This could be explained by the disparity of improvement and the diffusion of renewables in the power generation portfolio among different plants. On the one hand, for some plants, the improvements in labor usage and energy savings were slower, which caused a larger gap between the plants. On the other hand, given that more renewable power was accessed to the grid, more thermal units needed to standby in case of the power discontinuity. Therefore, the labor force may not be fully utilized and the energy consumed may be wasted. These reasons have caused the absolute value of β_1 and β_3 to become even higher than before.

Moreover, β_4 has significantly decreased, which implies that on average, the power generation capacity has achieved its optimum,

Table 1
Data from coal-fired power enterprises.

Variables	Unit	Mean	Std. Dev.	Min	Max
2012(n = 495)					
L (Labor)	Person	711.49	789.88	12.00	10021.00
K (Assets)	Million yuan	4347.41	20810.37	14.34	460527.76
E (energy consumption)	Ton	1539777.93	1198101.32	67100.63	7536937.32
Y (generation capacity)	MWh	5120385.60	3990635.00	145602.70	25926000.00
B (CO_2)	Ton	4237698.75	3317864.95	167744.52	20801947.00
2013(n = 541)					
L (Labor)	Person	665.65	724.89	10.00	9958.00
K (Assets)	Million yuan	3558.92	5386.37	67.42	111827.17
E (energy consumption)	Ton	1577309.30	1248922.86	68823.48	7973770.56
Y (generation capacity)	MWh	5269963.80	4236047.60	151965.60	27706800.00
B (CO_2)	Ton	4372665.78	3498876.33	189952.80	22007606.75
2014(n = 322)					
L (Labor)	Person	706.92	739.20	17.00	9655.00
K (Assets)	Million yuan	3207.56	2541.93	115.23	15741.01
E (energy consumption)	Ton	1417894.50	1104668.41	54159.00	6080842.50
Y (generation capacity)	MWh	4725465.90	3663493.10	156764.60	20750993.80
B (CO_2)	Ton	3913388.85	3048884.80	149478.84	16783125.30

Table 2
Data from gas-fired power enterprises.

Variables	Unit	Mean	Std. Dev.	Min	Max
2012(n = 31)					
L (Labor)	Person	230.03	251.84	71.00	1211.00
K (Assets)	Million yuan	2157.36	1778.16	349.01	9214.00
E (energy consumption)	Ton	473381.94	325918.33	61788.55	1213526.42
Y (generation capacity)	MWh	2080266.80	1390494.30	246000.00	4576901.20
B (CO_2)	Ton	1306534.16	899534.59	170536.40	3349332.92
2013(n = 35)					
L (Labor)	Person	208.31	230.00	41	1199
K (Assets)	Million yuan	1678.65	999.81	294.92	4323.15
E (energy consumption)	Ton	550341.98	495712.94	34996.66	2506415.70
Y (generation capacity)	MWh	2334199.70	1607860.90	140000.00	6234800.00
B (CO_2)	Ton	1397302.36	1364912.55	96590.78	6917707.33
2014(n = 30)					
L (Labor)	Person	205.47	182.01	39.00	855.00
K (Assets)	Million yuan	1859.18	1130.05	275.15	5607.48
E (energy consumption)	Ton	437652.79	351003.01	9107.00	1648481.93
Y (generation capacity)	MWh	1833999.30	1435984.60	80628.90	6405350.00
B (CO_2)	Ton	1207921.71	968768.31	25135.32	4549810.13

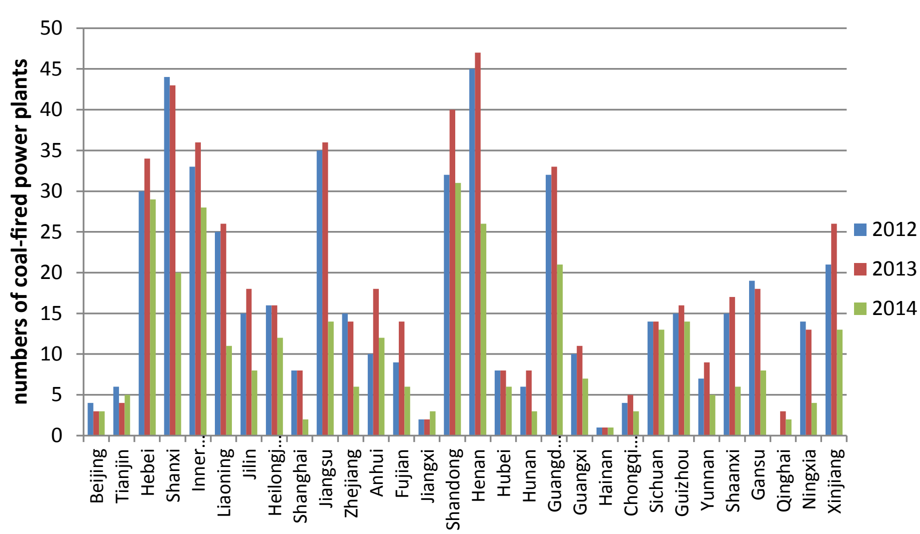

Fig. 1. Provincial distribution of coal-fired power plants.

Table 3
Notations and meanings.

Notations	Meaning
β	Overall inefficiency(improvement potential)
β_1	Labor inefficiency
β_2	Asset-used inefficiency
β_3	Energy-saving potential
β_4	Output improvement potential
β_5	Emission Abatement potential

and there is little room for further improvement. Thus, for those plants that have low values for β_4, reducing energy consumption and reducing the investment in labor and equipment are the primary considerations if they want to promote overall efficiency.

4.1.2. Gas-fired power plants

The sample of gas power plants was small and mainly located in Beijing, Jiangsu, Zhejiang and Guangdong. Fig. 3 represents the value of β in ascending order.

Compared with the others, it can be seen that approximately 1/3 to 1/2 of the power plants each year were globally efficient, which made $\beta = 0$. For the other plants, the highest β each year decreased over time. This indicates that the efficiency gap between the power plants was narrowing and the plant owners had put more efforts toward upgrading their technologies or optimizing their input utilization effectively.

Figs. 4–6 depict the energy consumption and β_3 of each gas-fired plant from 2012 to 2014. It should be noted that all the plants in the figure were independent of each other. The left vertical axis represents energy consumption (coal-equivalence), and the right axis represents the energy saving potential. Similar to β, β_3 decreased, and nearly half of the plants were globally efficient. In 2012, the highest β_3 reached 0.7279; that is, compared with the most effective plants, for this plant, 72.79% of the energy

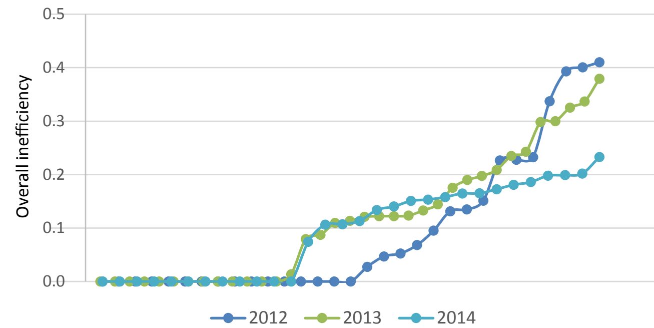

Fig. 3. Value of the overall inefficiency, β, of each gas power plant.

consumption could have been saved. The β_3 values for 2013 and 2014 were 0.6306 and 0.3336, respectively. Most of the plants had taken active measures to enhance the efficiency of power generation according to the results.

4.2. Efficiency difference among regions

To examine the regional efficiency differences, we divided all the provinces into six regions following the rule of CEC. Table 5 lists the provinces included in each region, and Table 6 shows the mean and standard deviation of β and the rank of each province. The rank is according to the results of the overall efficiency, and the regions with a higher overall efficiency will have higher ranks.

The overall efficiency has improved over time, which is consistent with previous results. Specifically, East and North China had the best performance in three years, which is the same as what Shi et al. (2010) discovered with data from 2000 to 2006. For East China, high efficiency may have resulted from the prosperous economy. With the highest GDP and most-developed industry and commerce, East China has taken a leading role in China's

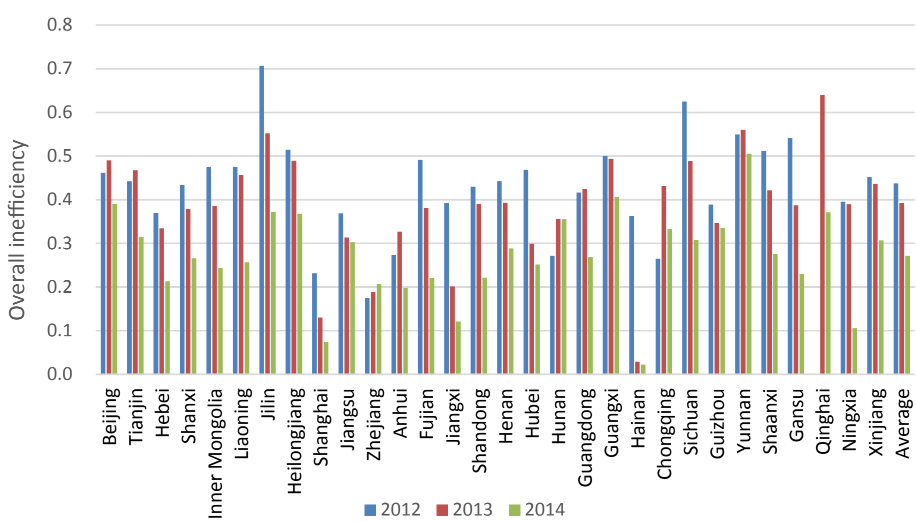

Fig. 2. The average value of overall inefficiency, **β**, in different provinces.

Table 4
2012–2014 inefficiency of all variables.

Mean (Std. dev)	β	β_1	β_2	β_3	β_4
2012	0.418(0.230)	0.264(0.230)	0.230(0.260)	0.232(0.265)	0.540(0.659)
2013	0.303(0.185)	0.189(0.229)	0.058(0.119)	0.335(0.281)	0.373(0.576)
2014	0.271(0.154)	0.431(0.295)	0.108(0.180)	0.436(0.293)	0.051(0.206)

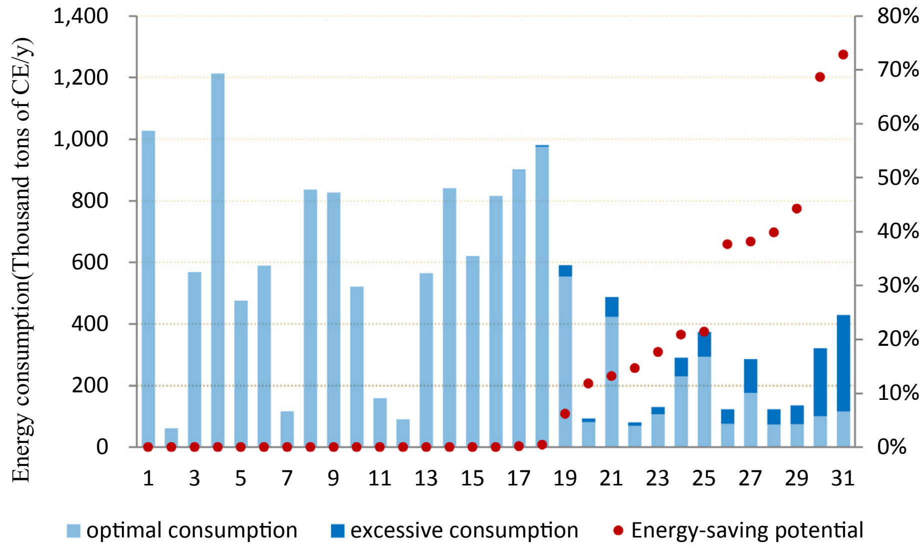

Fig. 4. The energy consumption and energy-saving potential, β_3, of each gas power plant in 2012.

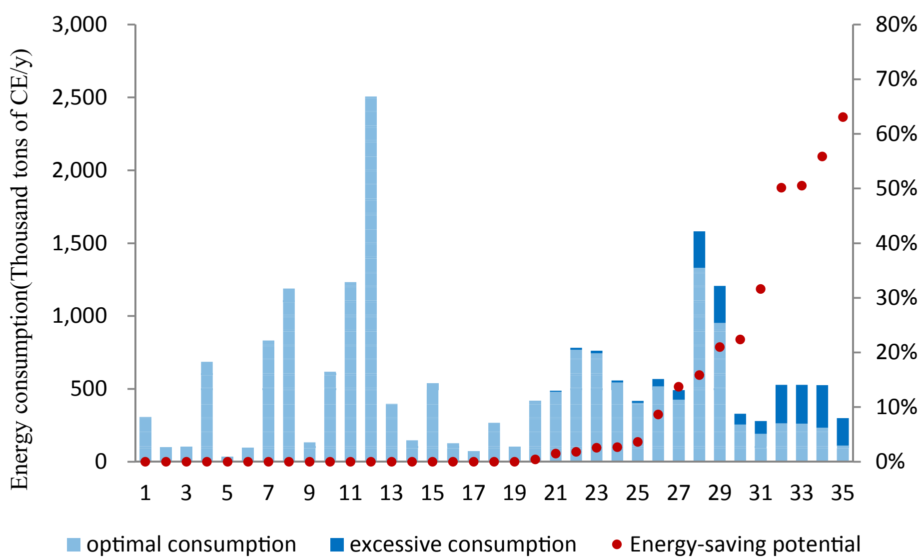

Fig. 5. The energy consumption and energy-saving potential, β_3, of each gas power plant in 2013.

development, and this has promoted investments in advanced technologies. For North China, which includes two municipalities, Beijing and Tianjin, policy-making and asset management were quite stringent, leading to better utilization in labor and capital. Additionally, the plants in Hebei stayed operational day and night and contributed to higher efficiency without the energy lost in the restarting or closing process. The efficiencies in the Southwest and Northeast were the two lowest among the six regions. In the Southwest, hydropower was the main source of energy, and thermal power mainly played the role of peak-shaving, especially in Yunnan and Guizhou. In the Northeast, there were many small thermal power plants that performed comparatively poorly due to the lack of advanced management and technology. The total generation hours were much lower than the national average (CEC report, 2016).

Furthermore, we sorted and located the plants whose β equaled 0. Figs. 7–9 show the distribution of the globally efficient plants each year. More than half of the plants were located in North and East China, especially in Zhejiang Province. The remaining plants were dispersedly in other regions. This is consistent with what we have discussed above.

4.3. Factor analysis on efficiency

To examine if the size of the plants and the type of ownership have a significant impact on overall efficiency, we classified the samples by different scales and ownership.

4.3.1. Scale difference

Total installed capacity is a popular index for distinguishing large and small plants. In this paper, we followed the rule by CEC and combined the plants into two groups. Plants with less than 1000 MW installed capacity were defined as small, and those with more than 1000 MW installed capacity were defined as large. A box plot was used to illustrate the differences between scales.

As shown in Fig. 10, the small plants had higher median values and variances than their large counterparts. Based on this finding, we assumed that there was a strong correlation between scale and

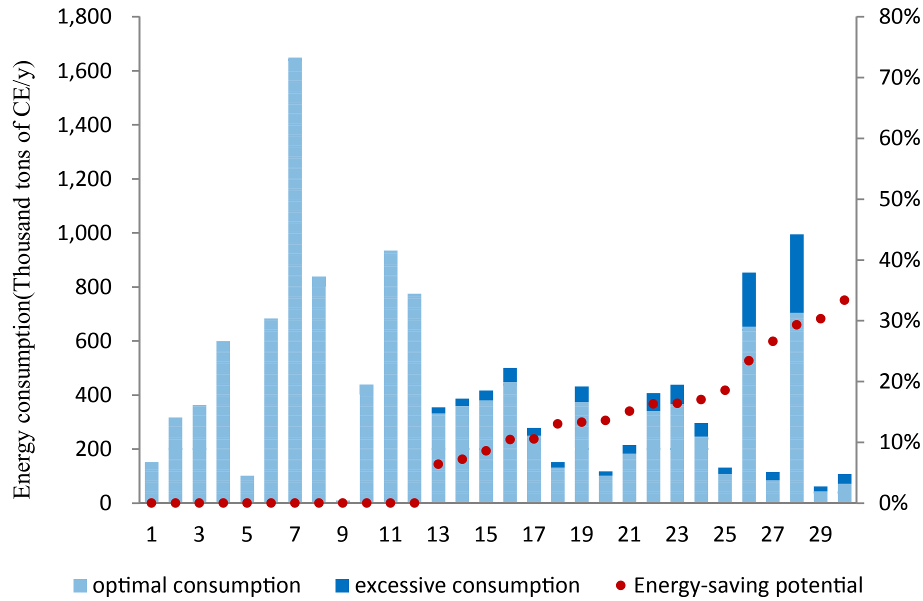

Fig. 6. The energy consumption and energy-saving potential, β_3, of each gas power plant in 2014.

Table 5
Classification of regions.

Regions	Provinces included
North China	Beijing, Tianjin,Hebei, Shanxi, Inner Mongolia
Northeast	Liaoning, Jilin,Heilongjiang
East	Shanghai, Jiangsu,Zhejiang, Fujian,Anhui, Jiangxi,Shandong
Middle&South	Henan, Hubei,Hunan, Guangxi,Guangdong
Southwest	Chongqing, Sichuan,Guizhou, Yunnan
Northwest	Shaanxi, Gansu,Ningxia, Qinghai,Xinjiang

efficiency. Then, Kolmogorov-Smirnov (K-S) and Mann-Whitney (M-W) tests were used to confirm our assumption. Table 7 shows the results of the two tests. They all refused the H_0 hypothesis that the large plants and small plants share the same pattern on overall efficiency. Generally, the large plants performed better than the small plants. The large plants could benefit from various returns of scale and well-developed management systems, which could further improve the efficiency of labor and capital use.

4.3.2. Ownership difference

4.3.2.1. Different groups. The five groups (Huaneng, Datang, Huadian, Guodian and Zhongdiantou, or FGs) are the dominant electricity-generating groups in China, and their annual generating capacity could account for approximately 50% of the total. According to CEC industrial statistics, in 2013, the total generating capacity of the FGs was 441,004 MW, comprising 51.1% of the total generation. In 2014, the values were 433,967 MW and 47.4%, respectively. Table 8 shows the number of different groups in the sample.

Before any testing, we assumed that the efficiency of the FGs should be higher than the non-FGs for their sufficient funds, advanced technology, and well-developed management, but the result shown in Fig. 11 negated our assumption. Similarly, we performed K-S and M-W tests, as shown in Table 9. Even under a confidence level of 10%, the H_0 hypothesis still cannot be rejected; that is, there was no significant difference in overall efficiency between the FGs and the non-FGs.

To further determine the reasons, we compared the inefficiency of each input and output. Fig. 12 shows the distribution of β_1.

In 2012, there was not much efficiency difference between the two groups, but in 2013 and 2014, the β_1 of the FGs were much higher than those of the non-FGs. This indicates that the labor force in the non-FGs was utilized more efficiently than the labor force in the FGs.

Table 10 shows the mean and standard deviation of β_2. It can be seen that the FGs performed better in capital utilization.

The difference in β_3 is reported in Fig. 13. In 2012, 2013, the energy-saving potential in the FGs was higher, and in 2014, they reversed this trend. This indicates that the FGs improved their efficiency of energy consumption and exceeded the performance of the non-FGs.

Similarly, we selected the globally efficient plants and collected the groups to which they belonged. Fig. 14 shows the constitution of the different groups. In 2012, 2014, the FGs had more efficient plants, and in 2013, the opposite was true. It is difficult to distinguish which group was better because of the fluctuation.

Table 6
β-value and ranks in different regions from 2012 to 2014.

	2012	Rank	2013	Rank	2014	Rank
North	0.4302(0.2461)	2	0.3742(0.2115)	2	0.2476(0.1250)	2
Northeast	0.5485(0.2882)	6	0.4937(0.1750)	6	0.3294(0.1847)	5
East	0.3521(0.2759)	1	0.3197(0.2202)	1	0.2268(0.1345)	1
Middle& South	0.4309(0.2436)	3	0.4000(0.2606)	3	0.2903(0.1687)	4
Southwest	0.4871(0.2570)	5	0.4450(0.2285)	5	0.3492(0.1456)	6
Northwest	0.4778(0.2302)	4	0.4215(0.1906)	4	0.2620(0.1492)	3

Fig. 7. Distribution of the globally efficient plants (β=0) in 2012.

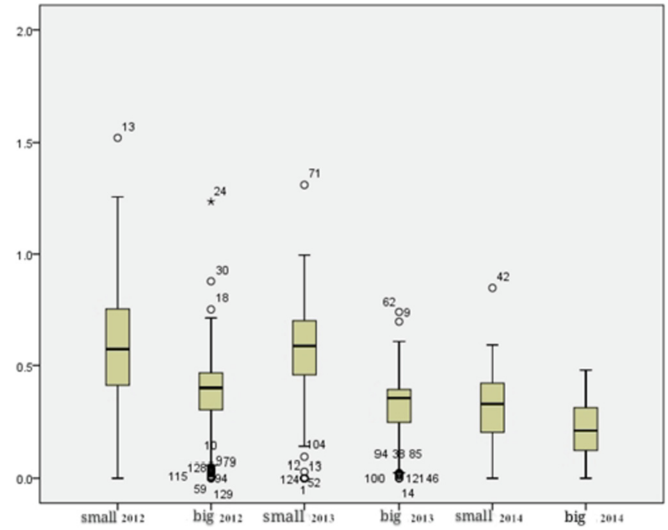

Fig. 10. The value distribution of β in two different scales from 2012 to 2014.

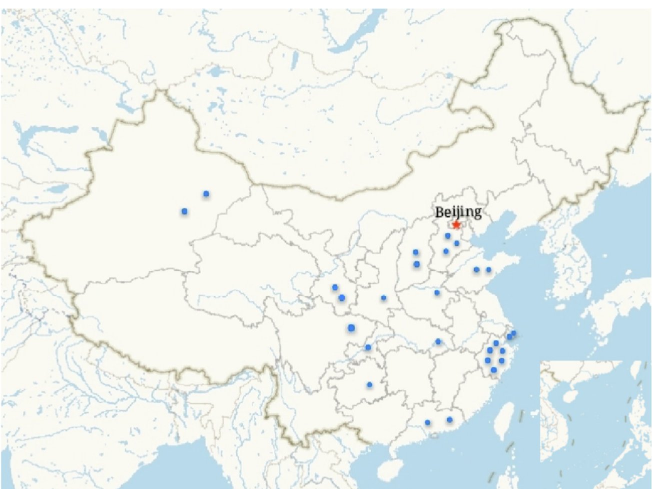

Fig. 8. Distribution of the globally efficient plants (β=0) in 2013.

Table 7
Results of the nonparametric tests.

	K-S Test	M-W Test
2012	0.500 (0.000)	−10.547 (0.000)
2013	0.604 (0.000)	−12.558(0.000)
2014	0.361 (0.000)	−6.294(0.000)

Table 8
Distribution of the FGs and non-FGs.

	Five groups	Non-five groups	Proportion of Five groups
2012	290	205	58.59%
2013	309	232	57.12%
2014	198	124	61.49%

Fig. 9. Distribution of globally efficient plants (β=0) in 2014.

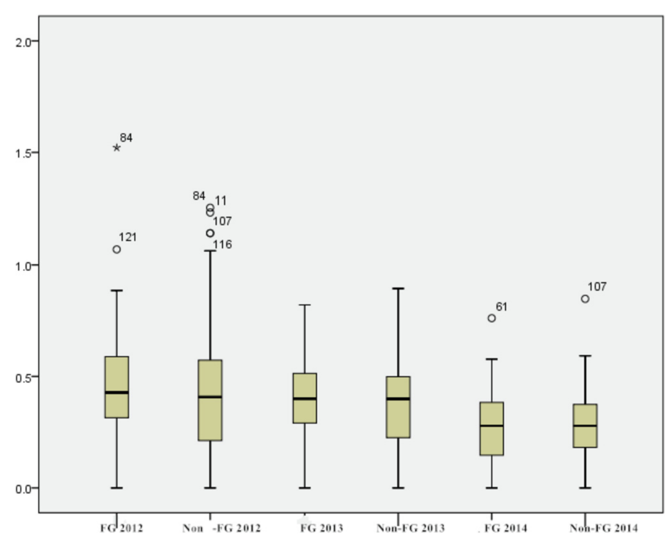

Fig. 11. The value distribution of β in the different groups from 2012 to 2014.

Table 9
Results of the nonparametric tests.

	K-S Test	M-W Test
2012	1.330(0.058)	−1.521(0.128)
2013	0.927(0.356)	−0.960(0.337)
2014	0.918(0.368)	−0.746(0.456)

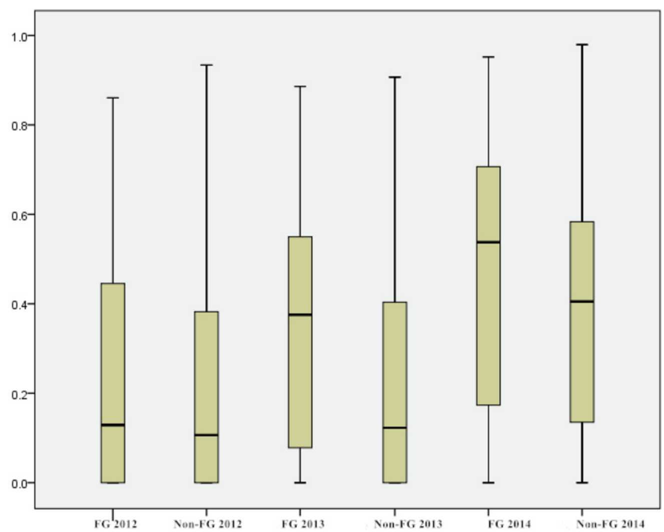

Fig. 12. The value distribution of β_1 in the different groups from 2012 to 2014.

Table 10
Mean and std. dev of β_2 in the different groups.

	Five groups	Non-five groups
2012	0.113(0.017)	0.083(0.016)
2013	0.286(0.028)	0.374(0.029)
2014	0.042(0.010)	0.084(0.016)

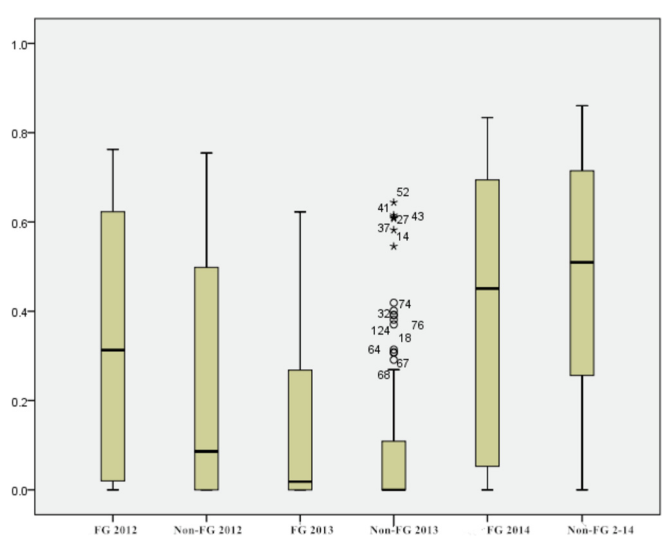

Fig. 13. The value distribution of β_3 in the different groups from 2012 to 2014.

Based on the results, the plants in the FGs outperformed in asset utilization, while the non-FGs had dominance in labor force usage and energy savings.

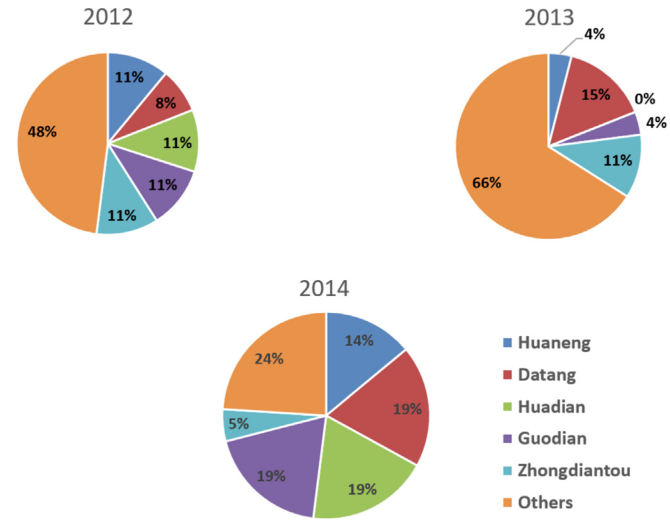

Fig. 14. The constitution of the different groups for the best performing (β=0) plants.

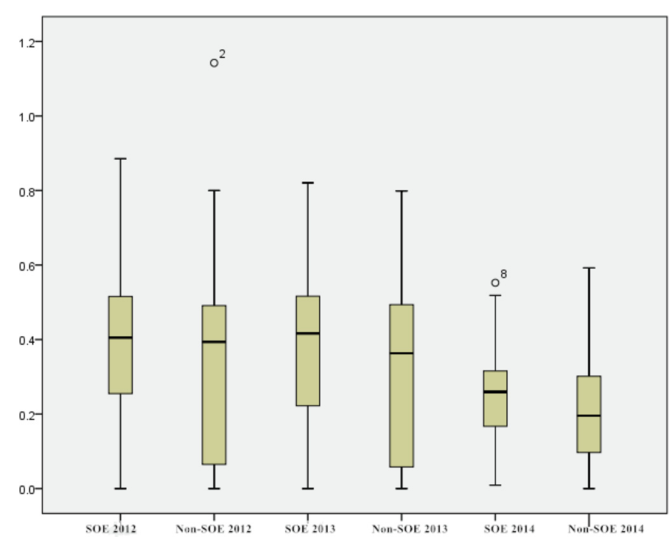

Fig. 15. The value distribution of β in the SOEs and the non-SOEs from 2012 to 2014.

Table 11
Results of the nonparametric tests.

	K-S Test	M-W Test
2012	1.355(0.050)	−2.248(0.025)
2013	1.749(0.004)	−2.736(0.006)
2014	1.684(0.007)	−2.910(0.004)

4.3.2.2. State-owned and nonstate-owned enterprises. We then discussed the correlation between efficiency and the state-owned enterprises (SOEs)/non-SOEs. Fig. 15 and Table 11 show the distribution of β and the results of the nonparametric tests.

Under the 5% confidence level, the H_0 hypothesis was rejected, and the β of the SOEs was higher than that of the non-SOEs. Based on this, we compared the inefficiency of each specific input and output as we did before. Figs. 16 and 17 show the results.

We sorted the plants with full efficiency and determined their ownership, as shown in Fig. 18. It is interesting to find that on average, the SOEs had worse performance than the non-SOEs (see Fig. 16), but more than 70% of the globally efficient plants also

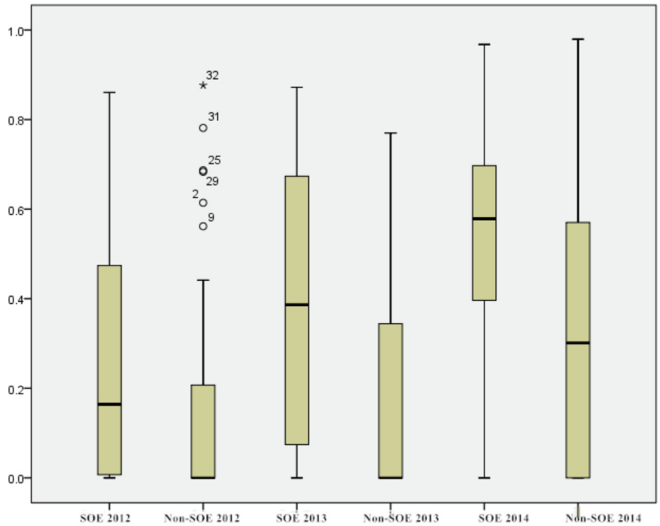

Fig. 16. The value distribution of β_1 in the SOEs and the non-SOEs from 2012 to 2014.

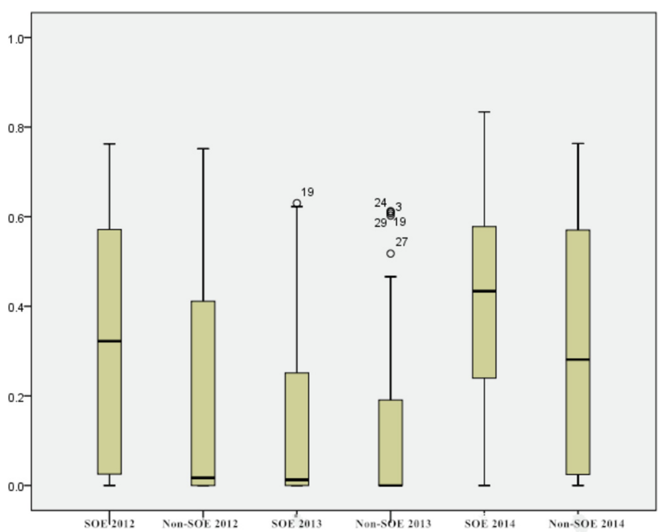

Fig. 17. The value distribution of β_3 in the SOEs and the non-SOEs from 2012 to 2014.

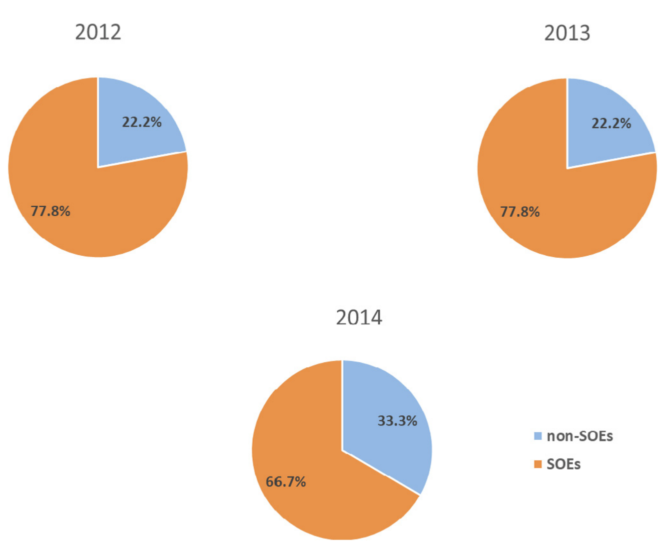

Fig. 18. The distribution of the SOEs/non-SOEs for the best performing (β=0) plants.

belonged to the SOEs. This implies the great diversity in the efficiency of the SOEs.

Based on this finding, the labor inefficiency of the SOEs is considerably higher than that of the non-SOEs, which implies that the SOEs have a severe workforce surplus. The energy saving potential, β_3, shows a similar pattern as β_1. For capital utilization, there is no significant difference between the two groups.

5. Conclusions

This paper has offered a general view of the overall efficiency of thermal power plants and shed light on the factor-specific potential for improvement. We found that East China outperformed the other regions because of its thriving economy and advanced technologies. For Southwest and Northeast China, the low efficiency resulted from the dominance of hydropower and small, poorly managed plants, respectively. This could be a reference for relevant policymaking. The provinces with poor performance can learn advanced technology and management systems from the better-performing provinces or they can cooperate if those plants specialize in different parts and learn the expertise of another. This could help take full advantage of the driving force of efficient power plants and reduce the excessive use of fossil energy.

In the efficiency comparison among the years, we found that in 2014, the overall efficiency was higher than that in the last two years, but the efficiency of labor and energy consumption were worse. Considering that the efficiency measured in this paper was relative to the other plants in the sample, the efficiency difference among the years could be explained by the different paces of management promotion or the popularization of new technologies generated in the different plants.

We also obtained interesting findings when studying the determinants of overall efficiency for the individual plants. Generally, the large plants performed better than the small plants. In China, small thermal power plants have often been established to balance the uneven distribution of thermal energy. In this case, the small plants were expected to aid in recognizing which factor contributes most to inefficiency and improve it accordingly with the reference of this model. If they have high efficiency in labor and asset utilization but poor efficiency in energy consumption, efforts should be made in technical transformation. If possible, shutting some of the inefficient plants down and establishing new plants with much higher installed capacity could also be an effective alternative in terms of emission abatement.

The plants in five groups (FGs) were thought to be more efficient than their counterparts for their dominance in power generation and technology investment. However, according to our study, there was not much difference between the FGs and the non-FGs in terms of overall efficiency. Although the plants in the FGs had high efficiency in asset utilization and invested more in technologies, they had poor performance in labor management, which weighed down the overall efficiency. This pattern could also be applied to the SOEs and the non-SOEs.

There are still some drawbacks in this research. The inefficiency we obtained from the DEA model is a relative concept, which is highly influenced by the sample selection and extreme values, therefore, the results may be somehow affected, especially when some efficient plants are missing. Furthermore, due to data limitations, we abandoned plants with incomplete data, which resulted in a small sample capacity and distortions. In this case, some slight deviation may exist in our analysis.

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