

Benchmarking Cleaner Production Performance of Coal-fired Power Plants Using Two-stage Super-efficiency Data Envelopment Analysis

Shao-lun Zeng and Yu-long Ren

Abstract—Benchmarking cleaner production performance is an effective way of pollution control and emission reduction in coal-fired power industry. A benchmarking method using two-stage super-efficiency data envelopment analysis for coal-fired power plants is proposed – firstly, to improve the cleaner production performance of DEA-inefficient or weakly DEA-efficient plants, then to select the benchmark from performance-improved power plants. An empirical study is carried out with the survey data of 24 coal-fired power plants. The result shows that in the first stage the performance of 16 plants is DEA-efficient and that of 8 plants is relatively inefficient. The target values for improving DEA-inefficient plants are acquired by projection analysis. The efficient performance of 24 power plants and the benchmarking plant is achieved in the second stage. The two-stage benchmarking method is practical to select the optimal benchmark in the cleaner production of coal-fired power industry and will continuously improve plants' cleaner production performance.

Keywords—benchmarking, cleaner production performance, coal-fired power plant, super-efficiency data envelopment analysis

I. INTRODUCTION

THE coal-fired power industry is an important part of the electric utilities and about 80% electricity generation is from coal-fired power plants at present in China. In 2007, the installed capacity of the thermal power was 554420 MW, accounting for 77.7% of the total; and 82.9% of the electricity production was from thermal power generation, with 76% from coal-fired power plants, which resulted in 34% coal consumption of the total coal output in China [1]. The dominant position of coal in the primary energy structure led to the generating pattern of coal-oriented power industry. The Energy Research Institute of China forecasted that by 2020 Chinese installed capacity of electric power would reach 961000 MW, with 600000 MW from the coal-fired power industry, still accounting for 60% [2]. In 2007, China's sulfur dioxide emissions were over 24.68 million tons, which made China become the largest emitting country of sulfur dioxide and

resulted in serious pollution of acid rain in one-third regions of China. Meanwhile, China's carbon dioxide emission was 62000 million tons (13.5% of the world) in 2007 [3], including 27000 million tons (about 43.5%) from the electric power sectors, and it would reach 32000 million tons by 2010 [4]. The carbon emission reduction pressure of China is getting bigger and bigger. With large amounts of carbon dioxide, sulfur dioxide, nitrogen oxides, dust, wastewater and other pollutants discharged in the power generation, the development of the power industry in China is severely restricted by the environment and climate issues.

Cleaner production, a creative idea, applies an integrated and preventative environment strategy to the producing, products and services, so that the eco-efficiency can be increased and the risks to the human and the environment can be reduced. This thinking also highlights the important concepts of overall prevention, eco-efficiency, environmental strategies, full life cycle, etc. and covers the whole procedure of raw materials, production, consumption and pollutant disposal, which has been well recognized for years by all countries in the world.

Implementing cleaner production technology and cleaner production management in coal-fired power industry to continuously improve the cleaner production performance (CPP) of power plants is one of the most effective measures to reduce emissions. In 1980, the US launched the clean coal technology to solve the environmental problems caused by coal-burning and made remarkable achievements. From 1980 to 1998, the coal consumption of coal-fired power plants in the US increased by 60%. Due to the cleaner production action, the emissions of sulfur dioxide and nitrogen oxide had decreased by 23% and 12% respectively. The investment on cleaner technology and management was 5200 million US dollars, while the economic benefits were 100000 million dollars [5]. In the recent years, Chinese government has promoted cleaner production technology and cleaner production benchmarking management in the electric industry. A series of developing plans have been formulated, such as *The Cleaner Production Promotion Law* approved by the National People's Congress of China, *The Cleaner Production Evaluation Index System for Thermal Power Industry* issued by the National Development and Reform Council (NDRC), and *The Cleaner Production Standards – Coal-fired Power Plant* developed by the Ministry of Environmental Protection (MEP). These policies and

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measures provide a basis for implementing cleaner production program in the coal-fired power industry.

II. LITERATURE REVIEW

The benchmarking method of cleaner production is actually based on measuring the CPP. The benchmark is selected from the enterprise with relatively efficient performance and stable and efficiency; and other enterprises will improve their efficiencies in the light of the benchmarks' input-output indicators. Therefore, the key to selecting optimal production benchmark is to establish an evaluation index and a measuring method for the CPP in practice.

At present, the evaluation index for cleaner production varies in different countries. The commonly used and accepted evaluation index mainly includes the following 6 indicators: ecological efficiency, climate change, environmental performance, environmental load, waste generating rate and emission-reduction trade. And in China, it generally includes indicators of raw materials, products, resources and pollutants, among which the index of environmental quality, pollution reduction, raw materials, energy consumption, environmental management, as well as comprehensive utilization of resources are mostly applied [6]–[8]. From the assessing contents of cleaner production, the evaluation of cleaner production degree, CPP assessment and measuring the potential for cleaner production, etc. are involved. The assessment method for cleaner production is mainly based on the Life Cycle Analysis (LCA), which can measure the environmental impact of the research objects [9], [10]. The LCA has been applied to the cleaner production assessment (CPA) of the electrolytic aluminum production, cement enterprises and so on [11], [12]. There are still other methods like the percentage method, the composite index analysis, fuzzy math method, etc. The fuzzy math method is widely used to evaluate the CPA of steel firms, electrolytic aluminum industry, cement enterprises, coal industry, paper industry, eco-industrial parks and so forth [13]–[18]. In addition, the CPA measured with the DEA model is a new method developed in the recent years. DEA is commonly used to assess the relative performance or efficiency of cleaner production so as to select the benchmark and to improve the CPA [19].

The benchmarking methods mainly include the ideal state analysis [17], the relative performance evaluation [20], [21], and production frontier analysis [22]. And major models applied benchmarking are DEA model or extended DEA models, for example, the optimal decision-making model for benchmarking cleaner production with qualitative information [23], benchmarking management of public sectors' performance with DEA [24], super-efficiency DEA model applied in benchmarking management [25], and sensitivity analysis of DEA benchmarking model [26]. In addition, the benchmarking management has been evolved to yardstick competition in enterprise management, that is, enterprises compete with each other to become the benchmark under the incentive regulation mechanism. Such a mechanism has been

fully applied in electric power generation and pollution reduction [27]–[29].

For the DEA model involved in the benchmarking management, whether CCR, BCC, G/DEA or SE-DEA has neglected an important issue, namely, the benchmark is acquired from measuring the original data with some DEA model. It is a method of selecting benchmark in the "bad sample", because there are some DEA-inefficient DMUs in the raw data. Thus the benchmarking DMU may not be the best choice. Therefore, it is practical to select benchmark based on DEA-efficient DMUs after improving the DEA-inefficient or weakly DEA-efficient DMUs.

III. METHOD AND MODEL

A. Super-efficiency DEA Model

There are mainly two DEA models – CCR model and BCC model [30], [31]. The CCR model can be used to evaluate the efficiencies of scale and technique simultaneously. In other words, the DEA-efficient decision making unit (DMU) in the CCR model is either appropriate in its scale or efficient in the technical management. The BCC model can only be used to assess the technique efficiency of DMUs. In addition, DEA model can be divided into two types: input-oriented model and output-oriented model. The input orientation means to achieve the efficiency by reducing input under the existing output level, while the output orientation tells what an efficient status is by increasing output under present input.

However, the CCR model can only figure out whether the DMUs are DEA-efficient or DEA-inefficient. It cannot distinguish the efficiencies of the DEA-efficient DMUs. On the basis of CCR model, Andersen and Petersen put forward the super-efficiency data envelopment analysis (SE-DEA) model (1) in 1993 [32]. In this model, the efficiency value will no longer be restricted in the scope of 0-1. That is to say, the efficiency value will probably be bigger than 1. Thereby, the DEA-efficient and DEA-inefficient DMUs can be ranked according to their super-efficiency values and the benchmark can be selected.

$$\left\{ \begin{array}{l} \min V_D = \theta - (\varepsilon\varepsilon^- + \hat{\varepsilon}s^+) \\ s.t. \sum_{\substack{j=1 \\ j \neq j_0}}^n \lambda_j X_j + s_j^- = \theta X_{j_0}, \sum_{\substack{j=1 \\ j \neq j_0}}^n \lambda_j Y_j - s_j^+ = Y_{j_0} \\ \lambda_j \geq 0, j = 1, 2, \dots, n; s_j^+ \geq 0, s_j^- \geq 0 \end{array} \right. \quad (1)$$

Literatures have studied the relationship between the CCR model and SE-DEA model (Fig. 1). When the sample DMUs are measured by the SE-DEA model, the super-efficiency values of the DEA-inefficient DMUs are the same as their DEA efficiencies respectively, still smaller than 1 (e.g. point B_1' point B_2' and in Fig. 1), and the input redundancies and output deficiencies are consistent with the values from the CCR model;

for the weakly DEA-efficient DMUs, their super-efficiency values are equal to 1 and input-output redundancies will not change (e.g. point A_1 and point A_2 in Fig. 1); the production frontier of the DEA-efficient DMUs has been changed and their super-efficiency values are greater than 1 (e.g. point B_1 , point B_2 , point C_1 , point C_2 , and point D_1 , point D_2 , in Fig. 1) [25], [33]. Therefore, we can directly evaluate the CPP of coal-fired power plants with the SE-DEA model, instead of using CCR model.

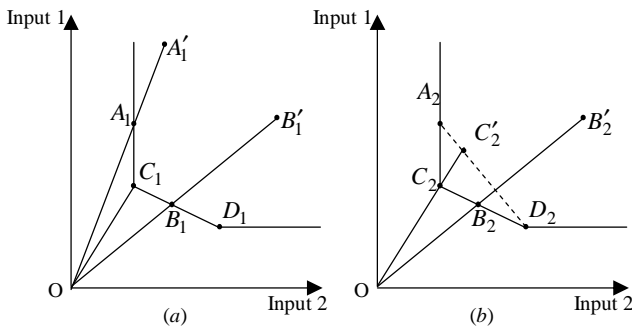


Fig. 1 CCR model (a) vs. SE-DEA model (b)

B. Projection Analysis

The super-efficiency values (θ^*), input redundancies (s^-) and output deficiencies (s^+) of all DMUs can be acquired with the SE-DEA model in (1), which will be used for the projection analysis of DEA-inefficient and/or weakly DEA-efficient DMUs. And the input-out data of these DMUs may be adjusted according to the projected values (input-output targets) so as to improve the productive efficiency. The projection analysis model can be expressed as (2).

$$\begin{cases} \hat{x}_j = \theta^* \cdot x_0 - s_j^- \\ \hat{y}_j = y_0 + s_j^+ \end{cases} \quad (2)$$

According to the principle of projection analysis, the projected values of DEA-inefficient and weakly DEA-efficient DMUs at the production frontier are DEA-efficient [34]. Thus all DMUs can achieve the DEA-efficient efficiencies.

C. Sensitivity Analysis

The benchmarking method requires that the efficiency benchmark be relatively efficient and stable with a wide variation range to maintain DMUs DEA-efficient. The range can be achieved through sensitivity analysis.

Suppose that the input-output data of a single DMU turns into $(1 \pm \gamma)$ times of the original data, namely, DMU_0 changes as:

$$\begin{cases} \hat{x}_0 = (1 + \gamma)x_0 \\ \hat{y}_0 = (1 - \gamma)y_0 \end{cases}, \quad 0 \leq \gamma < 1 \quad (3)$$

Then, the necessary and sufficient conditions for DMU_0

maintaining DEA-efficient are:

$$\theta_0 > 1, \quad 0 \leq \gamma \leq \frac{\theta_0 - 1}{\theta_0 + 1} = 1 - \frac{2}{\theta_0 + 1} \quad (4)$$

If all the DMUs change at the same time, considering the rest DMU_j change in the opposite direction of the change trend of DMU_0 (i.e. the most adverse cases), DMU_0 still changes based on (3), while the rest DMU_j change according to (5).

$$\begin{cases} \hat{x}_j = \frac{1}{1 + \gamma} x_j \\ \hat{y}_j = \frac{1}{1 - \gamma} y_j \end{cases}, \quad j=1, \dots, n, \quad j \neq 0 \quad (5)$$

Then, the necessary and sufficient conditions for DMU_0 maintaining DEA-efficient are:

$$\theta_0 > 1, \quad 0 \leq \gamma \leq \frac{\theta_0^{\frac{1}{2}} - 1}{\theta_0^{\frac{1}{2}} + 1} = 1 - \frac{2}{\theta_0^{\frac{1}{2}} + 1} \quad (6)$$

We can see from (4) and (6) that DMUs with high the super-efficiency values are with more stability and wide range maintaining DMUs DEA-efficient, whether a single DMU changes or all DMUs change simultaneously; that is, the DMU with the highest super-efficiency can serve as the benchmark [25], [33].

D. Benchmarking Process of Coal-fired Power Plant's CPP

On the basis of cleaner production benchmarking management and CPP evaluation, the benchmarking process of CPP for coal-fired power plants can be divided into two stages (Fig. 2).

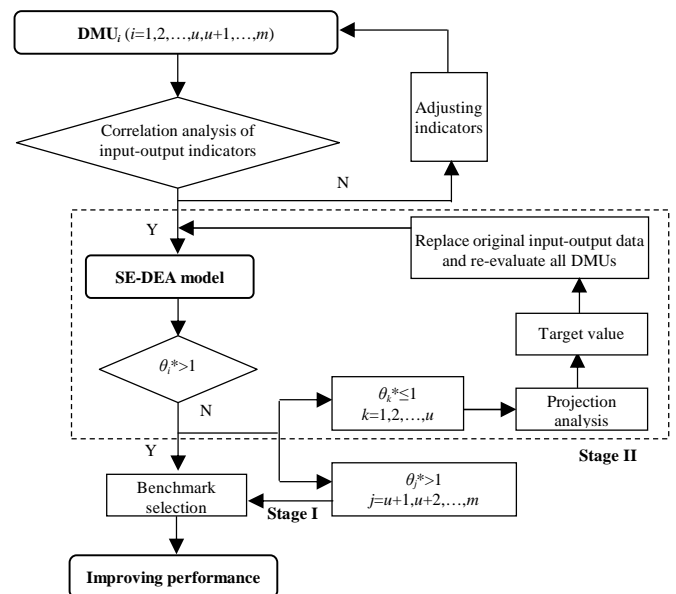


Fig. 2 Benchmarking process of cleaner production performance

Stage I: To carry out the correlation analysis of the original input-output data to test whether the input and output data meet the requirement of isotonicity; then the SE-DEA model in (1) will be used to evaluate the relative performance of all power plants DMU_i ($i = 1, 2, \dots, u, u+1, \dots, m$); and the super-efficiency value (θ_1^*), input redundancy (s_1^-), and output deficiency (s_1^{+*}) of each power plant can be figured out; the benchmark B_1 and the sensitivity γ_1 in Stage I can also be achieved. Then the target values of DEA-inefficient and/or weakly DEA-efficient DMUs ($j=1, 2, \dots, u$) are calculated by projection analysis in (2).

Stage II: Suppose that the DEA-inefficient and/or weakly DEA-efficient DMUs adjusting their input-output data based on the projection analysis to improve their CPP, the original input-output data of corresponding DMUs may be replaced with the target values achieved in Stage I and this new data set will be evaluated by the SE-DEA model to get the new super-efficiency value (θ_2^*), input redundancy (s_2^-), and output deficiency (s_2^{+*}). Using the sensitivity analysis by (4) and (6), the final benchmark B_2 and the sensitivity γ_2 of Stage II can be determined.

IV. EMPIRICAL STUDY

A. Input-output Indicators

At present, the DEA method has been applied in many fields. As to application to the cleaner production assessment, the key is to introduce the inefficient output of pollutant into the DEA model. In measuring efficiency, the more output is usually the better, but the pollutant emission is just the opposite. Obviously, to treat the pollutant as the output indicator cannot meet the

requirements of the model. From the perspective of cleaner production, pollutant emission, as a DMU of output, is an undesired output and it should be minimized. When the cleaner production assessment is carried out based on the output DMU of pollutants, neither CCR model nor SE-DEA model is available. Therefore, only when the pollutant emissions are considered as negative outputs or inputs, the calculation and evaluation can be operated by means of the DEA model [35], [36].

Combined with *The Cleaner Production Evaluation Index System for Thermal Power Industry* and *The Cleaner Production Standards – Coal-fired Power Plant* issued by NDRC and MEP of China, the input-output indicators for measuring the CPP of the coal-fired power plant is set up, considering the requirements of operating the SE-DEA model simultaneously.

Input indicators (per unit power generation): x_1 , coal consumption; x_2 , water consumption; x_3 , energy consumption; x_4 , flyash output volume; x_5 , smoke dust emission volume; x_6 , sulfur dioxide emissions; x_7 , nitrogen dioxide emissions; x_8 , wastewater emissions.

Output indicators: y_1 utilization rate of flyash; y_2 , utilization rate of recycled water; y_3 , total output value per unit power generation.

B. Sample Data and Isotonicity of Input-output Indicators

Golany & Roll proposed the good rule of thumb for the number of DMUs in applying DEA model, namely, the number of DMUs should be at least twice the number of inputs and

TABLE I
 SURVEY DATA OF 24 COAL-FIRED POWER PLANTS

Power plant	Input indicators ^{a, b}								Output indicators ^a		
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	y_1	y_2	y_3
P01	815	563	0.184	3296	2.99	5.06	2.129	1550	0.886	0.849	0.823
P02	514	723	0.154	6293	2.66	4.10	2.774	1830	0.643	0.745	0.734
P03	416	441	0.086	2303	2.89	2.70	0.631	810	0.632	0.649	0.701
P04	440	820	0.104	3527	1.95	2.94	0.611	820	0.631	0.750	0.598
P05	729	850	0.172	7091	3.17	2.24	1.560	1130	0.837	0.823	0.668
P06	404	800	0.108	2953	2.83	3.26	0.547	1330	0.568	0.650	0.621
P07	616	912	0.199	8849	3.35	4.99	1.568	1680	0.772	0.785	0.711
P08	533	494	0.135	7648	2.87	4.05	1.692	1780	0.651	0.620	0.655
P09	711	776	0.178	7345	1.96	2.82	0.993	1230	0.729	0.699	0.801
P10	854	903	0.184	2355	2.24	3.69	2.354	1645	0.898	0.800	0.794
P11	568	874	0.099	7327	2.57	3.66	0.897	999	0.821	0.802	0.886
P12	707	768	0.178	6684	3.99	4.99	2.205	1456	0.698	0.900	0.900
P13	495	692	0.186	6503	2.32	3.51	1.367	1698	0.768	0.733	0.653
P14	803	658	0.156	4897	1.98	4.35	2.094	1765	0.649	0.853	0.780
P15	799	593	0.171	5635	3.23	3.29	1.779	1811	0.850	0.784	0.787
P16	663	990	0.149	8735	3.17	4.45	0.999	1258	0.900	0.800	0.706
P17	623	789	0.128	6742	2.76	2.87	1.643	1603	0.822	0.865	0.863
P18	700	808	0.181	4963	2.12	3.35	2.680	1633	0.651	0.830	0.741
P19	822	954	0.172	5005	2.68	4.21	2.011	1599	0.729	0.739	0.805
P20	586	897	0.176	6120	2.54	4.25	1.782	1135	0.588	0.825	0.871
P21	737	803	0.165	6563	2.32	3.17	2.020	1369	0.773	0.758	0.820
P22	675	762	0.158	5869	2.16	3.88	1.886	1238	0.726	0.865	0.795
P23	642	735	0.155	4937	2.21	2.96	1.835	1457	0.689	0.830	0.785
P24	708	783	0.168	6097	2.49	4.12	1.692	1326	0.805	0.741	0.856

^a The carbon dioxide emissions from the power generation can be estimated based on the coal consumptions and the thermal efficiency of the boiler. There is the coal consumption indicator (x_1) in the resource consumption indicators and both the carbon dioxide emission and coal consumption are treated as the input in the model operation, so it is unnecessary to consider the indicator of carbon dioxide emissions in the waste discharge.

^b The evaluation in the SE-DEA model is dimensionless, so the unit of each indicator is omitted.

outputs considered [37]. There are 8 input indicators and 3 output indicators in measuring the CPP of the coal-fired power plant. Thus at least 22 DMUs should be involved in running the model. To satisfy this rule, this research investigated the power generation of 24 coal-fired power plants with similar technology and scale. The survey data based on the input-output indicators and the requirements of SE-DEA model is listed in Table I.

DEA model requires that the DMUs be homogeneous with comparability and the input-output indicators meet the requirement of isotonicity, namely, the output will not decrease along with the increase of input [38]. This can be tested by correlation analysis of the input-output data. It should be noted that this paper does not use the indicator of “flyash discharge per unit power generation” because it cannot satisfy the requirement of isotonicity. The correlation analysis result of the input-output indicators of 24 power plants is listed in Table II, from which we can see that the input-output indicators are positive related, indicating that the input-output indicators in this research meets the requirement of isotonicity and reflects the input-output relationship of implementing cleaner production of coal-fired power plants.

C. Evaluation of the Original Data

The original data in Table I is calculated with EMS software and the result is listed in Table III. The result shows the CPP of 16 plants is DEA-efficient and that of the rest 8 plants is relatively inefficient with input redundancy and output deficiency. The super-efficiencies of the 24 power plants are achieved and P03 is with the biggest super-efficiency and sensitivity.

D. Projection Analysis

The purpose of benchmarking CPP is to adjust and optimize relevant indicators of inefficient or weakly efficient DMUs so that the performance of coal-fired power plants can be improved. By operating (1) with super-efficiency values (Table III) and input-output slacks (Table IV), the projected values of 8 DEA-inefficient power plants can be figured out by (2), and these 8 power plants may improve the power generation process and input-output data based on the target values (Table V).

E. Benchmark Selection

According to the benchmarking process in the context, the original input-output data of the 8 DEA-inefficient power plants is replaced by the target values in Table V. The SE-DEA model in (1) is applied again to gain the measuring result of CPP of improved coal-fired power plants (Table VI). It can be seen that the CPP of all power plants are DEA-efficient. In the second stage, the super-efficiency and sensitivity of P10 are bigger than those of any other plant, that is, the final benchmark is no longer plant P03 but P10.

V. CONCLUSION

The benchmark selection of CPP for the coal-fired plant can be divided into two stages. In the first stage, the CPP assessment of the original data of all power plants and the projection

TABLE II
 CORRELATION COEFFICIENTS OF INPUT-OUTPUT INDICATORS

	y_1	y_2	y_3
x_1	0.5802	0.5327	0.5437
x_2	0.2203	0.3205	0.1582
x_3	0.3401	0.3957	0.2693
x_4	0.2463	0.1308	0.1434
x_5	0.2399	0.1074	0.0824
x_6	0.0988	0.2786	0.3117
x_7	0.0994	0.4828	0.4079
x_8	0.1450	0.1146	0.0692

TABLE III
 EVALUATION RESULT OF CPP OF 24 COAL-FIRED POWER PLANTS (STAGE I)

Power plant	DEA-efficient	γ_1	γ_1^*	SE-DEA efficiency	Rank
P01	Y	0.0826	0.0414	1.1801	6
P02	N	–	–	0.9508	20
P03	Y	0.2381	0.1208	1.6249	1
P04	Y	0.1680	0.0846	1.4039	3
P05	Y	0.1513	0.0761	1.3565	4
P06	Y	0.0351	0.0175	1.0727	13
P07	N	–	–	0.8242	24
P08	N	–	–	0.9135	21
P09	Y	0.0778	0.0390	1.1687	7
P10	Y	0.1718	0.0865	1.4148	2
P11	Y	0.1153	0.0578	1.2606	5
P12	N	–	–	0.8694	22
P13	Y	0.0461	0.0230	1.0966	10
P14	Y	0.0569	0.0285	1.1207	9
P15	Y	0.0418	0.0209	1.0873	11
P16	N	–	–	0.9516	19
P17	Y	0.0622	0.0311	1.1327	8
P18	Y	0.0005	0.0003	1.0011	16
P19	N	–	–	0.8630	23
P20	Y	0.0125	0.0063	1.0254	15
P21	N	–	–	0.9743	18
P22	Y	0.0347	0.0173	1.0718	14
P23	Y	0.0362	0.0181	1.0752	12
P24	N	–	–	0.9961	17

TABLE VI
 EVALUATION RESULT OF CPP OF 24 COAL-FIRED POWER PLANTS (STAGE II)

Power plant	DEA-efficient	γ_2	γ_2^*	SE-DEA efficiency	Rank
P01	Y	0.0653	0.0327	1.1398	6
P02	Y	0.0000	0.0000	1.0001	23
P03	Y	0.1496	0.0752	1.3517	3
P04	Y	0.1314	0.0660	1.3026	4
P05	Y	0.1513	0.0761	1.3565	2
P06	Y	0.0351	0.0175	1.0727	13
P07	Y	0.0018	0.0009	1.0037	16
P08	Y	0.0008	0.0004	1.0017	19
P09	Y	0.0666	0.0333	1.1427	5
P10	Y	0.1718	0.0865	1.4148	1
P11	Y	0.0636	0.0318	1.1359	7
P12	Y	0.0011	0.0006	1.0023	17
P13	Y	0.0412	0.0206	1.0859	11
P14	Y	0.0569	0.0285	1.1207	9
P15	Y	0.0418	0.0209	1.0873	10
P16	Y	0.0009	0.0004	1.0018	18
P17	Y	0.0622	0.0311	1.1327	8
P18	Y	0.0005	0.0003	1.0011	20
P19	Y	0.0003	0.0002	1.0007	21
P20	Y	0.0125	0.0063	1.0254	15
P21	Y	0.0000	0.0000	1.0001	24
P22	Y	0.0341	0.0171	1.0706	14
P23	Y	0.0362	0.0181	1.0752	12
P24	Y	0.0002	0.0001	1.0004	22

TABLE IV
 INPUT-OUTPUT REDUNDANCY OF 8 DEA-INEFFICIENT POWER PLANTS

Power plant	Input redundancy								Output deficiency		
	s_1^-	s_2^-	s_3^-	s_4^-	s_5^-	s_6^-	s_7^-	s_8^-	s_1^+	s_2^+	s_3^+
P02	0	0	0.040	1822	0.00	0.75	1.830	830	0.050	0.000	0.000
P07	0	63	0.020	2415	0.00	0.65	0.230	41	0.000	0.000	0.030
P08	0	0	0.010	4334	0.00	0.58	0.540	635	0.000	0.030	0.010
P12	0	0	0.020	1732	0.00	0.51	0.710	93	0.140	0.000	0.030
P16	12	0	0.020	1549	0.00	0.22	0.000	80	0.000	0.120	0.250
P19	0	0	0.000	0	0.00	0.05	0.000	0	0.070	0.050	0.000
P21	22	0	0.000	0	0.00	0.00	0.680	0	0.000	0.000	0.000
P24	0	0	0.020	0	0.00	0.24	0.290	0	0.000	0.070	0.000

TABLE V
 INPUT-OUTPUT TARGET VALUES OF 8 DEA-INEFFICIENT POWER PLANTS

Power plant	Target input						Target output				
	x_1	x_2	x_1	x_2	x_1	x_2	x_1	x_2	x_1	x_2	x_1
P02	489	687	0.106	4161	2.53	3.15	0.808	910	0.693	0.745	0.734
P07	508	689	0.144	4879	2.76	3.46	1.062	1344	0.772	0.785	0.741
P08	487	451	0.113	2653	2.62	3.12	1.006	991	0.651	0.650	0.665
P12	615	668	0.135	4079	3.47	3.83	1.207	1173	0.838	0.900	0.930
P16	619	942	0.122	6764	3.02	4.01	0.951	1117	0.900	0.920	0.956
P19	709	823	0.148	4319	2.31	3.58	1.735	1380	0.799	0.789	0.805
P21	696	782	0.161	6394	2.26	3.09	1.288	1334	0.773	0.758	0.820
P24	705	780	0.147	6073	2.48	3.86	1.395	1321	0.805	0.811	0.856

analysis for the DEA-inefficient DMUs are conducted to get the target input-output values, and the benchmark B_1 in the first stage is achieved simultaneously. The DEA-inefficient plants may adjust their input-output data according to the projected values. In the second stage, the CPP of the DEA-efficient plants and the improved DEA-inefficient DMUs will be evaluated again. All power plants will be DEA-efficient and the benchmark B_2 in the second stage (final benchmark) can be acquired. B_2 is different from B_1 because B_2 is obtained under the premise that all DMUs are DEA-efficient. In the first stage, DMU_{B_1} is DEA-efficient and its input-output data does not change during the second stage; in the second stage, both DMU_{B_1} and DMU_{B_2} are DEA-efficient, but the super-efficiency of B_2 is bigger than that of B_1 . In fact, the B_1 and B_2 can be regarded as "to select the best in the bad or in the good". The second stage can be considered as a re-benchmarking process. Therefore, B_2 is a more appropriate benchmark and we can put the two stages above into practice and improve the CPP of coal-fired power plants.

The above analysis shows that the CPP of coal-fired power plants can be measured, benchmarked, ranked, and improved through the SE-DEA model. An empirical study of 24 coal-fired power plants gives the fact that the efficiency benchmark will probably change. The benchmark B_1 achieved in the first stage may be not the best choice and the benchmark B_2 got in the second stage is better than B_1 . To select B_2 as a benchmark will be more conducive to improve the CPP.

It should be noted that the benchmarking based on SE-DEA model is a relative measuring method. In the process of implementing cleaner production and in the course of valuing and improving CPP of coal-fired power plants, the national or industrial standard methods should also be used to assess the developing level of cleaner production. Only to combine the relative assessment with the absolute evaluation can

continuously improve the CPP in the coal-fired power industry, and can the benchmarking of CPP guide the power generation and the emission reduction.

ACKNOWLEDGMENT

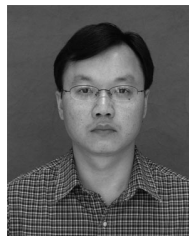
This research is supported by the Sichuan Circular Economy Research Centre at Southwest University of Science and Technology (Grant No. XHJJ-0905). Special thanks are addressed to Mr. Jiang-gang Yang, who has considerably help collect the research data.

REFERENCES

- [1] *National Electrical Industry Statistics of China 2007*. China Electricity Council, 2008.
- [2] *World Energy Outlook 2006*. Paris: International Energy Agency, 2006.
- [3] *Bulletin of Environmental Statistics 2007*. Ministry of Environmental Protection of China, 2008.
- [4] F. J. Xu, *Comparison of the Electric Power Industry of China and the US and the Potential of Greenhouse Gas Emission Reduction of Chinese Electric Sector*. China Research Center for Public Policy, 2008.
- [5] I. Dincer, "Energy and environmental impacts: present and future perspectives," *Energy Sources*, vol. 20, no. 4-5, pp. 427-453, May 1998.
- [6] A. J. Jia, M. Jin, X. L. Zhang, "A review on the evaluation index of cleaner production," *Shaanxi Environment*, vol. 10, no. 3, pp.31-35, June 2003.
- [7] D. Vernon, *A Benchmark of Current Cleaner Production Practices*. Cleaner Industries Section, Environment Protection Group, Environment Australia, 1997.
- [8] W. Altham, "Benchmarking to trigger cleaner production in small businesses: drycleaning case study," *Journal of Cleaner Production*, vol. 15, no. 8-9, pp. 798-813, 2007, 15:798-813.
- [9] P. L. Spath, M. K. Mann, D. R. Kerr, *Life Cycle Assessment of Coal-fired Power Production*. Colorado, USA: National Renewable Energy Laboratory, 1999.
- [10] Q. H. Sun, "The application prospect of life cycle assessment in cleaner production," *Research of Environmental Sciences*, vol. 15, no. 4, pp. 4-6, Aug. 2002.
- [11] D. N. Song, L. Y. Chai, D. W. He, "Study on life cycle assessment of cleaner production evaluation index of electrolytic aluminium," *Environmental Technology*, no. 6, pp. 9-13, Dec. 2005.

- [12] W. Q. Xiong, X. Wang, "Application of life-cycle assessment on auditing of cleaner production for the cement factory," *Environmental Science Survey*, vol. 26, no. 2, pp. 15-17, April 2007.
- [13] W. Q. Xiong, G. Yin, Q. C. Liu, "Research on grey correlation analysis for cleaner production," *Journal of Chongqing University*, vol. 32, no. 11, pp. 1352-1356, Nov. 2009.
- [14] F. Zhang, *Study on Cleaner Production Performance Estimation of Iron and Steel Enterprise*. Chongqing: Chongqing University, 2004.
- [15] M. Q. Cai, *The Application Research of Fuzzy Synthesis Evaluation in CPA*. Lanzhou: Lanzhou University, 2008.
- [16] L. M. Sun, Y. Y. Bai, Z. Chen, "Cleaner production assessment model of coal preparation plant," *Journal of Liaoning Technical University*, vol. 26, no. 1, pp. 151-154, Feb. 2007.
- [17] J. Tian, Y. Wang, N. Liu, G. F. Lu, "The research on application of clean production assessment in environmental impact assessment about paper manufacturing industry," *Ecological Economy*, no. 5, pp. 101-105, May 2007.
- [18] X. L. Ma, *The Method Based on Bayesian Network in Assessment of Cleaner Production in Eco-Industrial Park*. Changchun: Jilin University, 2007.
- [19] X. S. Song, Y. H. Wang, X. P. Lu, "Application on cleaner production assessment of data envelopment analysis model," *Sichuan Environment*, vol.22, no. 5, pp.58-62, Oct. 2003.
- [20] *Comparative Study Report on EU-China Benchmarking of Energy Efficiency and Industrial Emissions*. Nanjing Research Institute for Environmental Protection, 2008.
- [21] D. Bongardt, L. Jarczyński, C. Michelsen, *Energy Efficiency and Environmental Data from the European Union Industry Sector: Benchmarking Report*. The Wuppertal Institute for Climate, Energy and Environment, 2007.
- [22] M. Kortelainen, *Production Frontier Methods in Environmental Performance Measurement and Analysis*. Faculty of Law, Economics and Business Administration, University of Joensuu, 2008.
- [23] D. G. Liu, J. R. Tang, "Decision model basing on circulate economic benchmarking of quantity," *Journal of Yunnan Normal University*, vol. 27, no. 1, pp. 27-31, Jan. 2007.
- [24] Z. R. Zhou, Q. Wang, J. H. Li, "Performance evaluation by means of improved DEA method," *Chinese Journal of Management Science*, vol. 11, no. 3, pp. 72-75, June 2003.
- [25] J. Y. Liu, "Benchmarking using super efficiency data envelopment analysis and its sensitivity analysis," *Industrial Engineering Journal*, vol.11, no.4, pp.74-77, July 2008.
- [26] G. Y. Miao, *Sensitivity Analysis on Fuzzy DEA-DA Model and DEA-Benchmarking Model*. Changchun: Jilin University, 2008.
- [27] T. Jamasb, *International Utility Benchmarking & Regulation: An Application to European Electricity Distribution Companies*. DAE Working Paper, No. 0115, Department of Applied Economics, University of Cambridge, 2002.
- [28] P. Burns, C. Jecnkns, C. Riechmann, "The role of benchmarking for yardstick competition," *Utilities Policy*, vol. 13, no.4, pp. 302-309, Dec. 2005.
- [29] P. J. Agrell, P. Bogetoft, J. Tind, "DEA and dynamic yardstick competition in Scandinavian electricity distribution," *Journal of Productivity Analysis*, vol. 23, pp. 173-201, May 2005.
- [30] A. Charnes, W. W. Cooper, E. Rhodes, "Measuring the efficiency of decision making units," *European Journal of Operational Research*, vol. 2, no. 6, pp. 429-444, Nov. 1978.
- [31] R. D. Banker, "Estimating most productive scale size using data envelopment analysis," *European Journal of Operational Research*, vol. 17, no.1, pp. 35-44, July 1984.
- [32] P. Andersen, N. C. Petersen, "A procedure for ranking efficient units in data envelopment analysis," *Management Science*, vol. 39, no. 10, pp. 1261-1264, Oct. 1993.
- [33] J. Zhu, "Super-efficiency and DEA sensitivity analysis," *European Journal of Operational Research*, vol. 129, no.2, pp. 443-455, Mar. 2001.
- [34] Q. L. Wei, *Data Envelopment Analysis*. Beijing: Science Press, 2004, p. 53.
- [35] H. Scheel, "Undesirable outputs in efficiency valuations," *European Journal of Operational Research*, vol. 132, no.2, pp. 400-410, July 2001.
- [36] P. J. Korhonen, M. Luptacik, "Eco-efficiency analysis of power plants: An extension of data envelopment analysis," *European Journal of Operational Research*, vol. 154, no. 2, pp. 437-446, April 2004.
- [37] B. Golany, Y. Roll, "An application procedure for DEA," *Omega*, vol. 17, no. 3, pp. 237-250, May 1989.
- [38] N. Zhu, Y. Liu, "On the development models and choice of routes of new industrialization of Chinese regions," *The Journal of Quantitative & Technical Economics*, no.5, pp. 3-16, May 2009.

BIOGRAPHY



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