Input-output efficiency analysis of Chinese thermal power enterprises based on three-stage DEA

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Abstract. Since the new round of power system reform, the pace of power market construction has accelerated, and the scale of power market-based transactions has grown rapidly. The fierce marketization competition has continuously reduced the on-grid electricity price of thermal power. Now the thermal power enterprises are facing a severe test of operating conditions. Based on the panel data of several listed thermal power companies in Shanghai and Shenzhen in recent three years, this paper uses three-stage DEA model to analyze the input-output efficiency of thermal power enterprises. The research shows that the input of listed thermal power companies increases year by year, while their output decreases. The comparison of the first and third stages of the DEA model shows that the first stage overestimates the scale efficiency of this type of power generation company and underestimates the pure technical efficiency. Based on the research results, this paper puts forward the development suggestions for thermal power enterprises to keep up with the reform of China's power market and improve their business conditions.

1. Introduction
In recent years, the sustainable development of China's thermal power industry has been under great pressure due to the multiple factors of market-oriented power reform, reducing excess capacity and high coal prices. In such a harsh environment, it is of great practical significance to study the input-output efficiency analysis in line with the operating conditions of thermal power companies, so as to improve the profitability of thermal power enterprises and strengthen risk control. At present, the DEA model for research performance evaluation has obtained the following advantages: no explicit function equation is required between the independent variables and the dependent variables, and no clear dimension is required for the input and output variables. Azadeh A. et al. [1] studied the power distribution efficiency in Iran based on the use of SDEA model. Odeck J. et al. [2] measured the performance of relevant industries by using the SFA stochastic frontier analysis method. Honma S. et al. [3] calculated the change of regional energy production efficiency in Japan using the DEA method and the Manquist index under the theoretical framework of total factor efficiency evaluation. Considering that the traditional DEA method ignores the influence of environment variables and random factors on the decision-making unit [4], and fails to conduct hypothesis testing for non-parametric estimation [5], the efficiency value obtained in this case is inaccurate and unscientific. More and more scholars realize that input-output efficiency is not a relatively isolated measurement result. It is closely
related to economy, environment and technology. There are different periods and judgment angles for evaluating input-output efficiency, and their specific measurement standards also differ.

The three-stage DEA method originated from a method literature proposed by Fird et al. In 2002 [5]. At present, the three-stage DEA model has been verified and applied to other fields, showing the superiority of its evaluation system. The results of the efficiency evaluation system using the three-stage DEA model are significantly different from those of the traditional DEA model. The efficiency results may be more valuable for reference by using three-stage DEA method and SFA regression analysis in the second stage, and removing external environmental factors and random errors.

Based on this, the author believes that the selection of the three-stage DEA method to analyze the input-output efficiency of the thermal power industry is of great significance for operating status of thermal power companies and exploring sustainable development paths.

2. Development status of thermal power industry

In the first quarter of 2019, China's thermal power generation capacity from above-scale power plants reached 1,265.8 billion kWh, up 2.0 percent year on year, 4.9 percentage points lower than the same period last year. The average utilization hours of thermal power equipment in China were 1,083 hours (including 1,122 hours for coal-fired power generation and 603 hours for gas-fired power generation), six hours lower than the same period last year.

In March 2019, 28 of 36 thermal power companies in CITIC's third-tier industry rose, 8 fell, and 0 sideways. In the following figure, for the sake of simplicity, the stock code is used instead of the company name. In the figure, the stock codes corresponding to the top three companies are respectively 000037 (55.56%), 000958 (25.93%), and 000720 (24.27%). Please note that the stock code is used instead of the company name for simplicity.
3. Three-stage DEA model construction and data processing

In the first stage, we use the original input and output data for initial efficiency evaluation. For any DMU, the dual-oriented BCC model under input guidance can be expressed as:

\[
\begin{align*}
\min \theta - \epsilon (\theta^2 S^+ + \epsilon^2 S^-) \\
\sum_{j=1}^n X_j \lambda_j + S^- = \theta X_0 \\
\text{s.t.} \sum_{j=1}^n Y_j \lambda_j - S^+ = Y_0 \\
\lambda_j \geq 0, S^- S^+ \geq 0
\end{align*}
\]

(1)

Among them, \(j = 1, 2, \ldots, n\) represent decision units. \(X, Y\) are input and output vectors, respectively. The DEA model is essentially a linear programming problem. If \(\theta = 1, S^+ = S^- = 0\), the decision unit DEA is valid; if \(\theta = 1, S^+ \neq 0\), or \(S^- \neq 0\), the decision unit weak DEA is valid; if \(\theta < 1\), the decision unit non-DEA is valid.

In the second stage, we mainly focus on the input relaxation variables in the first stage, which are composed of environmental factors, management inefficiency and statistical noise. Based on Fried [5], a regression function similar to SFA is constructed as follows (taking input orientation as an example)

\[
S_{ni} = f(Z_i \beta_n) + v_{ni} + \mu_{ni}; i = 1, 2, \ldots, I; n = 1, 2, \ldots, N
\]

(2)

Among them, \(S_{ni}\) is the relaxation value of the \(i\)-th decision unit and the \(n\)-th input; \(Z_i\) is the environment variable, \(\beta_n\) is the coefficient of the environment variable; \(v_{ni} + \mu_{ni}\) is the mixed error term, which \(v_{ni}\) indicates the random interference term, and \(\mu_{ni}\) indicates the inefficiency of management. \(v \sim N(0, \sigma_v^2)\) is the random error term, which indicates the influence of random interference factors on the input relaxation variables; \(\mu\) is management inefficiency, which indicates the influence of management factors on the input relaxation variables, assuming that it follows a normal distribution truncated at zero, that is \(\mu \sim N'(0, \sigma_{\mu}^2)\).

The purpose of SFA regression is to eliminate the influence of environmental factors and random factors on the efficiency measure in order to adjust all decision-making units in the same external environment. The adjustment formula based on Fried [5] is as follows:

\[
X_n^a = X_n + [\max(f(Z_i \beta_n)) - f(Z_i \beta_n)] + [\max(v_{ni}) - v_{ni}] \quad i = 1, 2, \ldots, I; n = 1, 2, \ldots, N
\]

(3)

Among them, \(X_n^a\) is the adjusted input; \(X_n\) is the input before adjustment; \(\max(f(Z_i \beta_n))\) is the adjustment of external environmental factors; \([\max(v_{ni}) - v_{ni}]\) puts all decision-making units at the same level of calculation.

The calculation of the most critical random error term is more complicated. The steps are as follows:
1) separate the management inefficiencies
The form of the separation formula is as follows:

\[
E(\mu|\epsilon) = \sigma, \quad \frac{\phi(\lambda, \frac{\epsilon}{\sigma})}{\phi(\frac{\lambda \sigma}{\sigma}, \frac{\sigma}{\sigma})} + \frac{\lambda \epsilon}{\sigma}, \quad \sigma = \frac{\sigma^2 + \sigma_{\mu}^2}{\sigma}, \quad \lambda = \sigma_{\mu}/\sigma_{\epsilon}
\]

(4)

This formula is referenced by Luo D. [6], Chen W. [7], and others.
2) The calculation formula for the random error term \(\mu\) is as follows:

\[
E[v_{ni} | v_{ni} + \mu_{ni}] = s_{ni} \cdot f(z_i \beta_n) - E[u_{ni} | v_{ni} + \mu_{ni}]
\]

(5)

3) Perform efficiency analysis on adjusted input-output variables. The usefulness of the data is improved after processing. The selected variables are displayed according to the SMART principle as follows:
Table 1. Variable table

| Input variables            | Output variables        |
|---------------------------|-------------------------|
| x₁-cost for core business | y₁-prime operating revenue |
| x₂-net value of fixed assets | y₂-net profit            |
| x₃-staff numbers          |                         |

In the specific selection of samples, the following situations are excluded: (1) listed thermal power companies that are not mainly engaged in power generation; (2) listed companies without relevant data; (3) the listed company whose data are not comparable (for example, only the company's headquarters is calculated when calculating the number of employees). (4) Those marked with * ST (* ST Nandian) indicated that its financial status was abnormal for three consecutive years of losses, and it was delisted for early warning. Finally, 29 listed thermal power companies were selected as the research samples. It is worth noting that negative numbers cannot exist in the DEA model, and in the process of index selection, negative numbers and zero exist for net profit and government subsidy. Through literature review, the standardized formula was found:

\[
Y = 0.1 + 0.9 \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}
\]

Note: X is the original value, Y is the adjusted value; \(X_{\text{min}}\) is the minimum value of the variable, and \(X_{\text{max}}\) is the maximum value. We'd better process the data from different years together. There will be only one maximum and minimum value for each variable. This method is used to normalize the raw data.

4. Efficiency Analysis of Thermal Power Enterprises

It can be seen from the data analysis results that the efficiency value of the company changed after eliminating environmental variables and random factors.

Static comparison of pure technical efficiency: before removing environmental variables and random factors, the average efficiency of 29 listed thermal power companies was 0.458, while the average value after processing was 0.465. It indicated that environmental factors and random factors inhibit pure technical efficiency, but there is not much difference between them.

Static comparison of pure scale efficiency: before dealing with environmental factors and random factors, the minimum value of scale efficiency of 29 listed thermal power companies was 0.383, and the average value was 0.883. After processing, the minimum value was 0.172 and the average value was 0.373. It indicated that environmental factors and random factors can stimulate the pure scale efficiency, and environmental factors and random factors have a great impact on the scale efficiency of different listed companies.

Compare the technical efficiency of these 29 listed thermal power companies: before removing environmental variables and random factors, the difference between the highest efficiency and the lowest efficiency value was 0.75, and the average efficiency of the technique was 0.462. The difference after processing was as high as 0.82, and the average efficiency of the technique was 0.492. This showed that environmental factors and random factors have a great impact on the overall efficiency of the listing, and the impact on different companies was also quite different.

According to the data, after processing environmental variables and random factors, the technical efficiency of the companies represented by stock codes such as 000958, 600011, 600027, 600795, 600886 and 601991 were 0.849, 1, 1, 1, 1, and 0.952 respectively. The data changes before and after were more than 35%.
Table 2. Efficiency values of the first and third stages from 2016 to 2018

| Year | the first stage | the second stage | the third stage |
|------|----------------|-----------------|----------------|
| 2016 |                |                 |                |
| 2017 |                |                 |                |
| 2018 |                |                 |                |

Note: For simplicity, the stock code is used instead of the company name.

Figure 3. Comparison of the average efficiency of the first and third stages in 2016-2018

Considering that the pure technical efficiency is already above 0.6, there is little room for improvement. Scale efficiency is about 0.37, which has a lot of room to improve. Therefore, for listed companies, the first task is to improve the efficiency of scale, followed by improving the overall technical efficiency. After removing environmental variables and random factors, the pure technical efficiency is improved, and the scale efficiency is greatly reduced. The improvement of pure technical efficiency is due to the fact that the thermal power industry is a very mature industry, and there is little difference between the technology and management level of listed companies. The input and output efficiency of most companies is effective, which is equal to 1. The scale of listed thermal power
companies continues to expand, and scale efficiency is greatly reduced. Especially the newly listed companies, these companies have not fully utilized the capital market to obtain the development dividend, which is the reason for the huge gap between them and the leading companies.

After eliminating the effects of random errors and external environment variables, the scale efficiency of the third stage decreased, but the overall and pure technical efficiency significantly improved. The improvement in overall efficiency at this stage is mainly due to the effect of pure technical efficiency, and the effect of scale efficiency is invalid. The result means that for thermal power industry, the main factors causing its low efficiency are backward management mechanism and low management level. In addition, the construction scale of thermal power industry has not been effectively controlled. At the same time, this means that in the first stage, the scale efficiency of China's thermal power generation industry is seriously overestimated, while the pure technical efficiency is underestimated.

5.Conclusions and Suggestions

5.1. Conclusions

In this paper, the three-stage DEA model is used to analyze the technical efficiency and scale efficiency of 29 thermal power companies listed on the Shanghai and Shenzhen stock exchanges from 2016 to 2018. In the first stage, the DEA model was used to analyze the efficiency of thermal power enterprises, which showed that the overall low efficiency of thermal power enterprises was mainly due to the low efficiency of pure technology and the overestimation of scale efficiency. In the second stage, three environmental variables were used to carry out SFA regression results on the input relaxation variables, which showed that environmental factors and random errors did have a great impact on the measurement results. In order to accurately evaluate the production efficiency of listed thermal power companies, environmental factors and random errors must be eliminated.

In the third stage, the input is adjusted according to the results of the two-stage regression analysis. The adjusted input data and raw output data were substituted for the BCC model, and the results were compared with the observations of the first phase. It was found that in the first stage, the scale efficiency of thermal power companies was overestimated, and pure technical efficiency was underestimated. According to the calculation results of the model, combined with the actual situation of production and operation of China's thermal power enterprises, it is concluded that the inefficiency of thermal power enterprises is caused by the accelerated market-oriented reforms and the lack of competitiveness of thermal power enterprises in the increasingly expanded market transactions, such as these: power generation costs are running at a high level, and profitability is not high, national environmental protection policies are tightening, and clean energy is taking up thermal power utilization hours, etc.

5.2. Suggestions

5.2.1. Speed up elimination of backward production capacity and optimize scale efficiency. Scale efficiency is the production efficiency affected by the scale factor of the enterprise. Some thermal power companies in China are large in scale but inefficient in production. Some of their generating units have a long production life, aging equipment and poor economic performance, which can no longer meet the national clean and efficient environmental protection requirements. The electricity production of these enterprises is greatly restricted and cannot produce better economic benefits. Cleaning up outdated production capacity and invalid assets of thermal power is an inevitable choice for thermal power companies to optimize asset allocation and achieve high-quality development. In addition, increasing the development and utilization of new energy supported by national policies, developing the comprehensive energy service and improving the proportion of clean energy are effective ways for thermal power companies to adapt to market-oriented reforms and optimize scale efficiency.
5.2.2. Improve technical efficiency through management innovation and technical optimization. Technical efficiency is the production efficiency influenced by management and technology. Thermal power companies can strengthen equipment management and fuel control, carry out technical transformation of existing assets such as ultra-clean emissions of coal power, energy-saving transformation, and cogeneration transformation. In addition, the companies can also carry out in-depth peak shaving to improve the flexible load capacity of the unit, and cut the generating costs by the flexible modification of blended burning transformation. All these are important means to promote the power supply of thermal power enterprises and improve the technical efficiency.

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