Energy Policy 70 (2014) 193–200

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

The effect of size-control policy on unified energy and carbon efficiency for Chinese fossil fuel power plants

Ning Zhang [a,*], Fanbin Kong [a], Yongrok Choi [b,**], P. Zhou [c,1]

[a] Institute of Poyang Lake Eco-economics, Jiangxi University of Finance and Economics, Nanchang 330013, China
[b] Department of International Trade, Inha University, 253 Yonghyun-dong, Nam-gu, Incheon 402-751, Republic of Korea
[c] College of Economics and Management & Research Centre for Soft Energy Science, Nanjing University of Aeronautics and Astronautics, 29 Yudao Street, Nanjing 210016, China

HIGHLIGHTS

- Two non-radial directional distance functions are presented for energy/carbon efficiency analysis.
- An empirical study of 252 fossil fuel power plants in China is conducted.
- The five state-owned companies show lower unified efficiency and energy–environmental performance.

ARTICLE INFO

Article history:
Received 24 January 2014
Received in revised form
1 March 2014
Accepted 21 March 2014
Available online 13 April 2014

Keywords:
Chinese power plants
Non-radial directional distance function
Energy and carbon efficiency

ABSTRACT

This paper examines the effect of size control policy on the energy and carbon efficiency for Chinese fossil fuel power industry. For this purpose, we propose two non-radial directional distance functions for energy/carbon efficiency analysis of fossil fuel electricity generation. One is named a total-factor directional distance function that incorporates the inefficiency of all input and output factors to measure the unified (operational and environmental) efficiency of fossil fuel power plants, and the other is called an energy–environmental directional distance function that can be used to measure the energy–environmental performance of fossil fuel electric power plants. Several standardized indicators for measuring unified efficiency and energy–environmental performance are derived from the two directional distance functions. An empirical study of 252 fossil fuel power plants in China is conducted by using the proposed approach. Our empirical results show that there exists a significant positive relationship between the plant size and unified efficiency, the five state-owned companies show lower unified efficiency and energy–environmental performance than other companies. It is suggested that Chinese government might need to consider private incentives and deregulation for its state-owned enterprises to improve their performance proactively.

1. Introduction

Fossil fuel electricity generation accounts for more than 40% of global CO_2 emissions and thus is a core issue in environmental management and sustainable development International Energy Agency (IEA) (2011). In China, fossil fuel electricity generation accounted for about 50% of coal consumption and 48% of CO_2 emissions from fossil fuel combustion in 2010 (Liu and Wang, 2011). Clearly, this sector plays an important role in reducing China's total CO_2 emissions. In this regard, it is crucial for fossil fuel power plants in China to improve their energy and operational efficiency to reduce CO_2 emissions. By taking a proactive approach to improving energy efficiency, power generation companies cannot only reduce CO_2 regulation risks but also improve their economic competitiveness through decreasing their costs.

During the 11th five-year plan (2006–2010), China's fossil fuel power industry was under substantial pressure to reduce its emissions to meet emission reduction targets. The Chinese government introduced a selective concentration policy to meet these targets. The country's “promoting large and closing small” policy implies the closure of small fossil fuel power plants by 2010 and

* Corresponding author.
** Joint corresponding author. Tel.: +82 32 860 7760; fax: +82 32 876 9328.
E-mail addresses: zn928@naver.com (N. Zhang), kongfanbin@aliyun.com (F. Kong), yrchoi@inha.ac.kr (Y. Choi), cemzp@nuaa.edu.cn (P. Zhou).
[1] Tel.: +86 25 8489 3751; fax: +86 25 8489 2751.

http://dx.doi.org/10.1016/j.enpol.2014.03.031
0301-4215/

the total loss of 76,830 MW (10.8% of the total capacity). This selective concentration policy during the 11th five-year period was very effective in that, with 2005 as the base year, the fossil fuel power sector reduced its CO_2 emissions by 1.74 billion tons (China Electricity Council, 2011). The aim of this study is to investigate the effect of the carbon reduction policy on the energy and carbon efficiency for Chinese fossil fuel power industry.

Several studies have conducted simple benchmark analyses to estimate the emission reduction potential of global electricity generation (Maruyama and Eckelman, 2009; Ang et al., 2011). This approach assumes that the efficiency of fossil fuel electricity generation for any country is greater than or equal to a certain level established by sample countries or regions. Despite the usefulness of findings based on this approach, it typically considers only one indicator and thus may be considered a single-factor analysis. However, electricity generation is a multi-factor production process in which energy as well as non-energy inputs such as labor and capital are employed to produce electricity. As discussed in Sueyoshi and Goto (2011), measuring the unified efficiency of electricity generation within a total-factor production framework can provide better insights into power managers' decision making.

Many studies have benchmarked energy and environmental performance from a production efficiency point of view (Zhou et al., 2008a). Along this line of research, data envelopment analysis (DEA) technique has gained popularity in assessing energy and environmental performance (Song et al., 2012). See, for example, Zhou et al. (2006, 2010); Picazo-Tadeo et al. (2011) and Wang et al. (2013a). In the case of electric power industry, a number of studies have employed DEA to analyze the efficiency of fossil fuel electricity generation (e.g., Barros and Peypoch, 2008; Liu et al., 2010; Yang and Pollitt, 2010; Sozen et al., 2010; Sueyoshi et al., 2010; Jaraite and Maria, 2012; Sueyoshi and Goto, 2011, 2012a, 2012b; Zhou et al., 2012, 2013; Bi et al., 2014). However, few have focused on the use of the directional distance function (DDF) for efficiency measurement of electric power industry. In comparison to traditional DEA models, DDF measures efficiency by increasing desirable outputs (e.g., electricity) and reducing undesirable ones (e.g., CO_2 emissions) simultaneously. At power plant level, Färe et al. (2007) employ the DDF to measure the environmental efficiency of coal-fired plants in the US. Zhang et al. (2013) develop a metafrontier DDF for measuring energy and carbon emission efficiency of Korean fossil-fuel power plants. Zhang and Choi (2014) proposes a comprehensive literature review on DDF in energy and environmental studies.

The conventional DDF reduces undesirable outputs (inputs) and increases desirable outputs at the same rate and may be regarded as a radial efficiency measure with several limitations. One limitation is that a radial measure may overestimate efficiency when there exist some slacks (Fukuyama and Weber, 2009). In addition, as Sueyoshi and Goto (2011) argued, a radial efficiency measure cannot distinguish between environmental performance and operational performance for power plants. Several studies have extended the conventional DDF to the non-radial DDF (NDDF) by incorporating slacks into efficiency measurement (Fukuyama and Weber, 2009; Färe and Grosskopf, 2010; Barros et al., 2012). More recently, Zhou et al. (2012) define a NDDF with desirable mathematical properties by taking an axiomatic approach to efficiency measurement. Wang et al. (2013c) use the NDDF to measure the Scenario-based energy efficiency and productivity.

The present paper proposes two NDDFs based on Zhou et al. (2012) to measure the unified efficiency (operational and environmental efficiency) and energy–environmental performance of fossil fuel power plants in China. Unlike Zhou et al. (2012), however, the paper considers not only energy inputs but also non-energy ones (capital and labor) because it focuses on benchmarking unified performance within a total-factor production framework. Another contribution is that this paper employs plant-level data, whereas country-level data are used by Zhou et al. (2012). To measure unified efficiency, we propose a total-factor NDDF (TNDDF) that incorporates inefficiencies for all the input and output factors. To measure energy–environmental performance, we introduce an energy–environmental NDDF (ENDDF) by fixing non-energy inputs. To the best of our knowledge, this paper is the first to empirically measure the unified efficiency of fossil fuel power plants in China. Some studies analyzed other environmental characteristics of Chinese fossil fuel power plants such as productivity growth (Zhang and Choi, 2013a) and shadow price of CO_2 emissions (Wei et al., 2013).

The rest of this paper is organized as follows: Section 2 describes the material and methods. Section 3 empirically estimates the unified efficiency and energy–environmental performance of fossil fuel power plants in China and presents the results, Section 4 presents the related discussions, and Section 5 concludes and proposes some policy suggestions.

2. Material and methods

2.1. Methods

Suppose that there are N fossil fuel power plants and that each plant uses capital (K), labor (L), and fossil fuel (F) as inputs to generate electricity (E), the desirable output, and CO_2 emissions (C), the undesirable output. The multi-output production technology can be described as follows:

$$T = \{(K, L, F, E, C) : (K, L, F) \text{ can produce } (E, C)\}, \tag{1}$$

where T is often assumed to satisfy the standard axioms of production theory (Färe and Grosskopf, 2005). For instance, inactivity is always possible, and finite amounts of inputs can only produce finite amounts of outputs. In addition, inputs and desirable output are often assumed to be strongly or freely disposable. For a reasonable modeling of joint-production technology, as described in Färe et al. (1989), the weak-disposability and null-jointness assumptions should be imposed on T. Technically, these two assumptions can be expressed as follows:

(i) If $(K, L, F, E, C) \in T$ and $0 \le \theta \le 1$, then $(K, L, F, \theta E, \theta C) \in T$,
(ii) If $(K, L, F, E, C) \in T$ and $C = 0$, then $E = 0$.

The weak-disposability assumption indicates that reducing CO_2 emissions is costly in terms of a proportional reduction in electricity generation, and the null-jointness assumption implies that CO_2 emissions are unavoidable in fossil fuel electricity generation and that the only way to remove all CO_2 emissions is to stop operating electric power plants.

Once the environmental production technology T is specified, the parametric translog/quadratic function or the nonparametric DEA method can be used to specify the environmental production technology. Based on Färe et al. (2007) and Zhou et al. (2012), the environmental production technology T for N power plants exhibiting constant returns to scale can be expressed as follows[2]:

$$T = \left\{ \begin{array}{l} (K, L, F, E, C) : \sum_{n=1}^{N} z_n K_n \le K, \ \sum_{n=1}^{N} z_n L_n \le L, \\ \sum_{n=1}^{N} z_n F_n \le F, \ \sum_{n=1}^{N} z_n E_n \ge E, \ \sum_{n=1}^{N} z_n C_n = C, z_n \ge 0, n = 1, 2, \ldots, N \end{array} \right\} \tag{2}$$

[2] The environmental technology is based on the assumption that exhibiting constant returns to scale. Although the assumption is widely adopted in literature, other cases like variable returns to scale could occur in real cases. Zhou et al. (2008b) discussed the characterization of environmental production exhibiting variable returns to scale.

Chung et al. (1997) are the first to use the DDF, introduced by Chambers et al. (1996), to examine environmental efficiency. The DDF is a relatively new methodology for performance measurement. Here, the traditional DDF is defined such that it seeks to maximize desirable outputs while reducing undesirable ones simultaneously:

$$\vec{D}(K, L, F, E, C; g) = \sup\{\boldsymbol{\beta} : ((K, L, F, E, C) + g \times \boldsymbol{\beta})) \in T\} \tag{3}$$

The conventional DDF is a measure of radial efficiency (inefficiency) that may overestimate efficiency when there exist slacks (Fukuyama and Weber, 2009). Fig. 1 visually explains why the radial DDF overestimates efficiency. The OABCDE area is assumed to be an output set corresponding to the environmental production technology defined in Eq. (2). For the point K located near the left side of the frontier, if the direction g is taken and the traditional radial DDF is used, then the point F is the benchmark point for evaluating K. However, if the non-radial DDF is used, then the benchmarking point is B because it produces a smaller quantity of undesirable outputs while generating the same quantity of desirable ones as F. Therefore, the distance BF is the slack in the radial DDF and is referred to as “slack-bias” (Fukuyama and Weber, 2010). Because the radial DDF does not take this sort of slacks into account, it has the potential to reduce inefficiencies and thus may overestimate the efficiency score.

Another limitation of the radial DDF derives from the fact that the radial DDF cannot distinguish between environmental and operational performance because radial DDF can only give the same rate of inefficiency (Sueyoshi and Goto, 2011). It is difficult to obtain integrated unified efficiency by using the radial DDF. Non-radial efficiency measures are often advocated to overcome this limitation in the measurement of energy and environmental performance because of their advantages (Zhou et al., 2007; Chang and Hu, 2010; Choi et al., 2012; Zhang and Choi., 2013b). Recently, Zhou et al. (2012) provide a formal definition of the non-radial DDF with undesirable outputs. Following Zhou et al. (2012), we define the non-radial DDF as follows:

$$\vec{D}(K, L, F, E, C; g) = \sup\{\mathbf{w}^T\boldsymbol{\beta} : ((K, L, F, E, C) + g \times diag(\boldsymbol{\beta})) \in T\} \tag{4}$$

where $\mathbf{w}^T = (w_K, w_L, w_F, w_E, w_C)^T$ denotes the normalized weight vector relevant to the numbers of inputs and outputs; $g = (-g_K, -g_L, -g_F, g_E, -g_C)$ is the explicit directional vector; and $\beta = (\beta_K, \beta_L, \beta_F, \beta_E, \beta_C)^T \geq 0$ denotes a vector of scaling factors representing individual inefficiency measures for each input/output. The symbol *diag* refers to diagonal matrices. Zhou et al. (2012) incorporate only fossil fuel inputs because they focus on measuring energy efficiency. Unlike Zhou et al. (2012), this paper also considers non-energy inputs because its objective is to benchmark

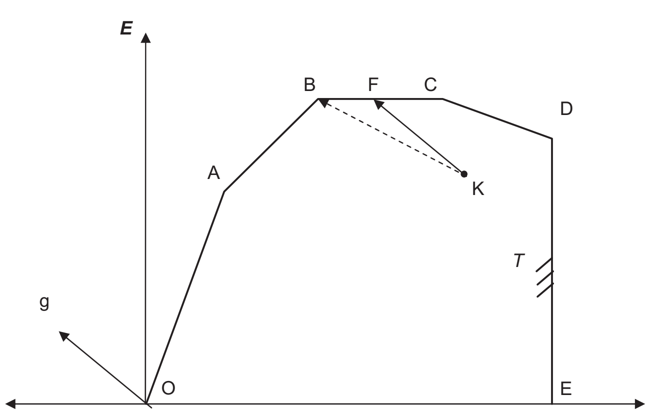

Fig. 1. Illustration of radial and non-radial directional distance functions.

unified efficiency within a total factor production framework. If we incorporate all inefficiencies for inputs and desirable and undesirable outputs into the objective function and constraints, we can define the measure as a total-factor non-radial distance function (TNDDF) because the DDF captures inefficiencies for all factors.

The TNDDF value, denoted as $\vec{D}_T(K, L, F, E, C; g)$, can be computed by solving the following DEA-type model[3]

$$\begin{aligned} \vec{D}_T(K, L, F, E, C; g) = {} & \max\ w_K\beta_K + w_L\beta_L + w_F\beta_F + w_E\beta_E + w_C\beta_C \\ \text{s.t.}\ & \sum_{n=1}^{N} z_n K_n \leq K - \beta_K g_K \\ & \sum_{n=1}^{N} z_n L_n \leq L - \beta_L g_L \\ & \sum_{n=1}^{N} z_n F_n \leq F - \beta_F g_F \\ & \sum_{n=1}^{N} z_n E_n \geq E + \beta_E g_E \\ & \sum_{n=1}^{N} z_n C_n = C - \beta_C g_C \\ & z_n \geq 0, n = 1, 2, \ldots, N \\ & \beta_K, \beta_L, \beta_F, \beta_E, \beta_C \geq 0 \end{aligned} \tag{5}$$

We may set the directional vector g in different ways based on different policy goals. If $\vec{D}_T(K, L, F, E, C; g) = 0$, then the power plant to be evaluated is located along the best-practice frontier in the g direction.

We can then develop an indicator to measure unified performance in the context of electricity generation. Because there are three inputs, one desirable output, and one undesirable output, we set the weight vector as (1/9, 1/9, 1/9, 1/3, 1/3)[4] and the directional vectors as $g = (-K, -L, -F, E, -C)$ based on Zhou et al. (2012) and Barros et al. (2012).[5]

Zhou et al. (2012) define the energy performance index as the ratio of actual energy efficiency to potential target energy efficiency and the carbon performance index as the ratio of potential carbon intensity to actual carbon intensity. Sueyoshi and Goto (2011) define unified efficiency as the average of all individual inefficiencies by subtracting each factor from unity. Following these two studies, we define the unified efficiency index (UEI) for a fossil fuel plant as the average efficiency of each factor. Suppose that $\beta_K^*, \beta_L^*, \beta_F^*, \beta_E^*$, and β_C^* represent the optimal solution to Eq. (5). Then the UEI can be formulated as follows:

$$\begin{aligned} UEI &= \frac{1/4[(1-\beta_K^*) + (1-\beta_L^*) + (1-\beta_F^*) + (1-\beta_C^*)]}{1+\beta_E^*} \\ &= \frac{1 - 1/4(\beta_K^* + \beta_L^* + \beta_F^* + \beta_C^*)}{1+\beta_E^*} \end{aligned} \tag{6}$$

Then, for measuring the pure environmental performance of fossil fuel power plants, it is better to fix non-energy inputs because fossil fuel is a key factor in emissions, whereas capital and labor do not contribute to emissions directly. Following Zhang and Choi (2013c), by setting the directional vector as $g = (0, 0, -g_F, g_E, -g_C)$ and the weight vector as (0, 0, 1/3, 1/3, 1/

[3] The DDF is based on the weak-disposability for modeling undesirable outputs. Recently, there are some relative new methodology for modeling environmental technology such as pollution-generating technologies (Murty et al., 2012) or nutrients balance approach (Hoang and Nguyen, 2013). We thank one referee for this comment.

[4] The arithmetic average of variable numbers is used as the weight, alternatively, the range-adjusted measure (RAM) approach could also be used for deciding the weight (Sueyoshi and Goto, 2011). We are grateful to this comment of one referee.

[5] The directional vectors are settled as the observations, recently, endogenous model of directional vector can be used as an alternative method (Asmild and Matthews, 2012) and has been used in energy and carbon efficiency analysis (Wang et al.,2013b). We thank one reviewer for pointing out this issue.

3), we remove the diluting effects of capital and labor from the objective function and constraints. We define this non-radial distance function as the energy–environmental non-radial DDF (ENDDF). The ENDDF value, denoted as $\vec{D}_E(K, L, F, E, C; g)$, can be calculated by solving the following linear programming model[6]

$$\begin{aligned}
\vec{D}_E(K, L, F, E, C; g) = \ & \max w_F\beta_F + w_E\beta_E + w_C\beta_C \\
\text{s.t. } & \sum_{n=1}^{N} z_n K_n \le K \\
& \sum_{n=1}^{N} z_n L_n \le L \\
& \sum_{n=1}^{N} z_n F_n \le F - \beta_F g_F \\
& \sum_{n=1}^{N} z_n E_n \ge E + \beta_E g_E \\
& \sum_{n=1}^{N} z_n C_n = C - \beta_C g_C \\
& z_n \ge 0, n = 1, 2, \cdots, N \\
& \beta_F, \beta_E, \beta_C \ge 0
\end{aligned} \tag{7}$$

Once Eq. (7) is solved, we can obtain the optimal solutions β_F^*, β_E^*, and β_C^*, and by following Zhou et al. (2012), we can express the energy–environmental performance index (EEPI) as:

$$\text{EEPI} = \frac{1/2[(1-\beta_F^*) + (1-\beta_C^*)]}{1+\beta_E^*} = \frac{1 - 1/2(\beta_F^* + \beta_C^*)}{1+\beta_E^*} \tag{8}$$

Clearly, the UEI and the EEPI both lie between zero and unity. The higher the UEI (EEPI), the better the unified (energy–environmental) performance. If the UEI (EEPI) is equal to unity, then the observation reflects the best unified (energy–environmental) efficiency located along the electricity generation technology frontier. In this study, although only carbon emission is considered in EEPI, obviously, other types of emissions (SO_x and NO_x) in thermal power plants can be incorporated into EEPI easily.

2.2. Data

The methodology described in Section 2 has been employed to analyze the unified efficiency and environmental performance of fossil fuel power plants in China. The sample consists of 252 large fossil fuel power plants with installed capacity exceeding 1000 MW. As shown in Table 1, about half of the power plants belong to five main state-owned companies referred to as “five big groups”: DATANG, GUODIAN, HUANENG, HUADIAN, and POWER INVESTMENT. Local companies also account for a large percentage of power plants (38.8%). In addition to these “five big groups” and local companies, China Resources (CR) Power, GUOHUA, and SDIC are also large power companies in China. These three companies, together with another company (Guangdong nuclear) are referred to as “four royal families.” Because the five main state-owned companies are major suppliers of electricity, it is meaningful to compare the unified efficiency of these companies with private and local companies.

We measure the electricity output (E) of each power plant by the gross amount of electricity generated and the capital input (K) and the fossil fuel input (F) by the installed generating capacity and fuel consumption, respectively, in standard coal equivalent. The labor input (L) is measured by the number of employees in each power plant. The data on input and output variables are

[6] Recently, managerial disposability in DEA environmental assessment proposed by Sueyoshi and Goto (2012c) has been employed for measuring energy and environmental efficiency in developed countries using the theory of Porter hypothesis. However, this approach is not suitable for China which is still a developing country. We thank one referee for suggesting us this issue.

Table 1
Classification of fossil fuel plants of electric power companies.

No	Electric power companies	No of plants	(%)
1	China DATANG Corporation	34	13.1
2	China GUODIAN Corporation	37	14.2
3	China HUANENG Group	36	13.8
4	China HUADIAN Corporation	25	9.6
5	China POWER INVESTMENT Corporation	7	2.7
6	China Resources Power Holdings Company	7	2.7
7	SHENHUA GUOHUA power	10	3.8
8	SDIC Power Holdings	3	1.2
9	Local Power Companies	93	38.8

Table 2
Descriptive statistics for variables (N=252).

Variable	Unit	Mean	Standard deviation	Maximum	Minimum
E	10^3 GW h	7.84	3.59	26.6	0.51
C	10^6 t	8.27	3.73	27.99	5.26
K	MW	1554.90	608.80	4800	1000
L	Persons	654	264	2016	201
F	10^6 t	24.39	10.89	84.59	1.53

respectively collected from the *China Electric Power Yearbook* 2011, *the Chinese Industrial Enterprises Database* 2011 and the *Compilation of statistics on Electric Power Industry* 2011. We also obtain some missing data by visiting the power company's website or contacting China electricity council and the company directly through survey. Finally, for plants not reporting the employees, we follow the methods of Zhao and Ma (2013) to estimate the employee numbers. According to Yang and Pollitt (2010) and Wei et al. (2013), CO_2 emissions of fossil fuel power plants can be estimated using the IPCC carbon emission factors by fuel types. Table 2 shows the descriptive statistics for inputs and output variables. The total installed capacity of sample plants reaches 404,274 MW, accounting for about 57.2% of China's total installed fossil fuel capacity in 2010. The total amount of CO_2 emissions by sample plants are 2150.2 million tons. According to BP (2011), China CO_2 emissions in 2010 are 8332.5 million tons. It implies that the 252 fossil fuel power plants accounted for over a quarter of China's total CO_2 emissions.

3. Results

The fossil fuel power industry in China was under large pressure to reduce the emissions. Chinese government introduces the size control policy named “promoting large and closing small” policy to close the small fossil fuel power plants in order to improve the overall generation efficiency. Based on such a policy, which seeks the “economies of scale” even in terms of the environmental efficiency of China's fossil fuel generation, we propose the following hypothesis:

H_0. The larger the power plant, the better the unified efficiency and environmental performance of the plant in the context of China's fossil fuel generation.

Table 3 shows the summary information of the unified efficiency index (UEI) and the energy–environmental performance index (EEPI) for the nine companies and all the power plants. The UEI for all power plants ranges from 0.268 to 1 (average = 0.713). This implies that, on average, the 252 power plants together can achieve a 28.7% increase in their unified efficiency if they all operate along the production technology frontier. The average EEPI is 0.913, which is higher than the average UEI, indicating that the

Table 3
Unified efficiency and energy/environmental performance of firms.

Company	UEI				EEPI			
	Mean	Std. Dev	Minimum	Maximum	Mean	Std. Dev	Minimum	Maximum
DATANG	0.711	0.089	0.431	0.921	0.915	0.080	0.614	0.995
GUODIAN	0.725	0.093	0.371	0.874	0.922	0.086	0.542	0.995
HUANENG	0.699	0.116	0.268	0.943	0.899	0.124	0.360	0.997
HUADIAN	0.703	0.063	0.591	0.840	0.911	0.065	0.748	0.990
POWER INVEST	0.610	0.167	0.364	0.792	0.810	0.185	0.535	0.994
CR Power	0.762	0.097	0.556	0.837	0.958	0.086	0.763	0.996
GUOHUA	0.752	0.151	0.360	0.944	0.923	0.142	0.525	0.998
SDIC Power	0.721	0.010	0.713	0.733	0.954	0.009	0.945	0.963
Local Power Companies	0.735	0.109	0.367	1.000	0.923	0.088	0.538	1.000
Total Plants	0.713	0.099	0.268	1.000	0.913	0.096	0.360	1.000

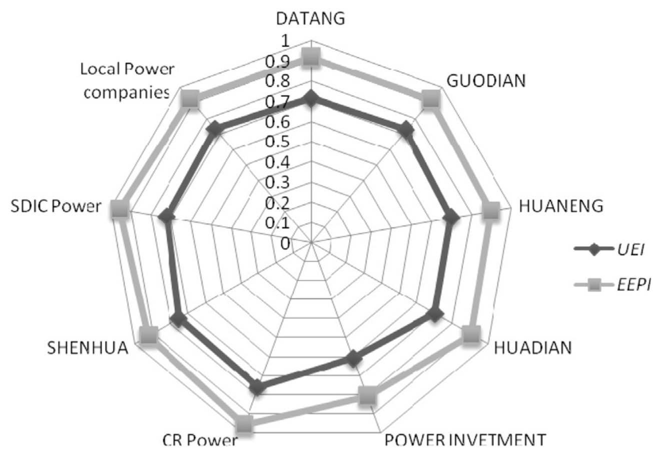

Fig. 2. Comparison of the UEI and the EEPI for companies.

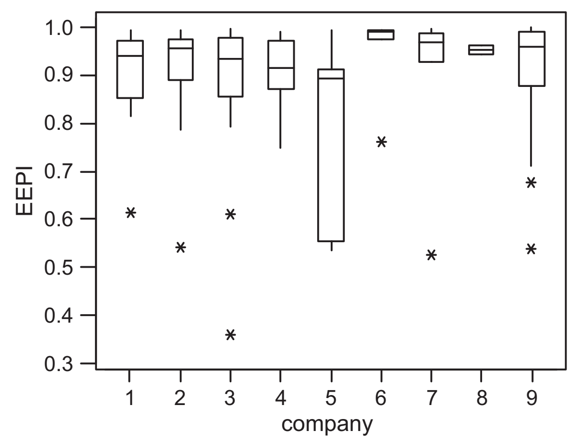

Fig. 4. Boxplots of the EEPI for different companies.

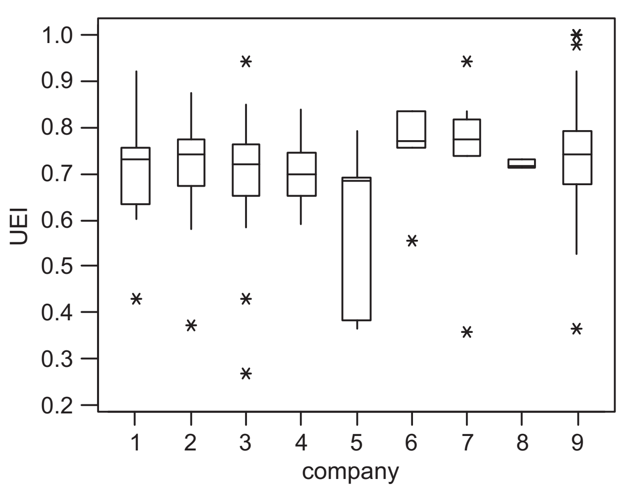

Fig. 3. Boxplots of the UEI for different companies.

power plants show better performance in EEPI than UEI. For individual power plants, the local companies Baosteel and Waigaoqiao2 (in Shanghai) show the highest UEI and EEPI values (unity). Ligang (Jiangsu) and Taizhou (Zhejiang) also show the highest UEI and EEPI values. This reflects the fact that economically developed regions such as Shanghai and Zhejiang are more likely to show greater efficiency even in terms of environmental performance (Choi et al., 2012).

Table 4
Kruskal–Wallis test of companies.

Index	Null hypothesis (H_0)	KW Statistics	*p*-Value
UEI	$Mean(UEI_1)=Mean(UEI_2)=\ldots Mean(UEI_9)$	15.703	0.047
EEPI	$Mean(EEPI_1)=Mean(EEPI_2)=\ldots Mean(EEPI_9)$	13.87	0.085

Fig. 2 shows the comparative results for the average efficiency score for different companies. At the company level, CR Power shows the highest average UEI and EEPI values (0.762 and 0.958, respectively). POWER INVEST shows the lowest average UEI and EEPI values (0.61 and 0.81, respectively).

4. Discussion

The above results may be due to the fact that private companies such as CR Power (in Hong Kong) are more motivated to improve management performance in terms of the UEI and the EEPI than state-owned companies such as POWER INVEST.

Figs. 3 and 4 show the boxplots of the UEI and EEPI for different companies, based on which we can compare the standard deviations of the UEI and the EEPI between different companies. SDIC Power shows the lowest standard deviations for both the UEI and the EEPI, indicating that its power plants operate under relatively similar technology conditions. On the other hand, the power plants of POWER INVEST show the highest standard deviations, suggesting a relatively large performance gap between this company's individual power plants. State-owned companies such as POWER INVEST have the missing link in their innovation networks and thus require much more effort to enable their individual power plants to share technological experiences.

The average UEI and EEPI values for "five big groups" are 0.705 and 0.907, respectively, whereas those for other companies are 0.737 and 0.926, respectively. This indicates that these five state-owned companies show lower unified efficiency and environmental performance than other companies. Therefore, state-owned companies need to be provided with more management incentives as well as R&D investment for better performance-oriented governance.

As shown in Table 4, we employ the Kruskal–Wallis rank-sum test to determine any significant differences in the UEI and the EEPI between different companies. The results reject the null hypothesis at the 10% level, and there are rank differences in the two indices between sample companies. In addition, most of EEPI shows the higher performance compared with UEI. This implies that the Chinese government's efforts to reduce CO_2 emissions has led to an increase in environmental performance and thus plays a leading role in reducing CO_2 emissions from electric power plants.

Since our sample covers most regions in China, a provincial comparison is expected to provide important implications. Table 5 shows the average unified efficiency and energy–environmental performance of power plants by province. In terms of the UEI, Zhejiang shows the highest average value (0.847). In terms of the EEPI, Tianjin shows the highest average value (0.987). On the other hand, Jilin shows the lowest UEI (average=0.593) and EEPI (average=0.805) values. These results imply that the level of economic development may be positively related to the economic and environmental efficiency of power plants. Economic

Table 5
Unified efficiency and environmental performance of power plants by province.

Provinces	No of plants	*UEI*	*EEPI*
Anhui	13	0.744	0.978
Fujian	7	0.640	0.831
Gansu	3	0.635	0.853
Guangdong	20	0.732	0.928
Guangxi	4	0.750	0.979
Guizhou	8	0.721	0.912
Hainan	1	0.740	0.941
Hebei	14	0.757	0.961
Henan	17	0.701	0.911
Heilongjiang	5	0.620	0.831
Hubei	9	0.647	0.868
Hunan	8	0.654	0.871
Jilin	5	0.593	0.805
Jiangsu	22	0.769	0.959
Jiangxi	6	0.666	0.891
Liaoning	9	0.702	0.911
Inner Mongolia	16	0.666	0.873
Ningxia	4	0.765	0.939
Shandong	15	0.743	0.949
Shanxi	17	0.745	0.956
Shaanxi	10	0.689	0.906
Shanghai	10	0.726	0.864
Sichuan	3	0.683	0.882
Tianjin	5	0.765	**0.987**
Xinjiang	1	0.677	0.887
Yunan	5	0.680	0.902
Zhejiang	14	**0.847**	0.885
Chongqing	1	0.670	0.856

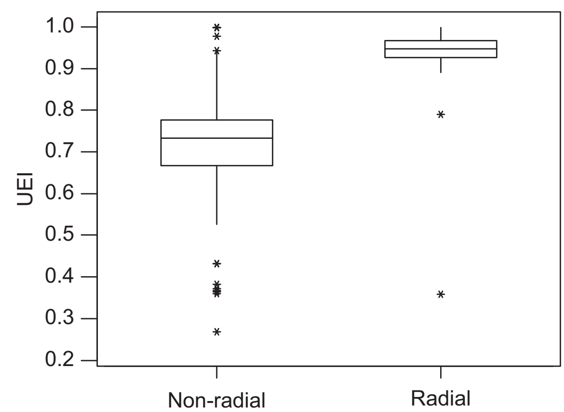

Fig. 6. Boxplots of the UEI for non-radial and radial measures.

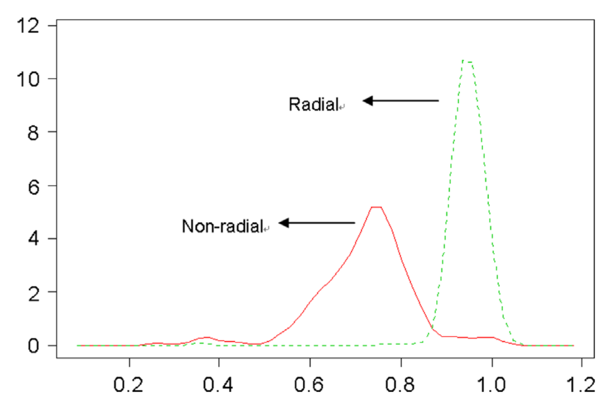

Fig. 7. Kernel density plots of non-radial and radial efficiency measures.

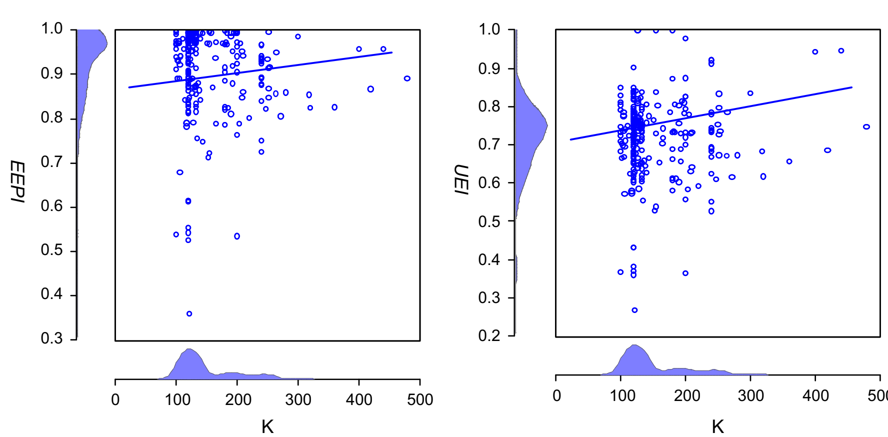

Fig. 5. Relationship between the performance index and the power plant scale.

Table 6
Results of the Kolmogorov–Smirnov test.

Test	Null hypothesis (H_0)	Statistics	*p*-Value
Mann–Whitney	Mean (*Radial UEI*)=Mean (*Non-radial UEI*)	1806	0.00
Kolmogorov–Smirnov	Distrubiton (*Radial UEI*)=Distrubiton (*Non-radial UEI*)	10.83	0.00

development enhances infrastructure and puts greater pressure on environmental issues, and therefore power plants in these provinces should make more effort to meet these conditions.

We further investigate the relationship between the size of power plants and unified efficiency (energy–environmental performance). Fig. 5 graphically displays the relationship, which indicates that the size of plants measured by the installed capacity is positively related to unified efficiency (energy–environmental performance). The Tobit and bootstrap truncated regression are further constructed to test the relationship. The results indicate a significant positive relationship between the installed capacity and unified efficiency (energy–environmental performance) with other control variables, providing support for our hypothesis about the relationship between the size and the performance of power plants.[7] The empirical results suggest that the size-control policy had significant effect on the efficiency of fossil fuel power plants in China.

We also examine the difference between unified efficiency based on the radial DDF and non-radial unified efficiency and find that the latter exceeds the former (see Fig. 6). This indicates that, with slack not considered, the conventional radial DDF overestimates real efficiency. The difference between radial efficiency and non-radial efficiency is referred to as slack-bias (Fukuyama and Weber, 2010).

The kernel density plot (Fig. 7) indicates some differences in the pattern of distributions between the two indices. We employ the Wilcoxon–Mann–Whitney rank-sum test to determine any significant differences between these two indices. As shown in Table 6, the results reject the null hypothesis at the 0.1% level, indicating a significant rank difference.

5. Conclusion and policy implications

Many studies have taken the DEA approach to measure the environmental efficiency of fossil fuel power plants, but few have employed the DDF for this sector. To overcome the limitations of the convention DDF, this paper develops two non-radial DDFs to measure the performance of fossil fuel electricity generation. Based on the TNDDF, we incorporate inefficiencies for all inputs and outputs to measure the unified (operational and environmental) efficiency of fossil fuel power plants. Using the ENDDF, we compute the pure energy–environmental performance of fossil fuel electric power plants.

We conduct an empirical analysis using a sample of 252 fossil fuel power plants in China for the year 2010. The results indicate significant differences in both unified efficiency and environmental performance across power companies as well as provinces. A significant positive relationship between the installed capacity and unified efficiency is confirmed, which suggest that the larger power plants have the better efficiency. The power plants of state-owned companies show lower unified and environmental efficiency than other companies, which suggests that privately motivated innovation plays a more important role in enhancing overall as well as environment performance. We also empirically find a significant difference in unified efficiency between the radial DDF and the non-radial DDF.

Based on the empirical results, we propose some policy implications, first, Chinese government is suggested to focus more on private incentives and deregulation for state-owned companies for the better governance of innovation networks. Second, the size-control policy had a significant effect on the improvement of efficiency for Chinese power companies; therefore, we suggest Chinese government continue to promote the size elective concentration policy to improve the generation efficiency. Finally, for the size-control policy, the government mainly focused on the mandatory shutdown method, we suggest that the government to use more effective market-based tool for size-control such as Merger and Acquisition. To reduce the side effect of mandatory size-control policy, the Chinese government could follow the experience of some developed countries, instead of shut downing the power plant entirely; the local government could stop the operation temporarily when the electricity demand is low while recover the operation of small plants when the electricity is relative high.

This study has inevitably some limitations. First, the empirical analysis is based only on cross-sectional data for year 2010. Although the efficiency of electricity generation is not likely to change in the short term, the empirical study can be extended by conducting a time series analysis. Second, we incorporate only one undesirable output, namely CO_2 emissions, into the empirical analysis. Given data availability, future research should include a wider range of pollutants to assess the energy and environmental performance of China's fossil fuel electricity generation in a more comprehensive way. For the future study, the effect of size-control policy on the productivity growth of fossil fuel power plant should be examined given the panel data is available.

Acknowledgement

We are grateful to the financial support provided by the National Science Foundation of China (No. 71273005), the Program for New Century Excellent Talents in University (No. NCET-10-0073), the major project of the National Social Science Foundation of China (No. 12&ZD213) and the major project of Philosophy and Social Science Foundation of Jiangxi province, China (ZDGG02).

References

Ang, B.W., Zhou, P., Tay, L.P., 2011. Potential for reducing global carbon emissions from electric production—a benchmarking analysis. Energy Policy 39, 2482–2489.
Asmild, M., Matthews, K., 2012. Multi-directional efficiency analysis of efficiency patterns in Chinese banks 1997–2008. Eur. J. Oper. Res. 219, 434–441.
Barros, C.P., Peypoch, N., 2008. Technical efficiency of thermoelectric power plants. Energy Econ. 30, 3118–3127.
Barros, C.P., Managi, S., Matousek, R., 2012. The technical efficiency of the Japanese banks: non-radial directional performance measurement with undesirable outputs. Omega 40, 1–8.
Bi, G., Song, W., Zhou, P., Liang, L., 2014. Does environmental regulation affect energy efficiency in China thermal power generation? Empirical evidence from a slacks-based DEA model. Energy Policy 66, 537–546.
Chambers, R.G., Chung, Y., Färe, R., 1996. Benefit and distance functions. J. Econ. Theory 70, 407–419.

[7] The significant level for installed capacity variable is 1% with labor coefficient and capital coefficient as the control variables following Lee and Zhang (2012).

Chang, T.P., Hu, J.L., 2010. Total-factor energy productivity growth, technical progress, and efficiency change: an empirical study of China. Appl. Energy 87, 3262–3270.
China Electricity Council, 2011. A Study on emission reduction of power industry in China, 2011. China market press, Beijing.
Choi, Y., Zhang, N., Zhou, P., 2012. Efficiency and abatement costs of energy-related CO_2 emissions in China: a slacks-based efficiency measure. Appl. Energy 98, 198–208.
Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: a directional distance function approach. J. Environ. Manage. 51, 229–240.
Färe, R., Grosskopf, S., 2005. New Directions: Efficiency and Productivity. Springer, New York.
Färe, R., Grosskopf, S., Pasurka, C.A., 2007. Environmental production functions and environmental directional distance functions. Energy 32, 1055–1066.
Färe, R., Grosskopf, S., 2010. Directional distance functions and slacks-based measures of efficiency. Eur. J. Oper. Res. 200, 320–322.
Färe, R., Grosskopf, S., Lovell, C.A.K., Pasurka, C., 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. Rev. Econ. Stat. 71, 90–98.
Fukuyama, H., Weber, W.L., 2009. A directional slacks-based measure of technical efficiency. Socio-Econ. Plann. Sci. 43, 274–287.
Fukuyama, H., Weber, W.L., 2010. A slacks-based inefficiency measure for a two-stage system with bad outputs. Omega 38, 389–409.
Hoang, V., Nguyen, T., 2013. Analysis of environmental efficiency variations: a nutrient balance approach. Ecol. Econ. 86, 37–46.
International Energy Agency (IEA), 2011. CO_2 Emissions from Fuel Combustion Highlights, Durban South Africa.
Jaraite, J., Maria, C.D., 2012. Efficiency, productivity and environmental policy: a case study of power generation in the EU. Energy Econ. 34, 1557–1568.
Lee, M., Zhang, N., 2012. Technical efficiency, shadow price of carbon dioxide emissions, and substitutability for energy in the Chinese manufacturing industries. Energy Econ. 34, 1492–1497.
Liu, C.H., Lin, S.J., Lewis, C., 2010. Evaluation of thermal power plant operational performance in Taiwan by data envelopment analysis. Energy Policy 38, 1049–1058.
Liu, X., Wang, S., 2011. sub-sector carbon dioxide emissions estimation from primal energy consumption in China, 2011. Sci. Technol. Dev. 48, 22–33 (In Chinese).
Maruyama, N., Eckelman, M.J., 2009. Long-term trends of electric efficiencies in electric generation in developing countries. Energy Policy 37, 1678–1686.
Murty, S., Russell, R., Levkoff, B., 2012. On modeling pollution-generating technologies. J. Environ. Econ. Manage. 64, 117–135.
Picazo-Tadeo, A.J., Gómez-Limón, J.A., Reig-Martínez, E., 2011. Assessing farming eco-efficiency: a data envelopment analysis approach. J. Environ. Manage. 92, 1154–1164.
Song, M.L., An, Q.X., Zhang, W., Wang, Z.Y., Wu, J., 2012. Environmental efficiency evaluation based on data envelopment analysis: a review. Renewable Sustainable Energy Rev. 16, 4465–4469.
Sozen, A., Alp, I., Özdemir, A., 2010. Assessment of operational and environmental performance of the thermal power plants in Turkey by using data envelopment analysis. Energy Policy 38, 6194–6203.
Sueyoshi, T., Goto, M., 2011. DEA approach for unified efficiency measurement: assessment of Japanese fossil fuel power generation. Energy Econ. 33, 292–303.
Sueyoshi, T., Goto, M., 2012a. Efficiency-based rank assessment for electric power industry: a combined use of data envelopment analysis (DEA) and DEA-discriminant analysis (DA). Energy Econ. 34, 634–644.
Sueyoshi, T., Goto, M., 2012b. DEA radial measurement for environmental assessment and planning: desirable procedures to evaluate fossil fuel power plants. Energy Policy 41, 422–432.
Sueyoshia, T., Goto, M., 2012c. Weak and strong disposability vs. natural and managerial disposability in DEA environmental assessment: comparison between Japanese electric power industry and manufacturing industries. Energy Econ. 34, 686–699.
Sueyoshi, T., Goto, M., Ueno, T., 2010. Performance analysis of US coal-fired power plants by measuring three DEA efficiencies. Energy Policy 38, 1675–1688.
Wang, H., Zhou, P., Zhou, D.Q., 2013a. Scenario-based energy efficiency and productivity in China: a non-radial directional distance function analysis. Energy Econ. 40, 795–803.
Wang, K., Wei, Y.M., Zhang, X., 2013b. Energy and emissions efficiency patterns of Chinese regions: a multi-directional efficiency analysis. Appl. Energy 104, 105–116.
Wang, Q., Zhao, Z., Zhou, P., Zhou, D., 2013c. Energy efficiency and production technology heterogeneity in China: a meta-frontier DEA approach. Econ. Modell. 35, 283–289.
Wei, C., Loschel, A., Liu, B., 2013. An empirical analysis of the CO_2 shadow price in Chinese thermal power enterprises. Energy Econ. 40, 22–31.
Yang, H., Pollitt, M., 2010. The necessity of distinguishing weak and strong disposability among undesirable outputs in DEA: environmental performance of Chinese coal-fired power plants. Energy Policy 38, 4440–4444.
Zhang, N., Choi, Y., 2013a. Total-factor carbon emission performance of fossil fuel power plants in China: a metafrontier non-radial Malmquist index analysis. Energy Econ. 40, 549–559.
Zhang, N., Choi, Y., 2013b. Environmental energy efficiency of China Regional Economies: a Non-oriented slacks-based measure approach. Soc. Sci. J. 50, 225–234.
Zhang, N., Choi, Y., 2013c. A comparative study of dynamic changes in CO_2 emission performance of fossil fuel power plants in China and Korea. Energy Policy 62, 324–332.
Zhang, N., Choi, Y., 2014. A note on the evolution of directional distance function and its development in energy and environmental studies 1997–2013. Renewable Sustainable Energy Rev. 33, 50–59.
Zhang, N., Zhou, P., Choi, Y., 2013. Energy efficiency, CO_2 emission performance and technology gaps in fossil fuel electricity generation in Korea: a meta-frontier non-radial directional distance function analysis. Energy Policy 56, 653–662.
Zhao, X., Ma, C., 2013. Deregulation, vertical unbundling and the performance of China large coal-fired power plants. Energy Econ. 40, 474–483.
Zhou, P., Ang, B.W., Han, J.Y., 2010. Total factor carbon emission performance: a Malmquist index analysis. Energy Econ. 32, 194–201.
Zhou, P., Ang, B.W., Poh, K.L., 2006. Slacks-based efficiency measures for modeling environmental performance. Ecol. Econ. 60, 111–118.
Zhou, P., Ang, B.W., Poh, K.L., 2008a. A survey of data envelopment analysis in energy and environmental studies. Eur. J. Oper. Res. 189, 1–18.
Zhou, P., Ang, B.W., Poh, K.L., 2008b. Measuring environmental performance under different environmental DEA technologies. Energy Econ. 30, 1–14.
Zhou, P., Ang, B.W., Wang, H., 2012. Energy and CO_2 emission performance in electricity generation: a non-radial directional distance function approach. Eur. J. Oper. Res. 221, 625–635.
Zhou, P., Poh, K.L., Ang, B.W., 2007. A non-radial DEA approach to measuring environmental performance. Eur. J. Oper. Res. 178, 1–9.
Zhou, Y., Xing, X., Fang, K., Liang, D., Xu, C., 2013. Environmental efficiency analysis of power industry in China based on an entropy SBM model. Energy Policy 57, 68–75.