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The Relationship Between Production Efficiency and Factor Allocation Efficiency: A Case Study Based on Thermal Power in China

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Abstract: This paper introduces a novel decomposition method for analyzing production efficiency based on the Data Envelopment Analysis framework, addressing the limitations of traditional approaches that often fail to isolate the contributions of individual factors. The proposed method disaggregates production efficiency into capacity utilization, labor utilization efficiency, energy utilization efficiency, and technological change, providing a more granular view of how different factors contribute to overall efficiency. By incorporating both contemporaneous and intertemporal perspectives, this approach enables a comprehensive understanding of efficiency dynamics and factor interactions over time. To demonstrate the feasibility and robustness of the proposed method, we apply it to the thermal power industry using data from 30 Chinese provinces covering the period from 2011 to 2021. The empirical results validate the effectiveness of the decomposition framework, revealing distinct regional disparities in efficiency and providing insights for targeted resource optimization strategies. Based on these findings, we offer recommendations to enhance capacity utilization, improve energy efficiency, and support sustainable development within the thermal power sector. This research contributes a powerful analytical tool for disaggregating production efficiency and offers a theoretical foundation for future studies seeking to understand the nuanced relationships between comprehensive production efficiency and single-factor efficiencies, thereby supporting better policy and management decisions in complex production systems.

Keywords: production efficiency; data envelopment analysis; decomposition method; distance function; efficiency of factor allocation

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1. Introduction

In recent years, the global pursuit of sustainable development and resource optimization has intensified the need for more efficient production systems. Traditional resource allocation strategies typically focus on sectors with higher efficiency, using measures such as total factor productivity (TFP) [1,2] and production efficiency (PE) [3–5]. These metrics, while valuable, often lack the granularity needed to address the distinct contributions of individual factors like capacity, labor, and energy. Although previous studies have made significant progress in measuring overall efficiency and specific single-factor efficiencies [6,7], the complex relationship between comprehensive production efficiency and individual factor efficiencies remains underexplored, particularly in terms of how these efficiencies interact and influence one another.

This gap presents a crucial opportunity for further investigation. Understanding how single-factor efficiencies, such as energy and labor efficiency, contribute to comprehensive PE can provide deeper insights for policymakers and industry stakeholders. Specifically, a decomposition of PE into its core components allows for the identification of bottlenecks and areas for targeted improvement, offering a pathway to more efficient resource utilization and sustainable economic growth.

The primary motivation behind this study lies in addressing this gap by developing a mathematical framework that links PE with the efficiency of resource allocation. This decomposition method not only disaggregates PE into its constituent elements—capacity utilization, labor efficiency, and energy efficiency—but also accounts for the impact of technological change over time. By applying this approach to the thermal power sector in China, we aim to demonstrate how a detailed understanding of PE can drive improvements in energy efficiency, support low-carbon development, and contribute to green, sustainable industrial growth.

The innovation of this research lies in the introduction of a novel decomposition method based on Data Envelopment Analysis (DEA), which allows for the precise disaggregation of production efficiency. Unlike traditional approaches that focus on aggregate measures, our method offers a more nuanced analysis by isolating the contribution of each factor to overall efficiency. This approach provides practical insights for policymakers aiming to optimize resource allocation across different sectors, particularly in industries facing capacity constraints and energy challenges.

This paper utilizes thermal power industry data from 30 provinces in China, comprising a total of 330 samples covering the period from 2011 to 2021. This paper is organized as follows: Section 1 presents the introduction; Section 2 reviews the relevant literature; Section 3 outlines the theoretical model and details the proposed decomposition method; Section 4 discusses the data sources and case studies; Section 5 presents the empirical results, focusing on the decomposition outcomes in the thermal power industry; Section 6 provides a discussion, highlighting the differences in our method compared to existing studies; and Section 7 concludes the research. To enhance clarity, a list of abbreviations used in this paper is provided in Table 1.

Table 1. Abbreviation table.

Abbreviation	Full Name
DEA	Data Envelopment Analysis
DMU	Decision-making unit
SDA	Structural Decomposition Analysis
PDA	Production Theoretic Decomposition Analysis
LMDI	Logarithmic Mean Divisia Index
SFA	Stochastic Frontier Analysis
TFEE	Total factor energy efficiency
CCR	Charnes, Cooper, and Rhodes
BCC	Banker, Charnes, and Cooper
EU	Equipment utilization
EC	Efficiency change
TC	Technical change
SEC	Scale efficiency change
PE	Production efficiency
CU	Capacity utilization
LUE	Labor utilization efficiency
EUE	Energy utilization efficiency

Through this study, we aim to bridge the gap between economic theory and practical application, providing both a robust analytical tool and valuable guidance for enhancing production efficiency. Our findings are expected to have wide-ranging implications, from macroeconomic management to enterprise-level decision-making, contributing to more resilient and sustainable production systems.

2. Literature Review

2.1. Methods of Measuring Production Efficiency

Currently, methods for measuring production efficiency both domestically and internationally can be categorized into parametric and non-parametric approaches. The former includes techniques such as Cobb–Douglas production function regression, Solow residual calculation, and stochastic frontier production function analysis, while the primary non-parametric method is Data Envelopment Analysis. Originally proposed by Charnes et al. [8], DEA has evolved into an effective methodology for evaluating the performance of decision-making units (DMUs) and has been widely applied in various fields such as efficiency assessment in commercial banks [9], efficiency measurement in high-tech industries [10], and handling probabilistic linguistic information [11].

DEA is particularly noted for two main features [12]. First, it does not require any prior assumptions about the specific relationships between inputs and outputs for each DMU. This characteristic allows for flexibility in evaluating units with different operational contexts without the constraint of a predefined model structure. Second, DEA accommodates scenarios in which individual DMUs operate with multiple inputs and outputs. This capability is crucial for accurately assessing the performance of organizations or sectors where multiple factors contribute to the production process, allowing for a more holistic and comprehensive evaluation. These attributes have significantly contributed to DEA's widespread adoption and its reputation as a robust tool for performance evaluation across diverse contexts and industries.

In recent years, DEA research has seen several important methodological advancements and application expansions. For example, Zhu (2022) [12] proposed a network DEA framework that integrates big data analytics to better capture complex interconnections in transportation and logistics systems. Similarly, Yu et al. (2022) [13] applied a dynamic network DEA to measure the innovation performance of Chinese high-tech firms, considering multi-stage processes and time dynamics. Additionally, the application of robust network DEA by Peykani et al. (2024) [14] introduced robust optimization techniques to handle uncertainty in mutual fund performance evaluation, enhancing the model's discriminatory power. Tayal et al. (2023) [15] developed an integrated DEA-ML model for sustainable facility layout optimization, while Huang et al. (2024) [16] introduced an improved slack-based game cross-efficiency model to account for competitive relationships and undesirable outputs, achieving a fairer and more precise efficiency measurement through a Nash equilibrium solution.

Other studies have focused on integrating DEA with hybrid approaches to address more specialized problems. Dahooie et al. (2023) [17] combined DEA with dynamic multi-attribute decision-making to improve credit risk evaluation, while Ben Lahouel et al. (2023) [18] employed DEA for assessing corporate social performance, linking it to financial performance through dynamic panel models. Fenger Wu et al. [19] combined convolutional neural networks to create a new measurement of carbon emission performance. Koohathongsumrit and Meethom (2024) [20] applied a fuzzy DEA model for risk assessment in transportation networks, combining it with multiple-criteria decision-making methods.

In general, the wide application of DEA makes it an important method to measure efficiency. Therefore, this paper uses the DEA model to measure production efficiency.

2.2. Methods of Measuring Factor Allocation Efficiency

Efficiency in factor allocation is typically assessed using metrics such as capacity utilization (CU), labor productivity, and total factor energy efficiency (TFEE).

(1) There are various methods for measuring capacity utilization, including the survey method [21], production function approach [22], cost function approach [23], peak-load method [24], cointegration approach [25], stochastic frontier analysis (SFA) [26], and DEA [27]. Among these, only the DEA model, as proposed by Fare et al., directly establishes a link between technical efficiency and capacity utilization. The other methods generally involve estimating the maximum potential output and then calculating the ratio of actual output to the maximum potential output. Due to its direct approach and comprehensive framework, the DEA method has been widely adopted for evaluating capacity utilization.

Researchers such as Ray [28] and Aripin et al. [18] have applied the DEA method to measure CU in the U.S. manufacturing industry and the Malaysian barramundi aquaculture industry, respectively. Furthermore, Subhash C. Ray et al. [29] integrated the cost function approach with DEA to develop a new model for measuring CU, which effectively accommodates scenarios involving multiple fixed inputs and outputs. This integration offers a more flexible and precise framework for assessing capacity utilization across various industries.

(2) There are various methods for measuring labor productivity, including but not limited to the following approaches:

1. Simple Ratio Method: This is the most straightforward method, which involves analyzing the ratio of output to labor input (e.g., number of workers or total hours worked) to obtain the average output per unit of labor [30]. Although this method is easy to implement, it fails to effectively capture the contributions of different influencing factors.
2. Growth Accounting Method: This method, derived from the Solow model (Solow, 1957), decomposes labor productivity into contributions from technological progress, human capital, and capital input, allowing for the identification of the impact of various factors on labor productivity enhancement [31].
3. DEA: DEA is a non-parametric method that effectively measures the relative efficiency of different production units [32].
4. Logarithmic Mean Divisia Index (LMDI): LMDI is a multi-index decomposition method that enables perfect decomposition and time reversibility when analyzing productivity changes [33,34]. LMDI can disaggregate changes in labor productivity into several factors such as land productivity, labor intensity, and inter-regional resource allocation.

Among these, we find that DEA can also be applied to measure labor productivity, presenting a potential approach for analyzing labor utilization efficiency.

(3) Single-factor energy efficiency, defined intuitively and applied easily, is widely used to calculate and compare energy efficiency differences and influencing factors between countries [35,36], regions [37], and industries [38,39]. Despite its widespread application, the accuracy and rationality of single-factor energy efficiency metrics, such as energy intensity—which are crucial for assessing the stringency of energy policies—are questioned. Firstly, single-factor energy efficiency metrics do not compare optimal consumption with actual energy consumption, misaligning with the economic definition of efficiency and failing to account for technological progress. Secondly, the calculation of single-factor energy efficiency is significantly influenced by structural factors such as industrial structure, energy structure, and energy prices, which may mask the true state of technical efficiency [40,41]. Lastly, inconsistencies in data dimensions can mislead conclusions and production decisions. For example, comparisons of energy intensity between different countries are affected by GDP estimation methods, and results differ significantly whether using exchange rates or purchasing power parity (PPP), complicating effective international comparisons [42].

Hu and Wang developed a framework for assessing TFEE, integrating capital, labor, and energy as comprehensive input factors and employing the DEA model to gauge the energy component's contribution to economic output [43]. TFEE evaluates the energy efficiency of decision units by comparing actual energy input with the ideal (minimal) energy input determined by the model, with values ranging from 0 to 1. Low TFEE values signify significant redundancy and waste in a decision unit's energy use, whereas values close to 1 indicate higher energy efficiency.

In summary, we find that DEA is commonly applied in various methods for calculating factor allocation efficiency. Therefore, we consider employing DEA as the foundation for the decomposition of production efficiency. Ultimately, we focus on the decomposition method proposed by Fare et al. [44]. The primary reason for selecting this method is that it successfully establishes a robust link between production efficiency and capacity utilization, thereby providing a solid theoretical foundation for further exploration of the intrinsic relationship between production efficiency and factor allocation efficiency in this study.

2.3. Index Decomposition Analysis

Index Decomposition Analysis breaks down an index into several components to evaluate their respective contributions [45,46]. This analysis is widely applied in energy-related environmental research to identify drivers of sustainable development [47], analyze greenhouse gas emissions [48], explore connections between ecology and economy [49], and simulate carbon peak scenarios [50]. Primary decomposition methods include Structural Decomposition Analysis (SDA) [51,52], Production Theoretic Decomposition Analysis (PDA) [53,54], and Index Decomposition Analysis (IDA) [55,56]. Additionally, in the field of DEA, decomposition methods based on distance functions, such as the representative Malmquist decomposition, are extensively used.

SDA's decomposition is based on input–output tables with industry data, providing a detailed breakdown of overall changes in energy consumption and carbon emissions. Since SDA relies on input–output (IO) analysis, it can only analyze changes between fixed years [57], such as China's national I-O tables published every five years. This method was initially used to analyze the direct and indirect determinants of energy use in the United States [58,59]. Su and Ang used SDA's static analysis to decompose carbon emissions [60].

Based on production theory, PDA analyzes technical factors related to energy consumption and carbon emissions from a production efficiency perspective [61]. Compared to SDA and IDA, PDA can simulate general production processes.

The IDA method, due to its low data requirements and simplicity of operation, has developed a comprehensive decomposition framework over nearly four decades. This method can analyze changes for any year [62] and quantify the impact of factor changes using various indices, such as the Laspeyres index [63], Paasche index [64], arithmetic mean Divisia index [65], and LMDI [66].

The Malmquist index, based on DEA and introduced by Malmquist [67], is widely used to calculate TFP and decompose productivity into technological progress and efficiency improvements. It measures green TFP [68,69], carbon emission productivity [70], and productivity decomposition [71–73].

In summary, we plan to adopt the Malmquist index decomposition method for intertemporal analysis. This method is closely related to DEA, which enables us to establish a connection with the approach proposed by Fare et al. [44]. Consequently, we decide to apply the method by Fare et al. [44] for the contemporaneous decomposition and utilize the Malmquist index decomposition for intertemporal analysis.

3. Theoretical Model

3.1. Measurement of Production Efficiency

Before decomposing production efficiency, it is essential to first measure it. Here, we briefly introduce the distance function and the DEA model. The DEA model is employed to evaluate production efficiency, and it is fundamentally built upon the concept of the distance function.

In the analysis, involving n DMUs over the periods $t = 1, \ldots, T$, the potential production frontier set is represented as follows:

$$S^t = \left\{ \left(K^t, L^t, E^t, Y^t\right) : \left(K^t, L^t, E^t\right) \text{ can produce } Y^t \right\} \quad (1)$$

These variables include the capital stock $K^t \in \mathbb{R}^1_+$, labor $L^t \in \mathbb{R}^1_+$, m-dimensional energy input $E^t \in \mathbb{R}^m_+$, and s-dimensional output $Y^t \in \mathbb{R}^s_+$. Additionally, standard conditions necessary to define the output distance function are imposed on S, including S being a closed set and the inputs and outputs being freely disposable. The conditions and properties of the distance function are specified in the subsequent formula. The output distance function for period t is defined as follows:

$$D_o^t\left(K^t, L^t, E^t, Y^t\right) = \inf\{\theta : \left(K^t, L^t, E^t, \frac{Y^t}{\theta}\right) \in S^t\} \tag{2}$$

The output distance function, as mentioned above, $D_o^t\left(K^t, L^t, E^t, Y^t\right)$, represents the maximum feasible solution in period t given the inputs, outputs, and technology set S, where $D_o^t\left(K^t, L^t, E^t, Y^t\right) \le 1$ holds true if and only if $\left(K^t, L^t, E^t, Y^t\right) \in S^t$. Furthermore, $D_o^t\left(K^t, L^t, E^t, Y^t\right) = 1$ is true if and only if $\left(K^t, L^t, E^t, Y^t\right)$ is on the boundary or frontier of the technology set S.

The output distance function can be calculated using various DEA output-oriented models. Taking an output-oriented CCR-DEA model [8] as an example, the specific formulation is as follows. In practical applications, other DEA models can be used to calculate the output distance function and then be used in our decomposition model. So the DEA model below is just a simple example.

$$\begin{gathered} PE^{-1} = D_o^t\left(K^t, L^t, E^t, Y^t\right)^{-1} = \max\rho \\ s.t. K_o \ge \sum_{j=1}^{n} K_j\lambda_j; \\ L_o \ge \sum_{j=1}^{n} L_j\lambda_j; \\ E_{io} \ge \sum_{j=1}^{n} E_{ij}\lambda_j \ i = 1, 2, \ldots, m; \\ \rho Y_{ro} \le \sum_{j=1}^{n} Y_{rj}\lambda_j \ r = 1, 2, \ldots, s; \\ \lambda_j \ge 0 \ j = 1, 2, \ldots, n. \end{gathered} \tag{3}$$

where

- λ_j and ρ are the parameters to be estimated;
- K_j, L_j, E_{ij}, and Y_{rj} are the vectors representing fixed assets, labor, energy, and output of the decision-making unit DMUj;
- K_o, L_o, E_{io}, and Y_{ro} are the corresponding vectors for the evaluated decision-making unit DMUo;
- λ_j denotes the weight vector of the decision-making units that constitute the production frontier;
- ρ represents the reciprocal of the production efficiency of DMUo, where $\rho \ge 1$. The efficiency of a decision-making unit is considered effective if and only if $\rho = 1$, indicating that the unit is on the production frontier.

Equation (3) illustrates that, in the output-oriented DEA model, the reciprocal of the objective value corresponds to the production efficiency and the output distance function.

3.2. Existing Decomposition Methods

3.2.1. Existing Contemporaneous Decomposition Methods

Using the decomposition method based on distance functions, Fare et al. [44] establish a link between PE and CU by breaking down PE into capacity and equipment utilization rates. The reciprocal of the optimal solution of the model represents the value of the output distance function for decision-making unit k. In defining CU, it is expressed as the ratio of the actual production level to the potential maximum output of the capital stock. Therefore, in measuring CU using DEA, the potential maximum output of the capital stock is represented as follows:

$$\overline{Y} = \rho^{k^*}Y = Y/D_o^t(K, Y) \tag{4}$$

In this context, the actual level of production is denoted by Y, while the potential maximum output level of the capital stock is also represented by $\rho^{k^*}Y$. Here, ρ^{k^*} refers to the solution of the DEA output-oriented model when only the capital stock K is used as input and Y as output, which can be denoted as $1/\mathrm{D}_{\mathrm{o}}^{\mathrm{t}}(\mathrm{K},\mathrm{Y})$.

According to the decomposition method described by Fare [44], the relationship between CU and PE is as follows:

$$\begin{aligned} \mathrm{CU} &= \frac{\mathrm{Y}}{\overline{\mathrm{Y}}} \\ &= \frac{\mathrm{Y}}{\frac{\mathrm{Y}}{\mathrm{D}_{\mathrm{o}}^{\mathrm{t}}(\mathrm{F},\mathrm{Y})}} \\ &= \mathrm{D}_{\mathrm{o}}^{\mathrm{t}}(\mathrm{F},\mathrm{Y}) \\ &= \frac{\mathrm{D}_{\mathrm{o}}^{\mathrm{t}}(\mathrm{F},\mathrm{Y})}{\mathrm{D}_{\mathrm{o}}^{\mathrm{t}}(\mathrm{F},\mathrm{V},\mathrm{Y})} \times \mathrm{D}_{\mathrm{o}}^{\mathrm{t}}(\mathrm{F},\mathrm{V},\mathrm{Y}) \\ &= \mathrm{EU} \times \mathrm{PE} \end{aligned} \tag{5}$$

In the formulation, F represents fixed inputs such as capital stock, V represents variable inputs such as labor and energy, and Y denotes outputs. EU stands for equipment utilization rate. Fare expresses CU as the product of equipment utilization rate and PE.

3.2.2. Malmquist Intertemporal Decomposition

Considering the utilization of distance functions in the decomposition of the Malmquist Productivity Index (MPI), this paper will adopt the MPI's decomposition approach for intertemporal analysis. The MPI is widely used for intertemporal decomposition, segmenting changes into efficiency change (EC), technological change (TC), and Scale Efficiency Change (SEC) using distance functions. A key advantage of the MPI's approach is its ability to break down the original formula into interpretable factors that are economically meaningful. This paper will employ a similar method to extend the proposed decomposition approach to intertemporal analysis.

$$\begin{aligned} M^{t,t+1}\left(x^t,y^t,x^{t+1},y^{t+1}\right) &= \left[M^t\left(x^t,y^t,x^{t+1},y^{t+1}\right) \times M^{t+1}\left(x^t,y^t,x^{t+1},y^{t+1}\right)\right]^{\frac{1}{2}} \\ &= \left[\frac{D_c^t\left(x^{t+1},y^{t+1}\right)}{D_c^t\left(x^t,y^t\right)} \times \frac{D_c^{t+1}\left(x^{t+1},y^{t+1}\right)}{D_c^{t+1}\left(x^t,y^t\right)}\right]^{\frac{1}{2}} \\ &= \underbrace{\frac{D_v^{t+1}\left(x^{t+1},y^{t+1}\right)}{D_v^t\left(x^t,y^t\right)}}_{EC} \times \underbrace{\left[\frac{D_v^t\left(x^t,y^t\right)}{D_v^{t+1}\left(x^t,y^t\right)} \times \frac{D_v^t\left(x^{t+1},y^{t+1}\right)}{D_v^{t+1}\left(x^{t+1},y^{t+1}\right)}\right]^{\frac{1}{2}}}_{TC} \times \underbrace{\left[\frac{\frac{D_c^t\left(x^{t+1},y^{t+1}\right)}{D_v^t\left(x^{t+1},y^{t+1}\right)}}{\frac{D_c^t\left(x^t,y^t\right)}{D_v^t\left(x^t,y^t\right)}} \times \frac{\frac{D_c^{t+1}\left(x^{t+1},y^{t+1}\right)}{D_v^{t+1}\left(x^{t+1},y^{t+1}\right)}}{\frac{D_c^{t+1}\left(x^t,y^t\right)}{D_v^{t+1}\left(x^t,y^t\right)}}\right]^{\frac{1}{2}}}_{SEC} \\ &= EC \times TC \times SEC \end{aligned} \tag{6}$$

The distance function, denoted with subscript v in the formula, is measured using a DEA model under the assumption of Variable Returns to Scale. This paper does not provide further details on the components EC, TC, and SEC, as these elements are not directly pertinent to the extended decomposition method discussed herein.

3.3. Proposed Decomposition Method

3.3.1. Contemporaneous Decomposition Methodology

In this paper, adopting the approach developed by Fare et al. [44], PE is decomposed into the product of various factor allocation efficiencies. The specific formula is presented as follows:

$$
\begin{aligned}
\mathrm{CU^t} &= \frac{\mathrm{Y^t}}{\overline{\mathrm{Y}}^{\mathrm{t}}} \\
&= \frac{\mathrm{Y^t}}{\mathrm{Y^t}/\mathrm{D_o^t}(\mathrm{K^t},\mathrm{Y^t})} \\
&= \frac{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{Y^t})}{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{Y^t})} \times \frac{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{Y^t})}{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{E^t},\mathrm{Y^t})} \times \mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{E^t},\mathrm{Y^t}) \\
&= \frac{1}{\frac{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{Y^t})}{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{Y^t})}} \times \frac{1}{\frac{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{E^t},\mathrm{Y^t})}{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{Y^t})}} \times \mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{E^t},\mathrm{Y^t}) \\
&= \frac{1}{\mathrm{LUE^t}} \times \frac{1}{\mathrm{EUE^t}} \times \mathrm{PE^t}
\end{aligned} \tag{7}
$$

This means

$$
\begin{aligned}
\mathrm{PE^t} &= \mathrm{D_o^t}(\mathrm{K^t},\mathrm{Y^t}) \times \frac{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{Y^t})}{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{Y^t})} \times \frac{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{E^t},\mathrm{Y^t})}{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{Y^t})} \\
&= \mathrm{CU^t} \times \mathrm{LUE^t} \times \mathrm{EUE^t}
\end{aligned} \tag{8}
$$

In this context, LUE stands for labor utilization efficiency, while EUE represents energy utilization efficiency. Formula (9) decomposes PE into the efficiencies of various inputs, highlighting how each input factor contributes to and constrains PE. This decomposition offers clear guidance for optimizing the performance of DMUs.

CU, LUE, and EUE are all derived from the values of the output distance function, which is the reciprocal of the efficiency value obtained from the DEA output-oriented model. The range of the output-oriented distance function is (0, 1], indicating that the value ranges for CU, LUE, and EUE, based on their definitions, are as follows:

$$
\begin{aligned}
\mathrm{CU^t} &= \mathrm{D_o^t}(\mathrm{K^t},\mathrm{Y^t}) \in (0,1] \\
\mathrm{LUE^t} &= \frac{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{Y^t})}{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{Y^t})} \in \mathrm{R^+} \\
\mathrm{EUE^t} &= \frac{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{E^t},\mathrm{Y^t})}{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{Y^t})} \in \mathrm{R^+}
\end{aligned} \tag{9}
$$

LUE and EUE are expressed as fractions, where, typically, the differences between the numerators and denominators are minimal. These differences are due to the distance functions being measured with only one differing input factor. Generally, the values of LUE and EUE are close to 1. A higher LUE signifies greater labor utilization efficiency in a DMU, while a higher EUE indicates more efficient energy utilization.

3.3.2. Rationality of Decomposition Method

In Formula (8), this paper decomposes PE into CU, LUE, and EUE. Employing a similar approach, this decomposition can be extended to other forms, as illustrated below.

$$
\begin{aligned}
\mathrm{PE^t} &= \mathrm{D_o^t}(\mathrm{L^t},\mathrm{Y^t}) \times \frac{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{Y^t})}{\mathrm{D_o^t}(\mathrm{L^t},\mathrm{Y^t})} \times \frac{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{E^t},\mathrm{Y^t})}{\mathrm{D_o^t}(\mathrm{K^t},\mathrm{L^t},\mathrm{Y^t})} \\
&= \mathrm{LU^t} \times \mathrm{KUE^t} \times \mathrm{EUE^t}
\end{aligned} \tag{10}
$$

Formula (10) structures the decomposition into labor utilization efficiency, capacity utilization efficiency, and energy utilization efficiency similar to Formula (8). However, this decomposition does not align with actual production scenarios. In practice, capital stock is a relatively fixed input, labor complements the capital stock, and energy complements both. These dynamics suggest a different interplay and sequencing of inputs in real production environments. The sequence of decomposition in Formula (8) accurately mirrors the actual process of production adjustments, where fixed inputs like capital are considered first, followed by the more variable inputs such as labor and energy. This method makes it preferable by reflecting true production dynamics. Therefore, decomposition should follow the methodology outlined in Formula (8).

3.3.3. Economic Implications of Decomposition Results

Formula (8) decomposes PE into three dimensions: CU, LUE, and EUE. While the definition of CU aligns with the existing literature, the economic implications of LUE and EUE require further elucidation.

Economically, LUE enhances PE through the current labor input. Uniquely, Formula (9) does not include labor in the denominator, distinguishing it from other formulations. This distinction is evident in the measurement process: the numerator incorporates capital stock, labor, and output in the DEA model, while the denominator considers only capital stock and output. Taking the DEA model in Formula (3) as an example, the main difference lies in the omission of labor constraints in the denominator.

However, the denominator implicitly accounts for labor constraints under the assumption that the labor-to-fixed-assets ratio remains constant. For example, if the ratio of fixed assets to labor for all decision units is consistently 3:1, the labor constraint can be omitted because satisfying the fixed asset constraint implies that the labor constraint is also met. Therefore, the solution for the denominator can be seen as a special case of the numerator (i.e., when the ratio of K to L is constant), thus viewing LUE as a comparison of efficiency between actual labor input and potential labor input.

This discussion clarifies the economic impact of current labor input on PE as measured by LUE. A value of LUE equal to 1 suggests optimal coordination between labor and capital, not significantly influencing PE. A value below 1 indicates excessive labor relative to capital, reducing efficiency and indicating room for improvement. Conversely, a value above 1 suggests that labor is highly effective relative to capital, enhancing PE and indicating higher labor productivity.

The economic definition of EUE similarly assesses the impact of current energy input on PE. An EUE value of 1 indicates that the current energy input is optimally matched with other production inputs, neither detracting from nor enhancing PE. Conversely, an EUE value less than 1 suggests that the energy input exceeds what is necessary relative to other inputs, negatively impacting PE and highlighting areas for potential efficiency gains. Conversely, an EUE value greater than 1 denotes a well-coordinated energy input relative to other inputs, enhancing overall energy efficiency and indicating superior energy productivity.

Armed with these definitions, this paper aims to precisely quantify and interpret the impacts of labor and energy inputs on PE. This approach offers a method for quantifying labor and energy utilization within the broader framework of PE.

3.3.4. Intertemporal Expansion of Decomposition Methods

This paper will further analyze intertemporal changes in PE by employing the decomposition method associated with the MPI. This method incorporates distance functions for various periods, which are subsequently integrated into a comprehensive formula.

First, the interperiod distance function is defined as follows:

$$\mathrm{D}_{\mathrm{o}}^{\mathrm{t+i}}(\mathrm{K}^{\mathrm{t}}, \mathrm{L}^{\mathrm{t}}, \mathrm{E}^{\mathrm{t}}, \mathrm{Y}^{\mathrm{t}}) = \inf\{\theta : \left(\mathrm{K}^{\mathrm{t}}, \mathrm{L}^{\mathrm{t}}, \mathrm{E}^{\mathrm{t}}, \frac{\mathrm{Y}^{\mathrm{t}}}{\theta}\right) \in \mathrm{S}^{\mathrm{t+i}}\} \tag{11}$$

The distance function is represented by the formula on the left, where the superscript $t + i$ indicates it is constructed based on the production possibility set of period $t + i$. Consequently, the superscript $t + i$ is also applied to S on the right side of the formula, maintaining consistency across the terms. The subscript o on the distance function signifies its output orientation.

For periods t and $t + i$, this paper integrates the decomposition method described in Section 3.2 with the intertemporal decomposition approach of the MPI, culminating in the following decomposition method:

$$
\begin{aligned}
\Delta PE &= \frac{PE^{t+i}}{PE^{t}} \\
&= \frac{D_o^{t+i}\left(K^{t+i},L^{t+i},E^{t+i},Y^{t+i}\right)}{D_o^{t}\left(K^{t},L^{t},E^{t},Y^{t}\right)} \\
&= \frac{D_o^{t+i}\left(K^{t+i},L^{t+i},E^{t+i},Y^{t+i}\right)}{D_o^{t+i}\left(K^{t},L^{t},E^{t},Y^{t}\right)} \times \frac{D_o^{t+i}\left(K^{t},L^{t},E^{t},Y^{t}\right)}{D_o^{t}\left(K^{t},L^{t},E^{t},Y^{t}\right)} \\
&= \frac{\frac{D_o^{t+i}\left(K^{t+i},L^{t+i},E^{t+i},Y^{t+i}\right)}{D_o^{t+i}\left(K^{t+i},L^{t+i},Y^{t+i}\right)} \times \frac{D_o^{t+i}\left(K^{t+i},L^{t+i},Y^{t+i}\right)}{D_o^{t+i}\left(K^{t+i},Y^{t+i}\right)} \times D_o^{t+i}\left(K^{t+i},Y^{t+i}\right)}{\frac{D_o^{t+i}\left(K^{t},L^{t},E^{t},Y^{t}\right)}{D_o^{t+i}\left(K^{t},L^{t},Y^{t}\right)} \times \frac{D_o^{t+i}\left(K^{t},L^{t},Y^{t}\right)}{D_o^{t+i}\left(K^{t},Y^{t}\right)} \times D_o^{t+i}\left(K^{t},Y^{t}\right)} \\
&\quad \times \frac{D_o^{t+i}\left(K^{t},L^{t},E^{t},Y^{t}\right)}{D_o^{t}\left(K^{t},L^{t},E^{t},Y^{t}\right)} \\
&= \left[\frac{D_o^{t+i}\left(K^{t+i},L^{t+i},E^{t+i},Y^{t+i}\right)}{D_o^{t+i}\left(K^{t+i},L^{t+i},Y^{t+i}\right)} \times \frac{D_o^{t+i}\left(K^{t},L^{t},Y^{t}\right)}{D_o^{t+i}\left(K^{t},L^{t},E^{t},Y^{t}\right)}\right] \\
&\quad \times \left[\frac{D_o^{t+i}\left(K^{t+i},L^{t+i},Y^{t+i}\right)}{D_o^{t+i}\left(K^{t+i},Y^{t+i}\right)} \times \frac{D_o^{t+i}\left(K^{t},Y^{t}\right)}{D_o^{t+i}\left(K^{t},L^{t},Y^{t}\right)}\right] \times \left[\frac{D_o^{t+i}\left(K^{t+i},Y^{t+i}\right)}{D_o^{t+i}\left(K^{t},Y^{t}\right)}\right] \times \left[\frac{D_o^{t+i}\left(K^{t},L^{t},E^{t},Y^{t}\right)}{D_o^{t}\left(K^{t},L^{t},E^{t},Y^{t}\right)}\right] \\
&= \Delta EUE \times \Delta LUE \times \Delta CU \times TC
\end{aligned}
\tag{12}
$$

This analysis evaluates PE using production frontiers from different periods, such as $D_o^{t+i}\left(K^t, L^t, E^t, Y^t\right)$, $D_o^{t+i}\left(K^t, L^t, Y^t\right)$, and $D_o^{t+i}\left(K^t, Y^t\right)$. The distance functions utilize data from period t while measuring them against the production frontier of period $t+i$, following the method described in Formula (3) but applied to a different frontier. In the DEA model outlined in Section 3.1, the constraints on the right side of the equation are constructed with data from period $t+i$, whereas the data on the left side use period t.

By employing the decomposition method in Formula (12), this paper breaks down the changes in intertemporal PE into ΔEUE, ΔLUE, ΔCU, and TC. Specifically, ΔEUE is calculated as the ratio of EUE at the production frontier of period $t+i$ for DMUs in period $t+i$ to EUE in period t. ΔLUE is the ratio of LUE at the production frontier of period $t+i$ for DMUs in period $t+i$ to LUE in period t. ΔCU is calculated as the ratio of CU at the production frontier of period $t+i$ for DMUs in period $t+i$ to CU in period t. TC represents the technological change, calculated as the ratio of PE measured using period t data at the production frontier of period $t+i$ to PE measured at the production frontier of period t.

This structured decomposition approach offers a detailed insight into how technological advancements, resource utilization, and operational efficiencies drive changes in PE. It establishes a comprehensive framework for assessing the dynamic evolution of performance in the thermal power industry. This analysis helps pinpoint critical areas for improvement and strategic adjustments essential for enhancing competitiveness and sustainability.

4. Case Data

4.1. Background of Thermal Power Industry Research

This paper employs the SBM (Slack-Based Measure) game cross-efficiency output-oriented model proposed by Huang et al. [16] to measure production efficiency, followed by the application of the proposed decomposition method to further disaggregate the efficiency results. In the thermal power sector, regions with higher electricity output often produce more carbon emissions; however, their electricity can also be transmitted and consumed across other regions [74]. Notably, China's power grid strategy, characterized by "West-to-East power transmission, North-to-South mutual supply, and nationwide grid interconnection," intensifies the competition over environmental responsibilities within the power generation industry [75]. Traditional DEA models used in this context typically rely on self-evaluation, thereby neglecting the competitive dynamics among regions. To date, the game cross-efficiency DEA model has not yet been applied to analyze production efficiency and resource allocation efficiency in China's electric power industry, making this research a novel application in this field.

4.2. Data Source and Variable Selection

The data for this paper were sourced from various annual reports, including the China Electric Power Yearbook, the China Energy Statistical Yearbook, the China Labor Statistical Yearbook, and the China Statistical Yearbook. Due to missing data and accessibility issues, Tibet, Hong Kong, Macao, and Taiwan were not included in this analysis. This paper analyzes data from 30 provinces, comprising a total of 330 samples covering the years from 2011 to 2021.

The input data used in this paper include the installed capacity of the thermal power industry, workforce numbers, and the amount of standard coal used. The output data comprise electricity generated and CO_2 emissions. The energy consumption data are obtained by converting each energy consumption (such as raw coal, natural gas, etc.) into standard coal and then summing up. The labor data have missing values in 2012, and we substitute them with the average values of 2011 and 2013. Table 2 reports the descriptive statistical results for each variable.

Table 2. Descriptive statistics of data.

Variable	Unit	N	Mean	SD	Min	Max
Thermal power generation (TP)	108 kWh	330	1521.24	1203.69	101.00	5267.00
Installed capacity (K)	104 kW	330	3444.68	2545.09	193.00	11,599.00
Number of labor force (L)	Person	330	27,039.57	25,994.58	641.00	125,792.49
Energy consumption (E)	104 tons	330	8564.04	7132.25	404.58	33,350.82
CO_2 emissions (CO_2)	104 tons	330	13,454.82	10,622.07	1070.64	47,088.57

5. Result

This paper employs the output-oriented SBM game cross-efficiency model to analyze the PE of thermal power plants across various Chinese provinces from 2011 to 2021, highlighting their dynamic changes and regional differences. Due to length constraints, this paper presents the measurement results for selected years in Table 3.

The main findings are as follows:

1. Volatility in PE: Overall, the PE of thermal power in China exhibits significant fluctuations. Some provinces have achieved efficiency improvements or maintained high levels through TC, elimination of outdated capacity, and implementation of environmental policies, while others have experienced efficiency fluctuations due to changes in market demand and optimization of energy structures.
2. Declining Efficiency in Developed Cities: PE has declined in cities such as Beijing, Tianjin, and Shanghai, primarily due to inherent characteristics of the power industry. The power sector is demand-driven; when demand is insufficient, thermal power units operate at low loads, leading to decreased CU and, consequently, reduced PE. Additionally, in developed cities, environmental requirements have increased, the proportion of clean energy has risen, and industrial restructuring has occurred. These regions are responding to policies for green and low-carbon development, advancing the optimization of energy structures and reducing reliance on thermal power, which also leads to a decrease in PE.
3. Significant Efficiency Improvements in Less Developed Areas: In Xinjiang, PE has significantly improved due to optimal utilization of local coal resources, technological innovations, management optimizations, and enhanced energy infrastructure development under the Belt and Road Initiative.

The variation in thermal power PE across Chinese provinces arises from a combination of factors, including levels of economic development, technological capabilities, environmental policies, and resource endowments. These variations underscore the differing capabilities of the thermal power industry to adapt to energy structural adjustments and green, low-carbon development objectives. A detailed analysis of specific provinces offers critical insights into the current state of China's thermal power industry and promotes the enhancement of energy efficiency.

Table 3. Production efficiency of thermal power plants by province, 2011–2021.

Province	2011	2013	2015	2017	2019	2020	2021	Average	Rank
Beijing	0.7535	0.6960	0.7372	0.6685	0.7248	0.6943	0.6660	0.7249	26
Tianjin	0.8261	0.8047	0.7946	0.7506	0.7191	0.7946	0.7726	0.7800	19
Hebei	0.8500	0.8380	0.7982	0.7388	0.6864	0.7747	0.7305	0.7765	20
Shandong	0.7725	0.7820	0.7845	0.7758	0.6632	0.7503	0.7192	0.7532	23
Liaoning	0.8502	0.8898	0.8183	0.8084	0.7463	0.8041	0.7742	0.8147	14
Shanghai	0.8170	0.8329	0.7894	0.7485	0.6749	0.7196	0.6897	0.7611	22
Jiangsu	0.7439	0.7881	0.7507	0.7156	0.6700	0.7606	0.6865	0.7381	25
Zhejiang	0.6640	0.6863	0.6181	0.6243	0.6612	0.7392	0.6469	0.6584	29
Fujian	0.7988	0.8443	0.8020	0.7834	0.7849	0.8533	0.8280	0.8183	13
Guangdong	0.9002	0.8602	0.8763	0.8391	0.8122	0.8718	0.9051	0.8628	2
Hainan	0.8595	0.8832	0.8547	0.8165	0.7031	0.7829	0.7425	0.8112	15
Shanxi	0.8696	0.8539	0.8781	0.8504	0.7500	0.8168	0.7965	0.8345	10
Jilin	0.8389	0.8827	0.8777	0.8329	0.7561	0.8233	0.7983	0.8332	11
Heilongjiang	0.9095	0.8872	0.8515	0.8100	0.7365	0.7991	0.8707	0.8209	12
Anhui	0.8490	0.8719	0.8944	0.8291	0.7797	0.8554	0.8965	0.8511	6
Jiangxi	0.7498	0.7573	0.7115	0.6988	0.6138	0.6897	0.6287	0.6982	27
Henan	0.8318	0.8322	0.8708	0.8459	0.7862	0.8576	0.8637	0.8360	9
Hubei	0.8658	0.8348	0.7748	0.7901	0.7469	0.8097	0.8071	0.7972	17
Hunan	0.7910	0.8383	0.7759	0.7799	0.7342	0.8213	0.8035	0.7827	18
Inner Mongolia	0.6517	0.6215	0.5665	0.5340	0.5572	0.5908	0.6123	0.5783	30
Chongqing	0.9134	0.8719	0.8974	0.8710	0.7662	0.8344	0.8529	0.8595	3
Sichuan	0.8964	0.8584	0.8297	0.7866	0.8453	0.8944	0.9158	0.8553	5
Guangxi	0.8492	0.8766	0.9059	0.8449	0.7810	0.8725	0.8864	0.8559	4
Guizhou	0.8823	0.8964	0.8756	0.8118	0.7896	0.8565	0.8453	0.8494	7
Yunnan	0.8035	0.7764	0.6268	0.5790	0.5531	0.7236	0.6704	0.6609	28
Shaanxi	0.7454	0.7600	0.7386	0.7046	0.6967	0.7872	0.7486	0.7402	24
Gansu	0.8267	0.8155	0.7341	0.7158	0.7247	0.8065	0.7459	0.7654	21
Qinghai	0.8783	0.8536	0.7952	0.7285	0.6654	0.7549	0.8803	0.8021	16
Ningxia	0.8915	0.8605	0.8611	0.8341	0.7799	0.8384	0.8471	0.8387	8
Xinjiang	0.7612	0.8939	0.9035	0.8959	0.9222	0.8168	0.9605	0.8895	1

5.1. Analysis of the Decomposition Results of Production Efficiency in Partial Year

This section analyzes the decomposition of PE for thermal power plants across various Chinese provinces for the years 2011, 2016, and 2021. The aim is to reveal the driving factors behind the varying production efficiencies across provinces, providing a detailed and systematic perspective.

5.1.1. Analysis of Decomposition Results in 2011

In the 2011 PE assessment, CU and LUE were identified as the main factors influencing the rankings of various provinces. According to the data analysis in Table 4, the provinces with the highest PE—Chongqing, Heilongjiang, and Guangdong—shared a common trait: they ranked in the top 30% in terms of CU and LUE, yet were in the bottom 30% in terms of EUE. Although Ningxia ranked first in CU, its lower LUE (20th) placed it fifth in overall PE. Similarly, Hainan and Jilin achieved only moderate overall PE despite high capacity and energy utilization efficiencies, due to their low labor utilization. The case of Anhui province also shows that despite high rankings in LUE and EUE, a low CU restricted its overall PE to a mid-level position. Despite its excellent performance in LUE, Fujian's PE lagged due to poor capacity and EUE.

Table 4. Decomposition results for 2011.

Province	CU	Rank	LUE	Rank	EUE	Rank	PE	Rank
Beijing	0.7963	26	0.9325	16	1.0147	16	0.7535	25
Tianjin	0.8840	16	0.8788	21	1.0633	7	0.8261	18
Hebei	0.9156	12	0.8959	19	1.0362	9	0.8500	12
Shandong	0.8266	23	0.8514	25	1.0976	5	0.7725	23
Liaoning	0.8621	17	0.9718	9	1.0148	15	0.8502	11
Shanghai	0.8467	20	0.9442	12	1.0221	10	0.8170	19
Jiangsu	0.7532	28	0.9243	17	1.0687	6	0.7439	28
Zhejiang	0.6771	30	0.8585	23	1.1422	2	0.6640	29
Fujian	0.7323	29	1.1445	1	0.9531	29	0.7988	21
Guangdong	0.9510	7	0.9821	7	0.9638	27	0.9002	3
Hainan	0.9800	2	0.8589	22	1.0212	11	0.8595	10
Shanxi	0.9357	11	0.9330	15	0.9962	22	0.8696	8
Jilin	0.9709	4	0.8462	26	1.0212	11	0.8389	15
Heilongjiang	0.9483	8	0.9854	6	0.9734	26	0.9095	2
Anhui	0.8338	22	0.9990	3	1.0191	13	0.8490	14
Jiangxi	0.8607	18	0.7646	29	1.1393	3	0.7498	26
Henan	0.8340	21	0.9961	4	1.0012	21	0.8318	16
Hubei	0.8956	14	0.9556	11	1.0116	19	0.8658	9
Hunan	0.9136	13	0.8525	24	1.0157	14	0.7910	22
Inner Mongolia	0.7745	27	0.6505	30	1.2935	1	0.6517	30
Chongqing	0.9483	8	0.9773	8	0.9855	24	0.9134	1
Sichuan	0.9752	3	0.9421	13	0.9757	25	0.8964	4
Guangxi	0.8944	15	0.9381	14	1.0121	18	0.8492	13
Guizhou	0.9548	6	0.9633	10	0.9592	28	0.8823	6
Yunnan	0.8021	25	1.0087	2	0.9931	23	0.8035	20
Shaanxi	0.8047	24	0.8208	27	1.1285	4	0.7454	27
Gansu	0.8532	19	0.9157	18	1.0583	8	0.8267	17
Qinghai	0.9588	5	0.9937	5	0.9218	30	0.8783	7
Ningxia	1.0000	1	0.8881	20	1.0039	20	0.8915	5
Xinjiang	0.9478	10	0.7932	28	1.0126	17	0.7612	24

Furthermore, Inner Mongolia, Zhejiang, and Jiangsu ranked at the bottom in the 2011 PE assessment, sharing the common characteristic of high EUE combined with low CU and LUE. This observation suggests that although EUE impacts PE, its influence is limited by similar power unit energy consumption levels across provinces, which are insufficient to drive significant improvements. Thus, excellent performance in a single factor of efficiency does not directly translate into overall PE leadership in this context.

In economically developed provinces such as Zhejiang, Jiangsu, Beijing, and Fujian, low CU often results from excessive construction of power units, failure to eliminate outdated capacity, and insufficient electricity demand. Although these regions perform well in terms of EUE, the inefficient use of capacity and labor resources restricts their overall PE improvement. This highlights an important strategic direction: to optimize overall PE, it is necessary to focus not only on enhancing EUE but also on improving CU and LUE through optimizing the power market structure and equipment management.

5.1.2. Analysis of Decomposition Results in 2016

The 2016 analysis of the thermal power sector (Table 5) shows a notable trend where provinces with high PE demonstrated balanced development across three dimensions: CU, LUE, and EUE. Xinjiang, Chongqing, and Guangxi exemplified this balanced performance, thereby ranking among the provinces with the highest PE. This finding underscores the importance of comprehensive resource management and optimization, where standout performances in specific areas, such as Xinjiang's exceptional CU and Chongqing's excellent LUE, significantly propel PE.

Table 5. Decomposition results for 2016.

Province	CU	Rank	LUE	Rank	EUE	Rank	PE	Rank
Beijing	0.9466	10	0.9461	18	0.9066	24	0.8119	12
Tianjin	0.9432	12	0.8202	24	0.9963	7	0.7708	19
Hebei	0.9961	2	0.8294	23	0.9429	17	0.7790	16
Shandong	0.9971	1	0.8185	25	0.9555	13	0.7798	15
Liaoning	0.8452	21	0.9677	15	0.9489	14	0.7761	18
Shanghai	0.9609	7	0.9035	20	0.8956	25	0.7775	17
Jiangsu	0.9467	9	0.7826	26	1.0024	6	0.7427	21
Zhejiang	0.7825	24	0.7679	27	1.0096	4	0.6067	28
Fujian	0.8783	17	1.0424	7	0.8675	29	0.7942	13
Guangdong	0.8342	22	1.1007	4	0.9137	22	0.8390	8
Hainan	0.9959	3	0.9028	21	0.9127	23	0.8206	10
Shanxi	0.8836	15	1.0224	9	0.9351	20	0.8448	5
Jilin	0.9453	11	0.9530	17	0.9354	19	0.8426	7
Heilongjiang	0.7452	26	1.1993	2	0.8005	30	0.7154	24
Anhui	0.9620	6	0.9550	16	0.9187	21	0.8440	6
Jiangxi	0.8771	18	0.7359	29	1.0616	2	0.6852	27
Henan	0.8839	14	0.9896	12	0.9733	8	0.8514	4
Hubei	0.7494	25	0.9945	11	0.9731	9	0.7252	23
Hunan	0.7067	27	1.0208	10	0.9690	10	0.6990	26
Inner Mongolia	0.5215	29	0.6311	30	1.3463	1	0.4431	30
Chongqing	0.8491	20	1.0803	5	0.9467	15	0.8684	2
Sichuan	0.6183	28	1.2905	1	0.9368	18	0.7476	20
Guangxi	0.9332	13	0.9714	14	0.9465	16	0.8580	3
Guizhou	0.8816	16	1.0553	6	0.8848	27	0.8232	9
Yunnan	0.3856	30	1.1594	3	1.0478	3	0.4684	29
Shaanxi	0.9578	8	0.7587	28	1.0068	5	0.7317	22
Gansu	0.8153	23	0.9014	22	0.9688	12	0.7119	25
Qinghai	0.8629	19	1.0391	8	0.8793	28	0.7884	14
Ningxia	0.9716	5	0.9437	19	0.8926	26	0.8184	11
Xinjiang	0.9739	4	0.9773	13	0.9690	10	0.9223	1

In contrast, Inner Mongolia, Yunnan, and Hubei exhibited lower PE, primarily due to insufficient CU. Although Inner Mongolia led in EUE, its low capacity and labor utilization rates exposed issues of overcapacity and resource misallocation. Yunnan's case underscores that despite its excellent performance in labor and energy utilization efficiencies, the extremely low CU rate became a bottleneck limiting its PE enhancement, linked to its energy structure adjustment between thermal and hydroelectric power. The situation in Hubei indicates that despite relatively good labor and energy utilization efficiencies, enhancing CU is crucial for improving its PE.

The 2016 data reveal that the key to enhancing PE lies in the balanced development of CU, LUE, and EUE. Unlike in 2011, where high capacity and labor utilization efficiencies could ensure high PE, the 2016 analysis emphasized the importance of balanced development among all three aspects. Furthermore, poor EUE significantly reduces PE, as evidenced by the comparison between Guangxi and Guizhou, where Guizhou's lower EUE resulted in a significant efficiency gap.

This analysis emphasizes the importance of considering all factors comprehensively and making strategic adjustments to enhance the PE of the thermal power industry. It also highlights that the development of the thermal power sector should not only focus on technological and managerial improvements but also take into account regional characteristics and strategies for energy conservation and emission reduction to promote more efficient and sustainable improvements.

5.1.3. Analysis of Decomposition Results in 2021

The 2021 analysis of the thermal power industry's PE (Table 6) shows that the leading performances in Xinjiang, Sichuan, and Guangdong underscore the importance of balanced optimization among CU, LUE, and EUE. Xinjiang's efficient CU and Guangdong's excellent labor utilization result from successful strategic implementations in these specific areas. The exceptional performance of these provinces reflects the potential to maximize PE through comprehensive strategies and resource optimization.

Table 6. Decomposition results for 2021.

Province	CU	Rank	LUE	Rank	EUE	Rank	PE	Rank
Beijing	0.7787	28	0.8866	13	0.9647	25	0.6660	27
Tianjin	0.8546	21	0.8207	18	1.1015	6	0.7726	18
Hebei	0.8982	19	0.7502	23	1.0841	8	0.7305	22
Shandong	0.9494	11	0.6775	29	1.1181	3	0.7192	23
Liaoning	0.9007	17	0.8692	15	0.9890	24	0.7742	17
Shanghai	0.9870	1	0.7259	25	0.9626	26	0.6897	24
Jiangsu	0.8234	23	0.7557	22	1.1033	5	0.6865	25
Zhejiang	0.8177	24	0.7275	24	1.0874	7	0.6469	28
Fujian	0.7928	26	1.0894	2	0.9586	27	0.8280	12
Guangdong	0.8476	22	1.0670	3	1.0008	21	0.9051	3
Hainan	0.9570	8	0.7254	26	1.0697	11	0.7425	21
Shanxi	0.9717	5	0.7880	20	1.0403	15	0.7965	16
Jilin	0.9693	6	0.8054	19	1.0225	17	0.7983	15
Heilongjiang	0.9730	4	0.9916	5	0.9025	30	0.8707	7
Anhui	0.9767	3	0.9034	11	1.0160	19	0.8965	4
Jiangxi	0.7193	29	0.7205	28	1.2131	2	0.6287	29
Henan	0.9277	14	0.8902	12	1.0459	13	0.8637	8
Hubei	0.8850	20	0.8461	17	1.0779	9	0.8071	13
Hunan	0.9206	15	0.8570	16	1.0185	18	0.8035	14
Inner Mongolia	0.7816	27	0.6002	30	1.3051	1	0.6123	30
Chongqing	0.9286	13	0.8829	14	1.0404	14	0.8529	9
Sichuan	0.9333	12	0.9727	6	1.0088	20	0.9158	2
Guangxi	0.9055	16	0.9308	9	1.0516	12	0.8864	5
Guizhou	0.8983	18	1.0187	4	0.9238	29	0.8453	11
Yunnan	0.6642	30	0.9054	10	1.1149	4	0.6704	26
Shaanxi	0.9638	7	0.7235	27	1.0736	10	0.7486	19
Gansu	0.9500	9	0.7859	21	0.9991	22	0.7459	20
Qinghai	0.8093	25	1.0950	1	0.9934	23	0.8803	6
Ningxia	0.9500	9	0.9525	7	0.9362	28	0.8471	10
Xinjiang	0.9852	2	0.9406	8	1.0365	16	0.9605	1

Conversely, the relative underperformance in PE of Inner Mongolia, Yunnan, and Zhejiang was mainly attributed to dual challenges in CU and LUE. Despite its strong performance in EUE, Inner Mongolia's low LUE highlights issues in human resource management. In Yunnan and Zhejiang, problems of overcapacity and insufficient utilization were evident, as good performances in labor and energy utilization failed to effectively translate into higher PE.

The analysis for 2021 also indicated that LUE had the most significant impact on enhancing PE, followed by CU and EUE. For instance, Qinghai, Fujian, and Guangdong significantly improved their PE rankings through high LUE. This sharply contrasts with Inner Mongolia and Jiangxi, where, despite high EUE, deficiencies in other areas persisted, keeping their PE below par.

These insights offer critical strategic directions for decision-makers in the thermal power industry, aiming at more efficient and sustainable improvements in PE through integrated resource management and optimization. Additionally, they reveal that strategic execution in specific areas by different provinces can significantly impact overall PE, particularly in human resource management and capacity optimization. These insights provide critical strategic directions for decision-makers in the thermal power industry, aiming to achieve more efficient and sustainable PE improvements through integrated resource management and optimization.

This paper identifies several trends in the development of thermal power across Chinese provinces through decomposition analysis for the years 2011, 2016, and 2021. In 2011, provinces with extensive unit construction led in PE due to high capacity and labor utilization. Conversely, more developed provinces underperformed despite having numerous units, primarily because of low CU. By 2016, there was a growing emphasis on energy efficiency, and provinces with high PE took the lead due to their balanced development. In 2021, with an emphasis on energy efficiency, most provinces showed energy utilization efficiencies above 1. Yet, insufficient electricity demand and labor surplus emerged, exacerbated by the COVID-19 pandemic and the ban on cryptocurrency mining, leading to widespread factory suspensions and, thus, underutilized capacity.

In summary, the focus for improving PE in China's thermal power industry has evolved from optimizing capacity and labor utilization to embracing balanced resource management and enhancing energy efficiency. The industry has also confronted new challenges driven by macroeconomic shifts and specific policies. These changes underscore the sector's adaptability and resilience, emphasizing the ongoing need to optimize resource allocation, strengthen energy management, and maintain flexibility and innovation amid macroeconomic instability.

5.2. Interperiod Decomposition Analysis of Production Efficiency

This paper conducts a detailed analysis of thermal power PE in the Xinjiang Uygur Autonomous Region (hereafter referred to as Xinjiang) and Guangdong Province, the two regions with the highest average PE, from 2011 to 2021. It also compares these findings with those from the Inner Mongolia Autonomous Region (hereafter referred to as Inner Mongolia) and Zhejiang Province, which have the lowest average PE. The analysis identifies key factors and primary pathways for enhancing thermal power PE. Furthermore, it highlights both commonalities and differences in PE improvements across these provinces, providing vital strategic directions for the future development of the thermal power industry.

5.2.1. Intertemporal Decomposition Analysis of Provinces with High Average Production Efficiency

Xinjiang has implemented an efficient development strategy. Through the previous year-by-year analysis and Figure 1A, we can see that they do not expand production capacity but only focus on improving labor utilization efficiency and energy utilization efficiency. In the figure, TC in Xinjiang has been continuously and substantially declining, while changes in CU are small. Based on this phenomenon and combined with the information that Xinjiang's CU is very high, it can be seen that Xinjiang has not built a large number of new power plants. As a result, their skill level is declining relative to other provinces. Their low EUE ranking also shows this. Therefore, the secret to Xinjiang's leading ranking is to improve CU and LUE and make full use of existing units.

In contrast, Guangdong built a large number of thermal power units in the early stage. This has led to a significant decline in its capacity utilization, which has led to a continuous decline in TC. Therefore, even with a substantial increase in LUE (12.96%) and EUE (14.71%), Guangdong's total production efficiency is still declining. In the later period, Guangdong gradually eliminated the backward units, the capacity utilization rate rebounded, and the decline of TC was also reduced. However, due to the decline in labor utilization efficiency (−7.99%), Guangdong's production efficiency has not improved significantly.

These cases underline the importance of a multifaceted strategy that balances CU, LUE, and EUE to improve PE. While initial capacity expansion is necessary to meet demand, overconstruction can reduce PE and hinder sustainable development. Technological innovation and timely retirement of inefficient units are crucial for maintaining high PE, reducing energy consumption, and promoting environmental sustainability.

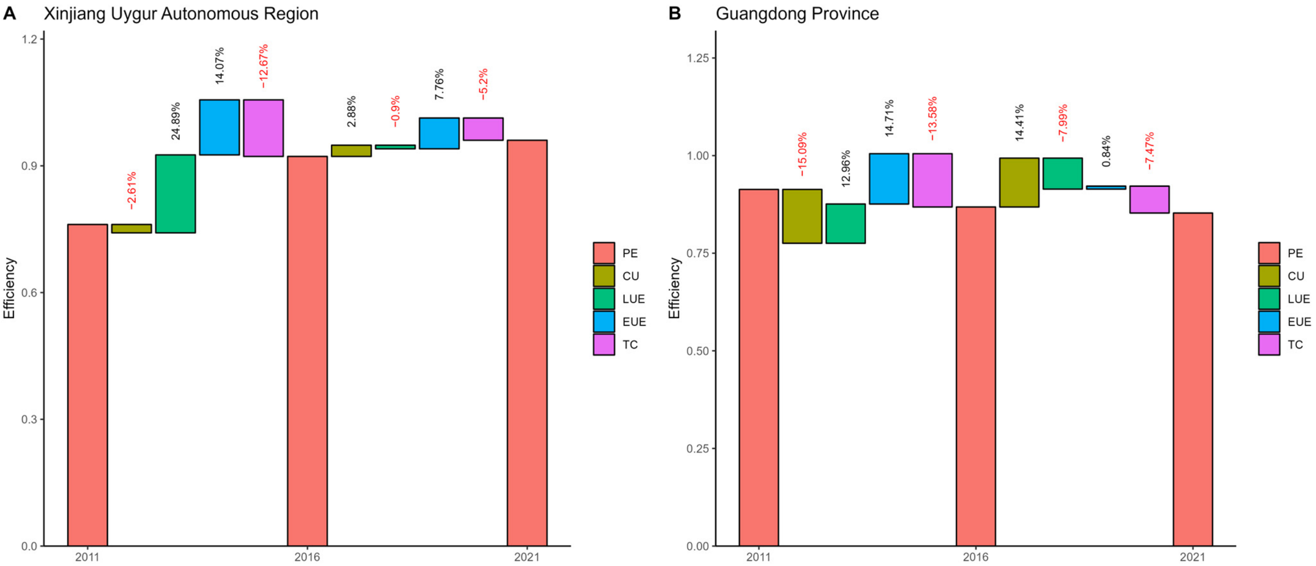

Figure 1. Changes in PE for provinces with high PE from 2011 to 2021. ((**A**) shows the interannual decomposition results for Xinjiang; (**B**) shows the interannual decomposition results for Guangdong. The black font in the figure represents growth and the red font represents decline.).

This analysis offers valuable insights for the thermal power industry: improving CU is key, labor and energy efficiencies are crucial for sustained PE, and technological innovation is essential for long-term sustainability. Provinces should adopt a holistic strategy encompassing capacity planning, labor management, and energy optimization to achieve balanced and sustainable development. These findings are instructive for the global energy sector, providing a pathway to a more efficient and sustainable future.

5.2.2. Interperiod Decomposition Analysis of Provinces with Low Average Production Efficiency

This section analyzes Inner Mongolia and Zhejiang, the provinces with the lowest thermal power PE, based on the decomposition of CU, LUE, EUE, and TC (Figure 2).

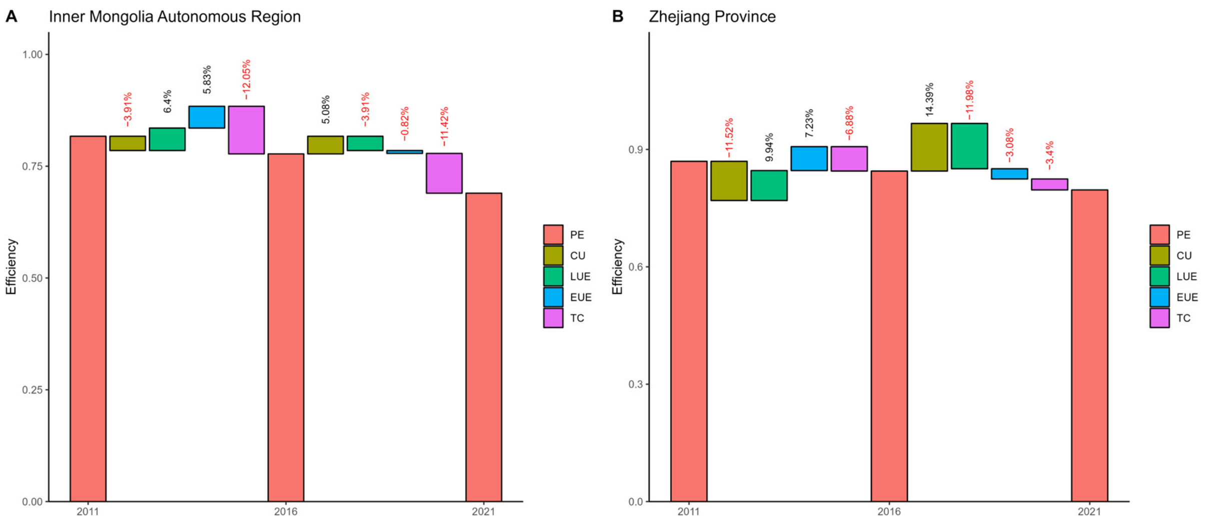

Figure 2. Changes in PE for provinces with low PE from 2011 to 2021. ((**A**) shows the interannual decomposition results for Inner Mongolia; (**B**) shows the interannual decomposition results for Zhejiang. The black font in the figure represents growth and the red font represents decline.).

Inner Mongolia's low PE is mainly due to persistent underutilization of capacity and labor, as well as a decline in technological levels (Figure 2A). Overcapacity and insufficient electricity demand result in low CU, while inefficient labor utilization exacerbates cost pressures. Despite high EUE reflecting effective energy management, it has not significantly improved overall PE. Technological stagnation further impedes competitiveness and development.

From the previous single-year analysis, it can be seen Zhejiang struggles with low CU and LUE, despite excelling in EUE. From 2011 to 2016, rapid capacity expansion outpaced demand, leading to declining CU (Figure 2B). While CU improved between 2016 and 2021, LUE decreased due to operational inefficiencies in newly added units. Technological investments initially focused on capacity expansion rather than efficiency, but later shifted to energy-saving technologies, improving EUE but limiting output growth.

These cases highlight that improving PE requires more than capacity expansion or technological upgrades. Overcapacity should be avoided through careful planning aligned with actual demand. Strategic adjustments, such as optimizing labor allocation and implementing high-efficiency technologies, are crucial for balancing economic benefits and sustainability. The experiences of Inner Mongolia and Zhejiang provide valuable guidance for other regions to enhance PE and achieve sustainable development.

6. Discussion

This paper successfully achieves a comprehensive decomposition of production efficiency. For contemporaneous decomposition, PE is divided into capacity utilization, labor utilization efficiency, and energy utilization efficiency. For intertemporal decomposition, changes in PE are further broken down into variations in capacity utilization, labor utilization efficiency, energy utilization efficiency, and technological progress. Using data from China's thermal power industry, we demonstrate the feasibility of this decomposition method. In the following discussion, we compare our proposed approach with existing decomposition methods and highlight the key differences.

For the decomposition methodology itself, there is currently no literature that simultaneously decomposes PE into these specific components. Therefore, our discussion focuses on the differences in the individual factor allocation efficiencies derived from our approach compared to those used in other studies.

First, regarding capacity utilization, our measurement formula is consistent with those used in other studies. In the contemporaneous decomposition, our capacity utilization metric aligns with the framework established by Fare et al. [44]. In the intertemporal decomposition, the formula for measuring changes in capacity utilization corresponds to the global capacity utilization change measurement in the study by Song et al. [76]. This consistency indicates that our approach to decomposing capacity utilization is theoretically sound and methodologically robust.

Second, for labor utilization efficiency, our measurement approach differs from the existing literature. In the study by Mugera et al. [31], labor productivity is decomposed into several contributing factors, which is not entirely consistent with the objectives of our research. However, the underlying logic of measuring labor productivity in their study—using the ratio of distance functions across different time periods—is similar to our method for evaluating changes in labor utilization efficiency. This parallel supports the validity of our approach.

Lastly, regarding energy utilization efficiency, our measurement approach diverges from that of other studies. For instance, Hu et al.'s [43] TFEE yields efficiency scores ranging from 0 to 1, which may result in multiple decision-making units having a TFEE value of 1, thus making comparisons difficult. In contrast, our efficiency values lie within the positive real number range R+, allowing for a higher degree of comparability. Additionally, Hu et al.'s [43] method calculates the potential maximum reduction in energy use without accounting for the influences of capital and labor inputs. Our decomposition method, on the other hand, isolates the impact of these factors by separately decomposing them, resulting in a more precise measurement of energy utilization efficiency.

In summary, we believe that our decomposition method offers significant theoretical contributions to the study of production efficiency. The decomposition results are not only precise but also provide meaningful insights into the distinct roles of capacity, labor, and energy utilization. Thus, our approach represents a valuable analytical tool for understanding the drivers of production efficiency and can serve as a practical guide for improving resource allocation efficiency in various industries.

7. Conclusions

7.1. Main Conclusions

This paper introduces a novel decomposition method for analyzing production efficiency and applies it to the thermal power industry across 30 provinces in China from 2011 to 2021. By disaggregating production efficiency into capacity utilization, labor utilization efficiency, energy utilization efficiency, and technological change, this method provides a comprehensive view of the key drivers behind efficiency changes. The approach is particularly effective in handling intertemporal data, allowing for a detailed assessment of both the immediate impacts and the long-term trends of various factors on production efficiency. This structured framework enables a clearer understanding of regional disparities and supports the development of targeted improvement strategies.

The empirical results show that provinces with relatively low production efficiency, such as Inner Mongolia and Zhejiang, often face a paradoxical situation where capacity utilization is low despite high energy utilization efficiency. This suggests potential overcapacity and bottlenecks in technological innovation. In contrast, high-efficiency provinces like Xinjiang and Guangdong exhibit strong performance in both capacity and labor utilization, maintaining a high level of overall production efficiency. Particularly, Xinjiang, despite a decline in technological change, sustained the highest average production efficiency through exceptional capacity and labor utilization performance. These findings indicate that optimizing capacity and labor utilization is crucial for enhancing efficiency in the thermal power sector.

7.2. Recommendations

Based on the findings, the following strategies are proposed:

1. For high-efficiency but low-energy-utilization regions, adopting advanced energy efficiency technologies, optimizing energy management practices, and enhancing workforce training will support the continuous improvement of energy utilization.
2. For low-efficiency regions with high energy utilization, efforts should focus on eliminating outdated capacity, shutting down inefficient power plants, and reallocating resources to more efficient units to boost overall production efficiency.

These actions will not only contribute to sustainable development in the thermal power industry but also have a significant impact on reducing energy consumption and lowering carbon emissions.

7.3. Limitations

Despite the robustness of the proposed method, it is subject to several limitations. Its effectiveness is highly dependent on the quality and completeness of the data, and the complexity of data collection could potentially affect the accuracy of the results. Additionally, while this method captures multiple dimensions of PE, it may not fully reflect the complex interactions between factors, nor adequately account for non-quantifiable influences such as policy shifts, market dynamics, and socio-economic factors.

Furthermore, the current decomposition method imposes certain constraints on input factors. With "data" becoming a core production element, future research should explore more innovative and inclusive decomposition strategies to address these evolving factors and better accommodate the complexities of modern production systems. This would ensure that the method remains adaptable and relevant for evaluating a broader set of production contexts.

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