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Environmental efficiency in China's thermal power industry: Disparity, dynamic evolution and convergence

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ABSTRACT

The thermal power generation industry plays a crucial role in China's energy conservation and emission reduction strategy. To effectively assess the environmental efficiency of this industry, we utilize a super efficiency slacks-based measure directional distance function integrated model in this study. Additionally, we employ the Dagum Gini coefficient and its decomposition method, the spatial Markov chain method, and stochastic convergence test method to empirically analyze the disparities, distributed dynamic evolution, and convergence of environmental efficiency within China's thermal power industry. The study's findings reveal several key insights. Firstly, the overall environmental efficiency of the thermal power industry is improving, although regional disparities persist. Secondly, the gap in regional spatial distribution is decreasing, with inter-regional disparities being the primary source of the environmental efficiency gap in China. Thirdly, there is a significant spatial dependence in the environmental efficiency of China's thermal power industry. Lastly, the evolution of environmental efficiency within the thermal power industry follows a pattern of stochastic convergence. These results provide a strong basis for addressing the efficiency gap and contribute to enhancing the coordinated development of China's thermal power industry.

KEYWORDS

Environmental efficiency; Thermal power industry; Data envelopment analysis; Disparity; Stochastic convergence

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1. Introduction

China's steadfast commitment to achieving high-quality development, characterized by a balanced approach to economic growth and environmental preservation, has garnered significant attention (Song et al., 2014). In pursuit of this objective, the Chinese government has implemented a comprehensive framework of laws, regulations, and strategic objectives dedicated to safeguarding the ecological environment, accompanied by a suite of incentive policies (Wang et al., 2018a; Hu, 2012). As corroborated by the BP World Energy Statistical Yearbook 2021, China's electric power system stands as the largest on the global stage, contributing to 29% of the world's total power generation in 2020 (BP, 2021). Notably, the thermal power industry holds a predominant position within China's power generation sector (Wang et al., 2018b), which, consequently, contributed to approximately 14.29% of the world's total carbon emissions resulting from fossil fuel combustion in the same year (CIEEC, 2021). Regrettably, this has led thermal power plants to emerge as the primary culprits of air pollution in the country (Huang et al., 2017). Specifically, coal power generation accounts for a substantial 89.42% of the total thermal power generation (NBSC, 2021) and, in turn, is responsible for the release of considerable amounts of harmful pollutants, including carbon dioxide (CO2) and sulfur dioxide (SO2).

Enhancing environmental efficiency within the thermal power industry has become a matter of utmost significance and urgency. In this study, we commence by assessing the environmental efficiency through the implementation of the DEA (Data Envelopment Analysis) model. The DEA method serves as a popular tool for energy and environmental efficiency evaluations (Miao et al., 2021; Lv et al., 2021b; Halkos & Bampatsou, 2022). In this study, we propose the adoption of a super-efficiency SBM-DDF integrated model, which effectively addresses undesirable outputs, to evaluate the environmental efficiency of thermal power generation in China. This model is capable of distinguishing between efficient and inefficient outcomes, ultimately deriving super-efficiency results.

As of 2020, the top 7 out of 30 provinces, municipalities, and autonomous regions in China accounted for more than 50% of the total thermal power generation (China Energy Statistical Yearbook, 2020). Nonetheless, the impact of environmental regulation varies significantly across these different regions, as highlighted by Xie and Li (2021), Xie and Zhou (2022), and Chen et al. (2021). The power industry in China possesses unique characteristics, such as an uneven distribution of natural resources and a partial mismatch between power generation and demand (Yang et al., 2015; Wang et al., 2014). By decomposing the Gini coefficient, the uneven characteristics and patterns can be revealed (Lau & Koo, 2022; Costa, 2021). Thus, the objective of our study is to explore regional disparities and the spatial pattern of environmental efficiency in the thermal power industry across China.

The Dagum Gini coefficient (Dagum, 1997) is employed to gauge the level of inequality among different groups and to discern the contributions of various factors to the overall gap (Miao et al., 2021; Wang & Xu,

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2021; Lv et al., 2021a). In order to identify the primary causes of regional disparities in the thermal power industry, we utilized the Dagum Gini Index decomposition method. Additionally, the interplay between resource allocation, economic development, and the output, technology, and pollution of thermal power plants varies across regions in China (Wang & Feng, 2013). Disparities also exist in economic, political, and thermal power generation modes across different regions (Li et al., 2017; Xie et al., 2021; Chen et al., 2021), with each region experiencing a unique combination of production factors, population migration, technology, and knowledge diffusion (Wang et al., 2014; Qin et al., 2019; Wu & Hu, 2021).

To examine the impact of adjacent regions' efficiency levels on a province's efficiency and trend (Lv et al., 2021a; Wang & Xu, 2021), we employed the Spatial Markov chain (Quah, 1996; Rey, 2001). Investigating whether the environmental efficiency of thermal power generation in China is converging or diverging and whether external factors affect the efficiency level or necessitate self-regulation by the market or national regulation is crucial. Cui et al. (2022) utilized a convergence model to analyze the spatiotemporal heterogeneity of carbon emissions among regions, while Wang & Zhang (2021) observed that China's green development performance diverged through absolute β convergence and conditional β convergence methods. The stochastic convergence test is applied to determine whether there is stochastic convergence in the evolution of the environmental efficiency of China's thermal power generation industry. Understanding the convergence or divergence of environmental efficiency in thermal power generation among regions or provinces is essential for devising relevant policies.

This study makes distinctive and valuable contributions by bridging the research gap pertaining to environmental efficiency in China's thermal power industry. We achieve this by conducting a thorough analysis of regional disparities, spatial patterns, and trend evolution. Furthermore, we introduce a comprehensive and systematic approach for measuring environmental efficiency in the industry, utilizing an innovative super efficiency SBM-DDF integration model. This model enables a more robust evaluation of the industry's environmental performance.

The remainder of this paper is organized as follows. Section 2 introduces the related methods. Section 3 presents data. Section 4 elaborates the empirical study conducted in this study. Finally, Section 5 draws the conclusion.

2. Methods

2.1 Super efficiency SBM-DDF integration model

Charnes et al. (1978) introduced DEA with the assumption of constant returns to scale, while Banker et al. (1984) proposed a novel model, assuming variable returns to scale. However, these traditional DEA models have limitations as they overlook the slackness of variables and fail to account for all invalid DMUs. To address these shortcomings, Tone (2003) incorporated slack variables into the objective function, presenting

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a non-radial, non-directed SBM model that considered undesired outputs. Nonetheless, this model had the drawback of being unable to distinguish the effective decision-making units (DMUs) accurately, resulting in imprecise evaluation outcomes. Subsequently, Tran et al. (2019) introduced the OneSupSBM model to address this concern effectively. Nevertheless, the OneSupSBM model had two disadvantages: it did not consider undesirable outputs and solely focused on constant returns to scale (CRS) models. To overcome these limitations, this paper proposes an improved integration model that enhances the OneSupSBM model. The newly developed integrated model combines SBM-DDF with a super-efficiency SBM-DDF, offering a comprehensive and refined estimation of the thermal power industry's environmental efficiency across the 30 provinces under study.

2.1.1 SBM-DDF model

DMU_j is used to represent the set of decision-making units. The input and output elements of the set decision-making units are expressed as follows. The input N is $x=(x_1^t,x_2^t,\cdots,x_N^t)\in R_+^N$; the desirable output M is $y=(y_1^t,y_2^t,\cdots,y_M^t)\in R_+^M$; and the undesirable output K is $b=(b_1^t,b_2^t,\cdots,b_K^t)\in R_+^K$. The parameter (x_j^t,y_j^t,b_j^t) is the input-output data for the t period of the j^{th} region. The parameter (g^x,g^y,g^b) is a directional vector, with a strictly positive value. In this paper, the direction vector is set as (x,y,b) ; the parameter (s_n^x,s_m^y,s_k^b) is the slack vector of input, desirable output, and the undesirable output to reach the efficiency frontier, respectively.

$$
\begin{aligned}
&\min \delta_o = 1-\frac{1}{2N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x}-\frac{1}{2\ M+K}\left(\sum_{m=1}^{M}\frac{s_m^y}{g_m^y}+\sum_{k=1}^{K}\frac{s_k^b}{g_k^b}\right)\\
&s.t.\sum_{j=1}^{J}x_{nj}^t\lambda_j^t+s_n^x=x_{no}^t,\ \ n=1,\cdots,N\\
&\quad\ \sum_{j=1}^{J}y_{mj}^t\lambda_j^t-s_m^y=y_{mo}^t,\ \ m=1,\cdots,M\\
&\quad\ \sum_{j=1}^{J}b_{kj}^t\lambda_j^t+s_k^b=b_{ko}^t,\ \ k=1,\cdots,K\\
&\quad\ \sum_{j=1}^{J}\lambda_j^t=1\\
&\quad\ \lambda_j^t\geq 0, s_n^x\geq 0, s_m^y\geq 0, s_k^b\geq 0
\end{aligned}
\tag{1}
$$

The parameter λ_j^t is a non-negative vector. In this model, all input-output data are positive; that is,

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$x_{nj}^{t} > 0,\ y_{mj}^{t} > 0,\ b_{kj}^{t} > 0$. The target value is less than or equal to 1. The parameter $\delta_o^* = 1$ denotes a valid DMU; and $\delta_o^* < 1$ denotes an invalid DMU, which needs to be improved.

2.1.2 Super efficiency SBM-DDF model

$$
\begin{aligned}
&\min \rho_o = 1 + \frac{1}{2N}\sum_{n=1}^{N}\frac{z_n^x}{g_n^x} + \frac{1}{2\ M+K}\left(\sum_{m=1}^{M}\frac{z_m^y}{g_m^y} + \sum_{k=1}^{K}\frac{z_k^b}{g_k^b}\right) \\
&s.t. \sum_{j=1, j\neq 0}^{J} x_{nj}^t \lambda_j^t - z_n^x \le x_{no}^t, \quad n = 1, \cdots, N \\
&\quad \sum_{j=1, j\neq 0}^{J} y_{mj}^t \lambda_j^t + z_m^y \ge y_{mo}^t, \quad m = 1, \cdots, M \\
&\quad \sum_{j=1, j\neq 0}^{J} b_{kj}^t \lambda_j^t - z_k^b \le b_{ko}^t, \quad k = 1, \cdots, K \\
&\quad \sum_{j=1, j\neq 0}^{J} \lambda_j^t = 1, \quad j = 1, \cdots, J, \quad j \neq 0 \\
&\quad \lambda_j^t \ge 0,\ z_n^x \ge 0,\ z_m^y \ge 0,\ z_k^b \ge 0
\end{aligned} \tag{2}
$$

In these expressions, z_n^x, z_m^y, z_k^b are slack variables of input, desirable output, and undesirable output respectively. The parameter λ_j^t is a non-negative vector; and x_n^t, y_m^t, b_k^t represent decision variables of input, desirable output, and undesirable output, respectively.

2.1.3 Integration model

Combining our own work and the work of Tran et al. (2019), we generated the integrated model of SBM-DDF and super-efficient SBM-DDF. This model directly generates the efficiency score of invalid DMUs and the super efficiency score of effective DMUs by solving the one-stage model, as shown in Fig. 1.

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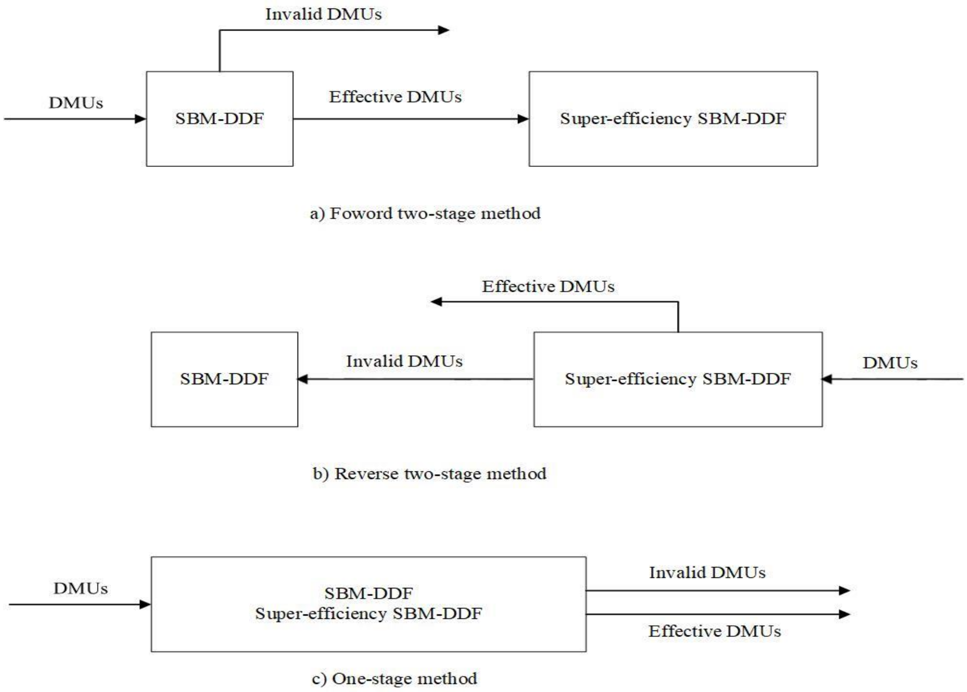

Figure 1 Explanation of the forward and reverse two-stage method and one-stage method

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The integration model is described as follows:

$$
\begin{aligned}
&\min \theta_o = \alpha\rho_0 + \ 1 - \alpha \ \ \delta_o \\
&s.t. : \frac{1}{2N}\sum_{n=1}^{N}\frac{z_n^x}{g_n^x} + \frac{1}{2 \ M+K}\left(\sum_{m=1}^{M}\frac{z_m^y}{g_m^y} + \sum_{k=1}^{K}\frac{z_k^b}{g_k^b}\right) \le \alpha\overline{M} \\
&\qquad \alpha \in \ 0;1 \\
&\qquad x_{no}^t = \sum_{j=1}^{J} x_{nj}^t \lambda_{1j}^t + s_n^x, \ n = 1,\cdots,N \\
&\qquad y_{mo}^t = \sum_{j=1}^{J} y_{mj}^t \lambda_{1j}^t - s_m^y, \ m = 1,\cdots,M \\
&\qquad b_{ko}^t = \sum_{j=1}^{J} b_{kj}^t \lambda_{1j}^t + s_k^b, \ k = 1,\cdots,K \\
&\qquad \sum_{j=1}^{J} \lambda_{1j}^t = 1, \ j = 1,\cdots,J \\
&\qquad \lambda_{1j}^t \ge 0, s_n^x \ge 0, s_m^y \ge 0, s_k^b \ge 0 \\
&\qquad x_{no}^t \ge \sum_{j=1, j\ne 0}^{J} x_{nj}^t \lambda_{2j}^t - z_n^x, \ n = 1,\cdots,N \\
&\qquad y_{mo}^t \le \sum_{j=1, j\ne 0}^{J} y_{mj}^t \lambda_{2j}^t + z_m^y, \ m = 1,\cdots,M \\
&\qquad b_{ko}^t \ge \sum_{j=1, j\ne 0}^{J} b_{kj}^t \lambda_{2j}^t - z_k^b, \ k = 1,\cdots,K \\
&\qquad \sum_{j=1, j\ne 0}^{J} \lambda_{2j}^t = 1, \ j = 1,\cdots,J, \ j \ne 0 \\
&\qquad \lambda_{2j}^t \ge 0, z_n^x \ge 0, z_m^y \ge 0, z_k^b \ge 0
\end{aligned}
\tag{3}
$$

In these expressions, $\overline{M}$ is a large positive number; and λ_{1j}, λ_{2j} are non-negative vectors of the SBM-DDF model and super-efficient SBM-DDF model, respectively. The objective function is used to measure the efficiency score of DMU, $\rho_0 = 1 + \frac{1}{2N}\sum_{n=1}^{N}\frac{z_n^x}{g_n^x} + \frac{1}{2 \ M+K}\left(\sum_{m=1}^{M}\frac{z_m^y}{g_m^y} + \sum_{k=1}^{K}\frac{z_k^b}{g_k^b}\right)$ for the super efficiency score of valid DMU, and $\delta_0 = 1 - \frac{1}{2N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x} - \frac{1}{2 \ M+K}\left(\sum_{m=1}^{M}\frac{s_m^y}{g_m^y} + \sum_{k=1}^{K}\frac{s_k^b}{g_k^b}\right)$ for the efficiency score of invalid DMU. In the objective function, we use the binary variable $\alpha \in \ 0;1$ to transform the efficiency measurement of the SBM-DDF model and the super-efficiency SBM-DDF model. If $\alpha = 1$, the super efficiency SBM-DDF

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model is selected to calculate the super efficiency score ρ_0 of valid DMU. If $\alpha = 0$, the SBM-DDF model is selected as the calculated efficiency score δ_0 of invalid DMU. Appendix explains how the one-stage integration model can adaptively identify the SBM-DDF model or the super-efficient SBM-DDF model based on the value of α.

2.2 Dagum Gini coefficient

In this paper, the Dagum Gini coefficient and its decomposition method were used to describe the regional disparities of environmental efficiency of China's thermal power industry in the six regions. According to Dagum (1997), the Gini coefficient is defined as:

$$G = \frac{\Delta}{2\bar{Y}} = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji} - y_{hr}\right|}{2n^2\bar{y}} \tag{4}$$

where G is the total Gini ratio; and Δ is the total Gini mean difference. For example, with respect to the environmental efficiency of thermal power generation, Δ is the mean value of the absolute value of every two levels of efficiency difference. Assume there are n provinces, divided into k subgroups (regions). Then, n_j (n_h) is the number of provinces in the $j^{th}(h^{th})$ subgroup (region). The parameter y_{ji} (y_{hr}) is the environmental efficiency of thermal power generation in $i^{th}(r^{th})$ province (or municipalities, autonomous regions) of the $j^{th}(h^{th})$ subgroup (region), $j = 1,2,...,k$, $h = 1,2,...,k$, $i = 1,2,...,n_j$, $r = 1,2,...,n_h$. The parameter $\bar{y}$ is the average value of environmental efficiency for the thermal power generation in all provinces of China.

Dagum (1997) described a new method for decomposing the Gini ratio, decomposing the ratio into three parts: the contribution of the gap within the subgroup G_w, the contribution of the gap between subgroups G_{nb}, and the contribution of hyper-variable density G_t. The relationship of the three parts satisfies $G = G_w + G_{nb} + G_t$. Before decomposing the Gini ratio, the first step is to rank the regions according to the mean environmental efficiency of thermal power generation in each subgroup (region): $\bar{Y}_h \leq \cdots \bar{Y}_j \leq \cdots \leq \bar{Y}_k$.

In this expression, $\bar{Y}_j, \bar{Y}_h$ represent the mean environmental efficiency of thermal power generation of the

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j^{th}, h^{th} subgroup (region), respectively.

Eq. (5) describes the Dagum decomposition method and calculation method in detail. The parameters G_{jj} and G_{jh} represent the Gini ratio within a subgroup and the Gini ratio between subgroups, respectively; and $\triangle_{jj}$ defines the mean difference of Gini ratio within j^{th} subgroup. Similarly, $\triangle_{jh}$ defines the mean difference of Gini ratio between j^{th} and h^{th} subgroups. According to Dagum (1997), the concept of economic prosperity, D_{jh} can be defined as the relative effectivity degree of thermal power environmental efficiency between j^{th} and h^{th} subgroups. The parameter d_{jh} is defined as the disparity of efficiency level between subgroups; it is the mathematical expectation of the sum of all $y_{ji} - y_{hr} > 0$ sample values between subgroups j^{th} and h^{th}. The parameter p_{jh} is defined as the super variable first-order distance, which is the mathematical expectation of the sum of all $y_{hi} - y_{jr} > 0$ sample values between subgroups j^{th} and h^{th}.

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$$
\begin{aligned}
& p_j = \frac{n_j}{n_J},\ s_j = \frac{n_j Y_j}{nY},\ j,h = 1,2,\ldots,k \\
& G_w = \sum_{j=1}^{k} G_{jj} p_j s_j \\
& G_{jj} = \frac{\Delta_{jj}}{2\overline{Y}_j} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h} \left| y_{ji} - y_{jr} \right|}{n_j^2} \\
& G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j) D_{jh} \\
& G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j)(1 - D_{jh}) \\
& G_{jh} = \frac{\Delta_{jh}}{\overline{Y}_j + \overline{Y}_h} \\
& \Delta_{jh} = d_{jh} + p_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h} \left| y_{ji} - y_{hr} \right|}{n_j n_h} \\
& D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}} \\
& d_{jh} = \int_0^\infty dF_j(y) \int_0^y (y - x) dF_h(x) \\
& p_{jh} = \int_0^\infty dF_h(y) \int_0^y (y - x) dF_j(y)
\end{aligned}
\tag{5}
$$

2.3 Spatial Markov chain

The Markov chain is mainly used to analyze the internal dynamics and evolution process of variables (Quah, 1996). In this study, a Markov transfer matrix was constructed to describe the dynamic evolution of the environmental efficiency level of thermal power generation in each region. The Markov chain is the state space of a random process $(X\ t\ , t \in T)$. We assume the random variable $X_t = j$; in other words, the system state in t period is j. Its value is a finite set; its spatial state is $I\{i, j, \cdots\}$; and the Markov chain of the system satisfies Eq. (6). This indicates that the probability that random variable X is in state j in period $t+1$ only depends on its state in period t.

$$
\begin{aligned}
& P\ \ X_{t+1} = j \mid X_0 = i_0, X_1 = i_1, X_2 = i_2, \cdots, X_{t-1} = i_{t-1}, X_t = i \\
& = P\ \ X_{t+1} = j \mid X_t = i \\
& = P_{ij}
\end{aligned}
\tag{6}
$$

We assume that P_{ij} is the transfer probability of the environmental efficiency of thermal power generation in a province from state i in year t to state j in year $t+1$. Using the maximum likelihood estimation

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method:

$$P_{ij} = \frac{n_{ij}}{n_i} \tag{7}$$

where n_{ij} refers to the number of all provinces in the sample period that are transferred from state i in year t to state j in year $t+1$; and n_i refers to the number of all provinces in state i throughout the sample period.

The transition of random variables from one state to another is called state transition. Assuming there is a total of k states, then we can construct a transition probability matrix of $k \times k$. Then, the state transition probability P_{ij} refers to the probability of transition from state i to state j. The $k \times k$ matrix of all P_{ij} is the state transition probability matrix P. The transition probability matrix is then used to determine the distribution dynamic evolution trend of each region in the economic system. The efficiency level of a region is affected by the efficiency level of neighboring regions, that is, the approximate values of random variables have an aggregation effect in space.

In this study, we applied the spatial Markov chain method, introducing the concept of spatial lag, to consider the spatial and geographical interaction effect of environmental efficiency of thermal power generation in China (Rey, 2001). The spatial lag value is the spatial weighting of the surrounding efficiency level of each province. We calculate the lag value based on the following equation:

$$F_r = \sum w_{sr} y_s \quad (s \neq r) \tag{8}$$

where F_r is the spatial lag value of province r; y_s is the efficiency value of province s; and W_{sr} is a spatial weight matrix. If other provinces border province r, then $w_{sr} = 1$; otherwise, $w_{sr} = 0$. The Spatial Markov chain decomposes the traditional $k \times k$ transfer probability matrix into the $k \times k \times k$ matrix. Therefore, P_{ij} becomes the probability of a province changing from t year state i to $t+1$ year state j in the case of spatial lag type k. This can reveal the impact of the space effect on the regional thermal power environmental efficiency gap.

2.4 Stochastic convergence test

China's thermal power generation industry is categorized as a traditional high-energy consumption sector, leading to the production of polluting gases such as carbon dioxide and sulfur dioxide. Prolonged and large-scale emissions of these pollutants exacerbate the greenhouse effect. The conventional development approach has inflicted significant environmental damage and deviates from the principles of sustainable development. Therefore, it is imperative to enhance the environmental efficiency of thermal power

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generation, curtail carbon emissions, and steer it towards a more sustainable trajectory that aligns with economic development, social stability, and environmental protection. However, achieving this convergence is challenging due to economic disparities among regions, varying resource endowments, and different economic development models, resulting in imbalanced environmental efficiency levels in thermal power generation across regions.

To evaluate the potential of long-term convergence and non-convergence in environmental efficiency, we employ the stochastic convergence method. The unit root test, initially proposed by Carlino et al. (1996) and Evans et al. (1996), serves as the primary methodology for examining the overall convergence of China's thermal power generation environmental efficiency at both national and regional levels.

The stochastic convergence needs to meet the following equation:

$$\lim_{k\to\infty} E_t \; y_{i,t+k} - \bar{y}_{t+k} \; = \mu_i - \frac{1}{n}\sum_{i=1}^{n}\mu_i , \quad i = 1,2,\cdots,n \tag{9}$$

In this study, two panel unit root test methods were utilized: the IPS test (IM, 2003) and the Hadri test (Hadri, 2000). The IPS test assumes that all series have unit roots, whereas the Hadri test presumes that all series are stationary. However, it is crucial to note that rejecting the original hypothesis based on the IPS test does not necessarily mean that all series are stable, and vice versa, rejecting the original hypothesis using the Hadri test does not imply that all series have unit roots. Relying solely on a single criterion as the test standard can jeopardize the reliability of empirical findings. To address this concern, Choi (2002) proposed the use of the confirmatory analysis (CA) method, which allows for a more robust conclusion by comparing results from various types of panel unit root tests. This approach can result in four potential situations, as outlined in Table 1, thereby enhancing the accuracy and credibility of our empirical findings.

Table 1 Situation and conclusions associated with the confirmatory analysis method

Situation	Test for rejection of assumptions	Conclusion
I	IPS test and Hadri test failed to reject the original hypothesis.	We cannot judge the stability of the sequence.
II	The IPS test rejects the hypothesis that the sequence possesses a unit root, while the Hadri test does not provide sufficient evidence to reject the original hypothesis that the sequence is stable.	Time series are stationary stochastic processes; that is, there is stochastic convergence among variables.
III	IPS test does not reject the possibility of a unit root for all series, while the Hadri test significantly rejects the original hypothesis of	All series have unit roots and there is random divergence among variables.

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	stationarity.	
IV	The IPS test and Hadri test both reject the original hypothesis.	This may be due to the random divergence or convergence of some series. The conclusion is not clear.

3. Data

In this study, we categorized the 30 provinces of China into six regions using the geographical divisions defined by the National Bureau of Statistics of the People's Republic of China in 2011 (see Fig. 2). The regions are as follows: North China, Northeast China, East China, Central China, Northwest China, and South China. The data used for analysis spanned from 2006 to 2015. However, due to missing data, we excluded Taiwan, Hong Kong, Macao, and Tibet from the study. The data were collected from the China Statistical Yearbook as our primary source.

Figure 2 China is divided into six areas for this study

The input, desirable output, and undesirable output were defined as follows:

(1) Input: Input variables include the labor force, installed capacity of thermal power generation, and energy consumption. Due to the unavailability of labor input data in the thermal power industry, labor in the power, heat, and supply industries, published in the 2007-2016 China Statistical Yearbook, were used in place of labor in the thermal power industry. Data on installed capacity of thermal power generation were collected

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from the China Power Yearbook. Fuels include coal, oil, and natural gas. Total energy consumption data were converted to standard coal. Data on coal, oil, and gas were collected from the China Energy Statistics Yearbook.

(2) Desirable output: The desirable output was thermal power generation. Power generation is the most important indicator of the power industry and reflects the operation efficiency of the power industry (Lam et al., 2001). This paper set the provincial thermal power generation as the expected output, and the data were collected from the China Energy Statistics Yearbook.

(3) Undesirable output: Undesired outputs included CO_2 and SO_2 emissions. The SO_2 emission data for the thermal power industry were collected from the annual report of China's environmental statistics[1]. There is no direct statistical monitoring data source on CO_2 emissions, so this paper used three kinds of fossil fuel (coal, oil and natural gas) consumption to calculate regional CO_2 emissions. The equation is as follows:

$$C_{it} = \sum E_{ijt} \times CEF_j \times COR_j \times \frac{44}{12} \tag{10}$$

where C_{it} represents the CO_2 emissions generated by the fuel required by the region i thermal power industry in year t. The parameter E_{ijt} represents the fuel consumption j of region i thermal power industry in year t. The parameter CEF_j is the carbon emission factor of fuel j; and COR_j is the carbon oxidation rate of fuel j. The data related to CEF_j and COR_j are shown in Table 2, which is consistent with Liu et al. (2016). Table 3 shows the descriptive statistics of input-output variables of China's thermal power industry from 2006 to 2015.

Table 2 Carbon emission factors and carbon oxidation rate associated with the consumption of three energy types

Type of energy consumption	Coal	Petroleum	Natural gas
Carbon emission factors (CEF)	0.75	0.58	0.44
Carbon oxidation rate (COR)	0.90	0.98	0.99

Note: the unit is 10000 tons of carbon / 10000 tons of standard coal.

[1] From 2016, the annual report of China's environmental statistics does not provide the data of SO_2 emission.

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Table 3 Descriptive statistics of input and output in 2006-2015

Variable	Input			Desirable Output	Undesirable Output	
	Labor	Installed capacity	Energy consumption	Thermal power generation	CO_2 Emissions	SO_2 Emissions
Mean	11.35	2466.04	3851.10	114.85	9462.96	27.81
Max	32.18	8754.00	14461.26	450.21	35822.20	93.31
Min	1.20	152.00	285.82	7.20	618.81	0.10
S.D.	6.05	1909.43	3053.32	92.86	7519.70	20.94

Note: the unit of installed capacity is 10,000 kW, the unit of labor force of thermal power is 10,000 persons, the energy consumption is expressed in 10000 tons of standard coal, the unit of power generation is TWH, and the unit of SO_2, CO_2 emissions is 10000 tons.

4. Empirical study

4.1 Environmental efficiency evaluation results

We applied the super efficiency SBM-DDF integration model to measure the environmental efficiency of China's thermal power industry in 2006-2015. We also analyzed the environmental efficiency levels and their changing trends in the six regions.

The box diagram in Fig. 3 displays the environmental efficiencies of thermal power industry in China's provinces from 2006 to 2015. Overall, the environmental efficiency levels were high for Shanghai (0.9264), Ningxia (0.9548), Beijing (0.9612), Tianjin (0.9632), Qinghai (0.9944) and Hainan (1.0000). This may be because there were fewer thermal power plants in these areas and the pollution caused by thermal power generation was small, or because the energy conservation and environmental protection measures taken in these areas were better. Therefore, with the same expected output, undesired output was less and efficiency was higher. These results closely relate to their significant development levels in the categories of the economy, society, technology and environmental protection. The environmental efficiency levels were lower for (0.5865), Liaoning (0.5806), Sichuan (0.4975), Inner Mongolia (0.3966), Guizhou (0.5068), Shandong (0.4504) and Henan (0.3847). This may be due to the early development of the thermal power industry in these regions, which mainly relied on traditional high-polluting power generation methods, resulting in excessive carbon dioxide and sulfur dioxide emissions and low environmental efficiency.

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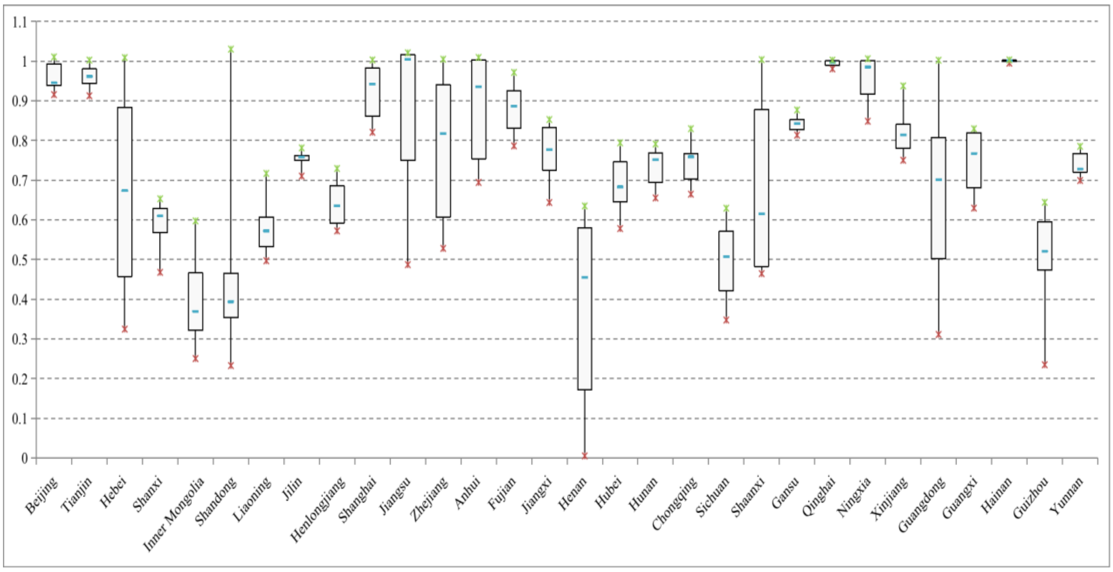

Figure 3 Environmental efficiency box diagram of the thermal power industry in the 30 provinces of China

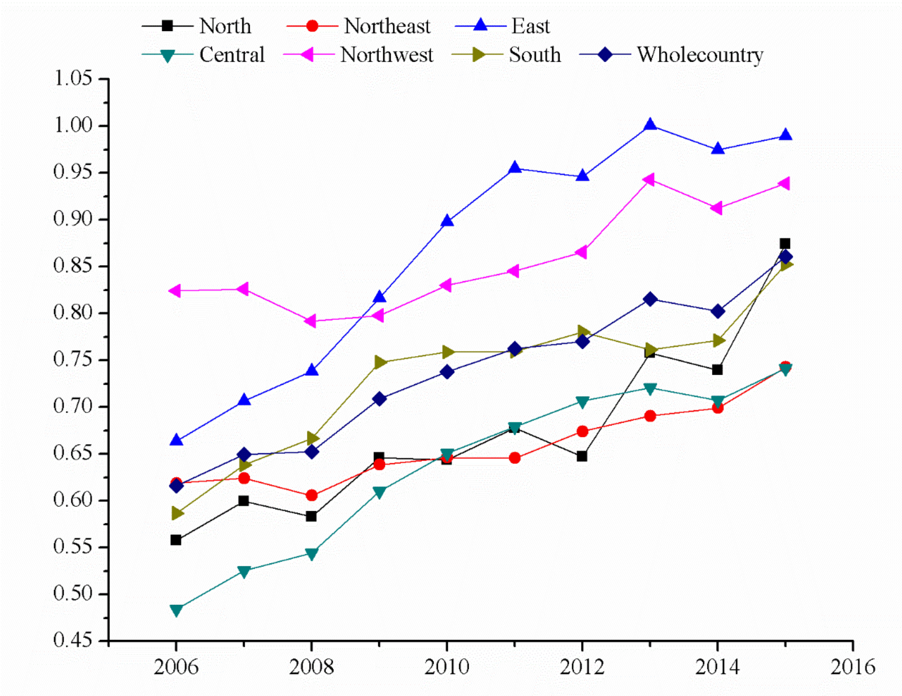

Figure 1 The changing trend in the environmental efficiency of the thermal power industry in the six regions of China from 2006 to 2015

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Fig. 4 shows the changing trend of environmental efficiency for the thermal power industry in six regions of China from 2006 to 2015. The overall environmental efficiency of the six regions showed an upward trend from 2006 to 2015, with as national average environmental efficiency value of 0.7376. From a regional perspective, the environmental efficiency value of the eastern region was the highest, at 0.8689, followed by the northwest region (0.8576), and the south region (0.7323). The indices for North China (0.6727), Northeast China (0.6585), and Central China (0.6370) were all lower than 0.7. The central region had the lowest index of all regions.

4.2 Regional disparity results

To identify the main sources of regional disparities, the Gini coefficient and decomposition method proposed by Dagum (1998) was used to calculate the environmental efficiency of thermal power generation in China from 2006 to 2015. The decomposition was done for six regions: North, Northeast, East, Central, Northwest, and South China. The calculation results are shown in Table 4.

Table 4 Dagum Gini coefficient and decomposition results of environmental efficiency

		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Total		0.191	0.175	0.165	0.139	0.141	0.153	0.138	0.132	0.127	0.111
Intra- group disparities	North	0.225	0.237	0.221	0.192	0.192	0.239	0.209	0.168	0.167	0.141
	Northeast	0.047	0.079	0.079	0.071	0.060	0.081	0.056	0.048	0.042	0.022
	East	0.085	0.071	0.058	0.044	0.049	0.035	0.032	0.009	0.019	0.019
	Central	0.189	0.156	0.168	0.138	0.118	0.079	0.095	0.102	0.088	0.081
	Northwest	0.117	0.117	0.107	0.097	0.089	0.072	0.071	0.043	0.064	0.035
	South	0.212	0.166	0.147	0.101	0.090	0.134	0.116	0.119	0.107	0.102
Inter-group disparities	N/NE	0.200	0.203	0.198	0.163	0.166	0.222	0.174	0.150	0.149	0.172
	N/E	0.188	0.188	0.189	0.168	0.197	0.203	0.204	0.160	0.156	0.097
	N/C	0.241	0.231	0.227	0.192	0.187	0.225	0.184	0.160	0.156	0.176
	N/NW	0.236	0.223	0.212	0.176	0.186	0.196	0.185	0.148	0.153	0.107
	N/S	0.230	0.211	0.210	0.176	0.183	0.214	0.191	0.154	0.153	0.137
	NE/E	0.089	0.091	0.103	0.122	0.165	0.203	0.178	0.203	0.181	0.162
	NE/C	0.149	0.145	0.143	0.128	0.107	0.085	0.084	0.092	0.077	0.068
	NE/NW	0.175	0.175	0.160	0.135	0.141	0.141	0.131	0.166	0.142	0.129
	NE/S	0.180	0.144	0.128	0.109	0.102	0.140	0.125	0.106	0.097	0.107
	E/C	0.165	0.149	0.148	0.142	0.164	0.183	0.159	0.186	0.178	0.165
	E/NW	0.138	0.126	0.099	0.078	0.077	0.076	0.067	0.038	0.055	0.038
	E/S	0.171	0.137	0.123	0.093	0.112	0.134	0.117	0.151	0.134	0.094
	C/NW	0.257	0.236	0.205	0.163	0.152	0.125	0.123	0.149	0.143	0.132
	C/S	0.225	0.184	0.177	0.146	0.121	0.131	0.122	0.119	0.108	0.118
	NW/S	0.217	0.183	0.157	0.115	0.113	0.114	0.105	0.129	0.116	0.086
Contribution rate	G_w	14.45	14.56	14.58	14.30	13.17	12.68	12.97	11.45	11.94	11.45
	G_{nb}	41.81	41.19	41.38	44.36	51.65	51.13	58.49	61.61	59.37	61.34
	G_t	43.74	44.25	44.04	41.34	35.18	36.19	28.54	26.94	28.68	27.22

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Note: “N” “NE” “E” “C” “NW” “S” refers to North China, Northeast China, East China, Central China, Northwest China, and South China, respectively. The unit of contribution rate is %.

4.2.1 Result of the overall regional gap

The data presented in Table 4 demonstrate a descending fluctuating trend in the overall Gini coefficient of China's thermal power generation environmental efficiency throughout the study period, with an average value of 0.147. Analyzing the changing trend, it is observed that from 2006 to 2009, the overall gap in China's thermal power generation environmental efficiency experienced a downward movement, particularly during 2008-2009, resulting in a decreased value of 0.026. Subsequently, from 2009 to 2010, there was an upward trend in the environmental efficiency of thermal power generation in China, followed by a year-to-year decrease in 2011 and 2015.

Fig. 5 provides a visual representation of the ten-year period from 2006 to 2015, illustrating that the maximum overall disparity in environmental efficiency of thermal power generation in China was recorded in 2006 with a value of 0.191, while the minimum value of 0.111 was observed in 2015. This indicates a substantial reduction of 72.2% in the overall disparity compared to 2006, highlighting a significant decline in regional disparities by the end of the study period.

The findings suggest that the overall disparity in environmental efficiency related to thermal power generation in China witnessed a considerable decrease over the course of the decade. Notably, the reduction in regional disparities became more pronounced in the later years, reflecting increased national attention to the environmental impact of thermal power generation.

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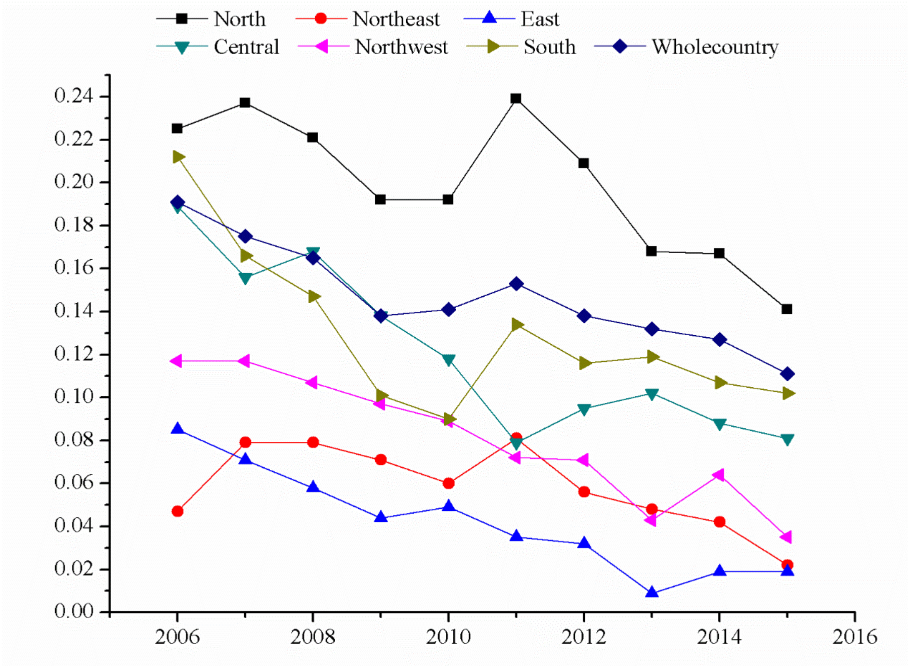

Figure 2 Intra-group disparities in emission efficiency

4.2.2 Results of intra-group disparity

Fig. 5 provides an overview of the trends in intra-group disparities among the six regions in China, revealing a general downward trend. Over the ten-year period from 2006 to 2015, eastern China exhibited the smallest gap in thermal power generation environmental efficiency, with an average value of only 0.042. This represents a substantial reduction of 77.7% and an annual decrease of 8.6%. In contrast, North China displayed the largest intra-group disparity, with an average value of 0.199. Although this region experienced a reduction of 37.3% in the gap and an annual decrease of 4.1%, it still maintained a higher average intra-group disparity compared to the national average of 0.147. This highlights the persistent issue of unbalanced development in North China. The low environmental efficiency of thermal power generation in Shanxi and Inner Mongolia in North China could be attributed to excessive emissions or underdeveloped thermal power generation technology.

The gaps in environmental efficiency of thermal power generation in Central China exhibited significant fluctuations, but the intra-group gap within this region experienced a total reduction of 57.4% and an annual decrease of 6.4%. Southern China saw a 52% overall reduction in the intra-group gap, with an annual decrease of 5.8%. Notably, the gap reached its minimum value of 0.09 in 2010.

In contrast, the intra-group gaps in thermal power generation environmental efficiency remained relatively

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stable in Northeast China and Northwest China. The gaps in these regions decreased by 53.4% and 70.1%, respectively, with an average annual decrease of 5.9% and 7.8%, respectively. Specifically, notable improvements were observed in the environmental efficiency of thermal power generation in provinces such as Liaoning, Heilongjiang, Shaanxi, Guangdong, Guangxi, and Guizhou. The disparities in efficiency levels can be attributed to differences in the scale of thermal power generation, varying policies for the adoption and promotion of new technologies in thermal power generation, and the level of attention given to environmental pollution caused by thermal power generation by the public and regional governments.

4.2.3 Results of inter-group disparity results

The environmental efficiency of thermal power generation in China exhibited a general downward trend during the study period, with an average value of 0.151. Among the regions, the inter-group disparity between Eastern and Northwest China was the lowest, with an average value of 0.079. The regional gap in environmental efficiency of thermal power generation in Eastern China experienced a significant downward trend throughout the study period, with a maximum average annual decrease of 8.1% and a total decrease of 72.5% over ten years. This can be attributed to the implementation of emission reduction policies, the development of green financial policies, and the adoption of clean energy sources, which led to the transformation and upgrading of the thermal power industry in the region and a reduction in the undesired outputs of thermal power generation, ultimately improving environmental efficiency.

Except for Shaanxi Province, the efficiency levels of other regions in Northwest China remained above 0.8, and Shaanxi Province witnessed a significant improvement in environmental efficiency over the study decade. Fig. 6 provides further insight into the regional gap and its evolutionary trend in thermal power generation environmental efficiency. The disparities in environmental efficiency between the listed regions exhibited a downward trend with fluctuations throughout the study period, except for the gap between the northeast and eastern regions. The data presented in Table 4 indicate that the regional disparity in thermal power generation environmental efficiency increased by 82% over the study decade, with an average value of 0.150 between Northeast and Eastern China, and an annual increase in the regional gap by 9.1%.

This result may be attributed to the implementation of emission reduction policies in the eastern region over the ten-year study period, resulting in a significant increase in environmental efficiency within the region. Throughout the study decade, the efficiency levels of Liaoning Province and Heilongjiang Province improved, except for Jilin Province. However, the rate of improvement was not as fast as in the eastern region, leading to an increasingly significant gap with the eastern region. Fig. 6 illustrates the disparity in the inter-group gap in environmental efficiency of thermal power generation, highlighting the uneven development levels between regions.

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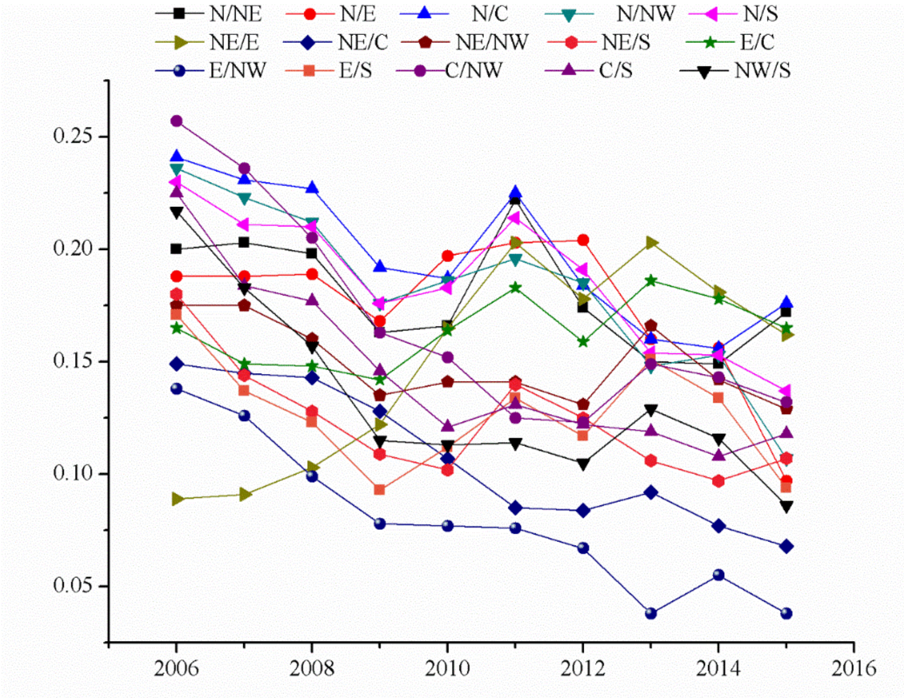

Figure 3 Inter-group disparities of environmental efficiency

4.2.4 Contribution analysis of regional disparity

Fig. 7 presents the sources of regional disparities in environmental efficiency regarding thermal power generation in China and the evolution of their contribution rates over the study period. The analysis reveals that the main driver of the gap is the inter-group disparity, accounting for an average contribution rate of 51.23%, which is more than three times higher than the contribution rate of the intra-group disparity at 13.15%. The contribution rate of the inter-group disparity exhibits a fluctuating upward trend, with an average annual growth of 5.19%. In contrast, the intra-group disparity and hyper-variable density display a downward trend. The contribution rate of the intra-group disparity decreases by 2.31% annually, while the contribution rate of the hyper-variable density decreases by 4.2% annually.

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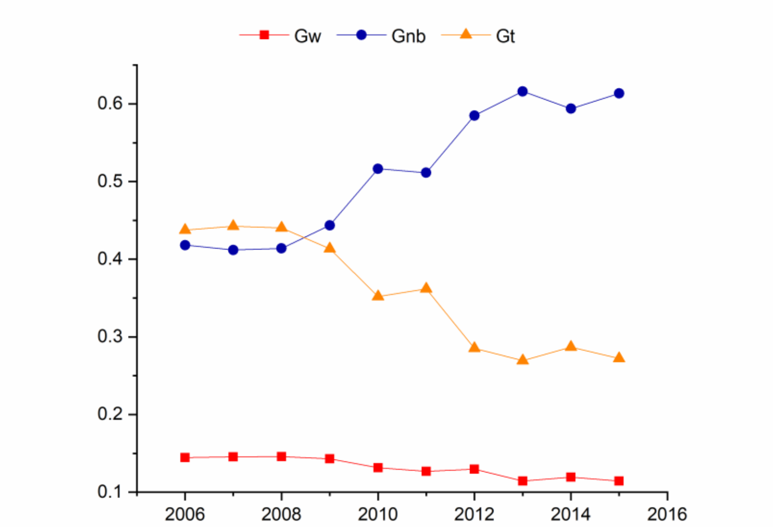

Figure 4. Contribution of regional disparities in environmental efficiency

Note: the contribution of the intra-group disparity G_w, the contribution of the inter-group disparity G_{nb}, and the contribution of hyper-variable density G_t.

These findings highlight that the disparity between groups is the primary driver of the overall regional disparity in environmental efficiency regarding thermal power generation in China. Therefore, reducing disparities between different groups is crucial for addressing regional imbalances. Moreover, the contribution rate of the hyper-variable density represents the impact of cross-term statistics on the overall efficiency disparity among the six subgroups (regions) in China. It reflects the contribution of the interaction between the disparity between groups and the disparity within groups to the overall efficiency disparities. The declining trend of the contribution rate of the hyper-variable density indicates that the interaction of disparities within and between groups gradually weakened over the study period.

4.3 Dynamic evolution results

4.3.1 Results of traditional Markov chain

We investigate the use of the traditional Markov chain and spatial Markov chain method to study the internal dynamics of environmental efficiency distribution of thermal power generation in China, and analyze the dynamic transfer characteristics of those efficiency levels. The study refers to the research ideas of Pu Ying-Xia, combined with the level of environmental efficiency of thermal power generation in China. The provinces in the previously defined six regions were divided into five types, listed in Table 5, according to their respective efficiency values (Qin et al., 2020): (1) lower than 0.50 (low efficiency level provinces – VL); (2) between 0.50 and 0.65 (low to medium efficiency level provinces - L); (3) between 0.65 and 0.80

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(medium efficiency level provinces - M); (4) between 0.80 and 0.95 (high efficiency level provinces - H); (5) greater than or equal to 0.95 (very high efficiency level provinces - VH).

Table 5 Classification of environmental efficiency

	VL	L	M	H	VH
Environmental efficiency of thermal power generation in China	<=0.50	0.50~0.65	0.65~0.80	0.80~0.95	>=0.95
Number of provinces met condition	42	54	80	62	62

Table 6 Markov chain transfer probability matrix of environmental efficiency

t/t+1	n_i	VL	L	M	H	VH
VL	42	0.667	0.310	0.000	0.000	0.024
L	49	0.082	0.694	0.204	0.000	0.020
M	74	0.014	0.014	0.770	0.176	0.027
H	55	0.000	0.000	0.091	0.709	0.200
VH	50	0.000	0.000	0.020	0.100	0.880

Table 6 presents the maximum likelihood estimation of the transfer probability of environmental efficiency in thermal power generation across different regions in China. The transfer stability and transfer path exhibit certain patterns. The elements on the main diagonal indicate the probability of a province maintaining its current efficiency level without any increase or decrease in the next period. The elements outside the main diagonal represent the probability of a province transitioning from its current state to another state. The findings from the Markov chain analysis in Table 6 yield the following results:

(1) The transfer probability on the main diagonal is relatively high. Provinces with medium and high environmental efficiency levels in thermal power generation have the highest probability of maintaining their previous efficiency levels, at 77% and 88% respectively. Provinces with other efficiency levels also have a probability of more than 65% of maintaining their previous levels. As a result, the overall distribution of environmental efficiency in thermal power generation across different regions remains relatively stable, with most provinces staying at their previous efficiency levels.

(2) Non-diagonal transfer probabilities are not all zero. Some probabilities are distributed on both sides of the diagonal, indicating that certain provinces may experience a transfer of environmental efficiency in thermal power generation to an adjacent level in two consecutive years.

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(3) Some off-diagonal transfer probabilities are scattered and not concentrated around the diagonal. This suggests significant changes in environmental efficiency of thermal power generation in certain provinces, indicating the possibility of multilevel transitions in environmental efficiency. For instance, 2.4% of provinces with a low efficiency level rapidly improve to a high efficiency level, 2% of provinces at the middle and low efficiency level quickly increase to a high efficiency level, 1.4% of provinces at the middle efficiency level drop to a low efficiency level, and 2.7% rapidly increase to a high efficiency level, while 2% of provinces at a high efficiency level decrease to a medium efficiency level.

(4) The probabilities of upward and downward non-diagonal transfers are asymmetric. In other words, the probability of an efficiency level improvement in the next year is significantly higher than the probability of a decline, particularly in the middle efficiency level, where the probability of upward transfer is more than 12 times higher than the probability of downward transfer.

These results indicate that in the later years of the study period, provinces in China made efforts to improve the environmental efficiency of thermal power generation, yielding some positive outcomes. However, the traditional Markov chain analysis does not consider the spatial interaction between regions and does not explain the spatial mechanism of regional efficiency convergence or divergence.

4.3.2 Result of spatial Markov chain

Table 7 presents a spatial Markov chain transfer matrix that incorporates the spatial lag effect, allowing for an exploration of the influence of neighboring provinces' efficiency environment on the environmental efficiency level of regional thermal power generation. The specific features observed are as follows:

(1) The neighboring environment significantly impacts the environmental efficiency of regional thermal power generation. In the spatial Markov matrix, the probabilities on the main diagonal are notably higher than those in other positions. This suggests that, when considering the neighbor environment, the environmental efficiency of thermal power generation in China demonstrates a high level of club stability throughout the research period. This matrix differs significantly from the traditional Markov matrix, further confirming the substantial influence of the neighbor environment on regional economic development. Table 7 reveals that neighbors have the most significant impact on a specific region when the efficiency level is high. When neighboring regions exhibit high efficiency levels, samples tend to remain at medium or high efficiency levels without transitioning. When the neighbor has a low efficiency level, there is a 22.2% probability of an upward transfer from a low efficiency level and a 28.6% probability from a low-middle efficiency level. The probability of upward and downward transfers from the medium efficiency level is 7.1%, suggesting the occurrence of cross-regional transfers. Furthermore, there is a 20% probability of a downward jump from the high efficiency level.

(2) Spatial correlation plays a crucial role in the environmental efficiency of thermal power generation. The probability of an upward transfer from a low efficiency level to adjacent regions with low or low-middle efficiency levels is 22.2% and 35.7%, respectively. When neighboring regions exhibit a high level of

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environmental efficiency in thermal power generation, the probability of an upward transfer from a low efficiency level region is highest, reaching 60%. In the traditional Markov chain, the maximum probability of an upward transfer from a low-efficiency area is 31%, significantly lower than in the spatial Markov chain. This highlights the important role of spatial correlation in the environmental efficiency of regional thermal power generation. Regions with low environmental efficiency in thermal power generation can enhance their efficiency more effectively when surrounded by a more developed regional environment.

(3) The neighbor environment also exerts some influence on regions with a high level of efficiency in thermal power generation. Table 7 reveals that, when adjacent regions have a low or medium-low efficiency environment, the region with a high efficiency level experiences the largest probability (20%) of a downward transfer compared to other neighbor environments. This value is also higher than the probability of a high efficiency level transitioning to a low efficiency level or a low-medium efficiency level in the traditional Markov matrix. This indicates that the neighbor environment also impacts regions with a high efficiency level.

Overall, these findings demonstrate that the neighbor environment significantly affects the environmental efficiency of thermal power generation in regions. Spatial correlation and the efficiency levels of neighboring regions play important roles in determining the upward or downward transfers of efficiency levels.

Table 7 Transfer probability matrix of the spatial Markov chain for environmental efficiency

Lag value	t/t+1	n_i	VL	L	M	H	VH
	VL	9	0.778	0.222	0	0	0
	L	7	0	0.714	0.286	0	0
VL	M	14	0.071	0.071	0.714	0.071	0.071
	H	0	0	0	0	0	0
	VH	5	0	0	0	0.200	0.800
	VL	14	0.643	0.357	0	0	0
	L	18	0.056	0.611	0.278	0	0.056
L	M	30	0	0	0.900	0.100	0
	H	12	0	0	0	0.833	0.167
	VH	5	0	0	0.200	0.200	0.600
	VL	14	0.786	0.214	0	0	0
	L	19	0.105	0.789	0.105	0	0
M	M	18	0	0	0.833	0.167	0
	H	23	0	0	0.043	0.739	0.217
	VH	21	0	0	0	0.095	0.905
H	VL	5	0.200	0.600	0	0	0.200

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	L	5	0.200	0.600	0.200	0	0
	M	12	0	0	0.417	0.500	0.083
	H	19	0	0	0.211	0.579	0.211
	VH	15	0	0	0.000	0.067	0.933
VH	VL	0	0	0	0	0	0
	L	0	0	0	0	0	0
	M	0	0	0	0	0	0
	H	1	0	0	0	1	0
	VH	4	0	0	0	0	1

4.4 Stochastic convergence test

The confirmatory analysis provides a more cautious explanation for the panel unit root test results, and generates a more robust conclusion. Therefore, Stata 15 was used for the analysis, using the confirmatory analysis method to assess whether there is stochastic convergence in the environmental efficiency with respect to thermal power generation in China.

4.4.1 Global random convergence test

Rejection of the null hypothesis of convergence for the whole panel does not rule out the existence of convergence in subgroups of the panel (Du, 2017). Table 8 shows that, even at the 10% significance level, the IPS test still rejects the original hypothesis of the unit root, and Hadri test significantly rejects the original hypothesis of stationarity. This belongs to the fourth case in confirmatory analysis, which indicates that the confirmatory analysis does not prove the existence of global random convergence trend and divergence trend, relative to the national average. This may be due to the random divergence of partial series and the random convergence of partial series.

Table 8 Confirmatory analysis results

Region	IPS	Prob	Hadri	Prob	CA result
All of China	-8.2159	0	7.2445	0	IV
North	-4.4665	0	0.9859	0.1621	II
Northeast	-2.3513	0.0094	1.3173	0.0939	IV
East	-2.8382	0.0023	3.4968	0.0002	IV

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Central	-4.8473	0	3.9030	0	IV
Northwest	-3.0905	0.0010	1.8437	0.0326	IV
South	-2.1712	0.0150	3.6282	0.0001	IV

We further applied the ADF, PP, and KPSS univariate unit root test methods to determine whether there is a convergence trend with respect to thermal power environmental efficiency in some provinces. Table 9 indicates that, according to the ADF test results, among the 30 provinces investigated, data for only 7 provinces reject the original hypothesis of the unit root. Of these, Shandong, Henan, Gansu, Qinghai Ningxia and Guangdong show significant results at a 1% significance level; and Xinjiang shows significant results at a 10% significance level. The environmental efficiency sequence of thermal power generation in the other 23 provinces do not reject the original hypothesis of the unit root.

Table 9 Univariate unit root test

Province	ADF	PP	KPSS	Province	ADF	PP	KPSS
Beijing	-0.168	-2.069	0.133*	Henan	-4.819***	-7.648***	0.148**
Tianjin	-1.847	-2.496	0.115	Hubei	-1.986	-2.672	0.0805
Hebei	-1.543	-2.611	0.116	Hunan	-0.183	-1.300	0.140*
Shanxi	-1.428	-1.700	0.0914	Chongqing	-2.196	-2.646	0.0967
Inner Mongolia	-0.921	-2.019	0.101	Sichuan	-0.841	0.7451	0.120*
Shandong	-5.601***	-2.871	0.0842	Shaanxi	-2.211	-2.345	0.102
Liaoning	-0.147	-2.707	0.145*	Gansu	-4.163***	-2.625	0.089
Jilin	-2.279	-10.954***	0.0576	Qinghai	-8.841***	-2.634	0.058
Heilong-jiang	-2.239	-3.749**	0.0807	Ningxia	-7.157***	-1.798	0.123*
Shanghai	-0.465	-1.677	0.123*	Xinjiang	-3.354*	-4.373***	0.0736
Jiangsu	-2.180	-1.088	0.139*	Guangdong	-8.083***	-2.242	0.124*
Zhejiang	-0.230	-1.326	0.130*	Guangxi	-0.144	-1.809	0.111
Anhui	-0.523	-1.162	0.126*	Hainan	-0.445	-2.888	0.117
Fujian	-1.852	-1.422	0.114	Guizhou	-2.890	-3.074	0.118
Jiangxi	-0.441	-0.627	0.142*	Yunnan	-1.178	-1.623	0.107

For the PP test, among the 30 provinces investigated, only 4 provinces rejected the original hypothesis of the existence of the unit root. Of these, the results for Jilin, Henan and Xinjiang show significance at a 1%

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significance level; and Heilongjiang shows significance at a 5% significance level. However, the environmental efficiency series of thermal power generation in other 25 provinces do not reject the original hypothesis of unit root.

For the KPSS test, of the 30 provinces investigated, 12 provinces did not meet the original hypothesis of stationarity; 18 provinces met the original hypothesis of stationarity, including Anhui, Beijing, Chongqing, Guangdong, Henan, Hunan, Jiangsu, Jiangxi, Liaoning, Ningxia, Shanghai and Zhejiang. These tests indicate that if the global random divergence of regions given in the confirmatory analysis is not determined, there may still be stochastic convergence of environmental efficiency with respect to thermal power generation in some provinces. In other words, global random divergence cannot negate the possibility of convergence subset.

4.4.2 Club identification based on stochastic convergence

In this study, the regional means of the six regions were used as benchmarks to assess the random convergence of each region. Table 8 presents the results, indicating that, at a 10% statistical significance level, the IPS test did not reject the possibility of unit roots in all series. Conversely, the Hadri test rejected the original hypothesis of stationarity, falling into the third case of confirmatory analysis. This implies that provinces exhibit random divergence in relation to their regional means. For North China, the IPS test rejected the original hypothesis of unit roots, while the Hadri test did not reject the hypothesis of stationarity for all series. This falls under the second case of confirmatory analysis, suggesting that all time series are stationary random processes, and the regional mean value of each province reflects stochastic convergence.

However, both the IPS test and Hadri test in the northeast, eastern, central, northwest, and southern regions rejected the original hypothesis, placing them in the fourth case of confirmatory analysis. This suggests the possibility of random divergence and convergence in some series. In the evolutionary process of environmental efficiency in thermal power generation in China, it is possible to form random convergence clubs. The convergence clubs within other regions require further identification.

The sequential analysis method used by Choi (2002) for identifying random convergence subsets has certain limitations. For instance, the selection of the initial prior information set is subjective. To address these limitations, a full subset analysis path is employed to identify the convergence clubs of environmental efficiency in thermal power generation within each region. The subsequent tables present the identification results of random convergence clubs at a 10% statistical significance level in five regions.

Table 10 reveals that the subset consisting of Shanghai, Zhejiang, and Anhui in the eastern region tends to converge towards its regional mean. The addition of other provinces to this subset would disrupt its convergence. Table 11 shows that Jiangxi, Hubei, Hunan, Chongqing, and Sichuan constitute a random convergence subset within the central region. Table 12 demonstrates that Gansu, Qinghai, and Xinjiang form a random convergence subset within the northwest region. Table 13 highlights that Guangdong and Hainan form a random convergence subset within the southern region. Lastly, Table 14 indicates that Jilin and

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Heilongjiang form a random convergence subset within the Southeast region.

In conclusion, the evolutionary process of environmental efficiency in thermal power generation in China exhibits a stochastic convergence club, and there may be convergence subsets within regions that experience random divergence.

Table 10 Results of random convergence club test in Eastern China

Region	P-IPS	P-Hadri	CA	Region	P-IPS	P-Hadri	CA
E1	0.0023	0.0002	IV	E6=E1-Shanghai	0.2002	0.0003	III
E2=E1-Fujian	0.2374	0.0002	III	E7=E2-Anhui	0.5062	0.0000	III
E3=E1-Anhui	0.5311	0.0000	III	E8=E3-Fujian	0.5062	0.0000	III
E4=E1-Zhejian	0.4195	0.0000	III	E9=E4-Fujian	0.7192	0.0000	III
E5=E1-Jiangsu	0.1491	0.0719	III	E10=E5-Fujian	0.0399	0.4678	II

Note: E1 includes Shanghai, Jiangsu, Zhejiang, Anhui and Fujian

Table 11 Results of random convergence club test in Central China

Region	P-IPS	P-Hadri	CA	Region	P-IPS	P-Hadri	CA
C1	0.0000	0.0000	IV	C5=C1-Hubei	0.0000	0.0002	IV
C2=C1-Sichuan	0.0005	0.0000	IV	C6=C1-Hunan	0.0000	0.0002	IV
C3=C1-Chongqing	0.0000	0.0002	IV	C7=C1-Henan	0.0004	0.2246	II
C4=C1-Jiangxi	0.0000	0.0001	IV				

Note: C1 includes Jiangxi, Henan, Hubei, Hunan, Chongqing and Sichuan

Table 12 Results of random convergence club test in Northwest China

Region	P-IPS	P-Hadri	CA	Region	P-IPS	P-Hadri	CA
W1	0.0010	0.0326	IV	W5=W1-Shaanxi	0.0087	0.0457	IV
W2=W1-Xinjiang	0.0169	0.0168	IV	W6=W5-Xinjiang	0.0033	0.0024	IV
W3=W1-Ningxia	0.1551	0.1566	I	W7=W5-Ningxia	0.0087	0.5056	II
W4=W1-Qinghai	0.1492	0.0103	III				

Note: W1 includes Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang

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Table 13 Results of random convergence club test in Southern China

Region	P-IPS	P-Hadri	CA	Region	P-IPS	P-Hadri	CA
N1	0.0150	0.0001	IV	N6=N1-Guangdong	0.0796	0.0004	IV
N2=N1-Yunnan	0.0013	0.0037	IV	N7=N4-Yunnan	0.0043	0.0052	IV
N3=N1-Guizhou	0.0000	0.0023	IV	N8=N4-Guangxi	0.1405	0.0020	III
N4=N1-Hainan	0.0244	0.0021	IV	N9=N8-Guizhou	0.0000	0.0053	IV
N5=N1-Guangxi	0.0011	0.0005	IV	N10=N8-Yunnan	0.0000	0.3847	II

Note: N1 includes Guangdong, Guangxi, Hainan, Guizhou and Yunnan

Table 14 Results of random convergence club test in Southeast China

Region	P-IPS	P-Hadri	CA	Region	P-IPS	P-Hadri	CA
S1	0.0094	0.0939	IV	S6=S1-Jilin	0.1232	0.2131	I
S5=S1-Heilongjiang	0.0655	0.0336	IV	S10=S8-Liaoning	0.0251	0.4220	II

Note: S1 includes Liaoning, Jilin and Heilongjiang

5. Conclusions and policy implication

This study presents a novel approach by introducing a super efficiency SBM-DDF integrated model to accurately distinguish decision-making units and calculate the environmental efficiency of thermal power generation in 30 provinces of China from 2006 to 2015. The analysis utilizes various methods such as the Dagum Gini coefficient and its decomposition method, spatial Markov chain, and a stochastic convergence test to examine efficiency levels, spatial dynamics, convergence patterns, and regional disparities in China's thermal power industry.

The key findings of the study are as follows. Firstly, the environmental efficiency of thermal power generation across the six regions of China exhibited steady growth over the study period, with the eastern region being the most efficient. Secondly, the overall Gini ratio of China's thermal power generation environmental efficiency demonstrated a general downward trend with slight fluctuations, averaging at 0.147. Notably, the intra-group disparity in the eastern region experienced the most significant decline, with an average annual rate of 8.6%. On the other hand, the intra-group disparity in North China showed the least reduction, with an average annual rate of 4.1%. The main driver of regional disparities in environmental efficiency was the inter-group disparity. Thirdly, the analysis of the spatial dynamic evolution pattern using the spatial Markov chain revealed a significant spatial dependence and notable spatial imbalance in the environmental efficiency of thermal power generation in China. Lastly, the study identified the existence of

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a stochastic convergence club in the evolution of environmental efficiency, particularly in North China where the efficiency tended to converge towards a common mean value. Convergence subsets were also observed in other regions characterized by random divergence or where convergence or divergence could not be definitively determined.

To promote balanced regional development in thermal power generation environmental efficiency, it is crucial to consider the unique characteristics and circumstances of each region. Strengthening multilateral technical cooperation and exploring the full potential of thermal power generation environmental efficiency in each region are essential. Regions should leverage their specific industry and resource advantages while fostering cooperation and exchanging technological innovations with neighboring provinces. By doing so, the overall growth of thermal power environmental efficiency can be facilitated.

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