Measuring carbon emission performance in China's energy market: Evidence from improved non-radial directional distance function data envelopment analysis

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Abstract: The most complex challenge facing the energy market is identifying effective solutions to reduce CO_2 emissions (CEs) and enhance environmental performance (EP). Coal production within the power sector is the primary source of these emissions. In this study, we developed a novel linear programming model that accounts for undesirable outputs to assess the EP of 15 power enterprises in eastern China from 2016 to 2020. In addition, we employed a global non-radial Malmquist-Luenberger productivity index (GNML) to analyse the mechanisms influencing changes in efficiency among these enterprises. Our findings indicate that, while the EP of the power industry in eastern China improved, it remains at a relatively low level and exhibits instability. Moreover, technological efficiency (TE) and scale efficiency (SE) play a significant role in determining production efficiency within the sector. Therefore, it is essential for industry managers to implement standardized production management regulations, enhance technological development and scale investments, and strengthen control over unintended emissions that could facilitate energy transition.

Keywords: Energy market; OR in Energy, Energy transition, Emission performance; Efficiency evaluation, NDDF-DEA, GNML.

1. Introduction

As global temperatures continue to rise, effectively decarbonizing the energy market has emerged as a key challenge for all countries (Tol, 2023; Bigerna et al., 2022). The recent flagship report on global energy-related CO_2 emissions (CEs) published by the IEA indicates that energy-related CEs reached 37.4 billion tons in 2023, marking an increase of 490 million tons compared to 2022 (IEA, 2023). Despite this, global energy consumption is on the rise (Huang, 2014; Meng et al., 2020). According to the 2024 BP World Energy Outlook, driven by rapid electricity consumption growth in emerging economies, global terminal electricity demand is projected to increase by approximately 75% by 2050 under the "current path scenario". For instance, the China Electricity Development Report (2023) states that China's electricity demand rose by 3.6% in 2022, with projections indicating total electricity consumption will reach between 9.8 trillion and 10.2 trillion KWh by 2025. Similarly, a recent research report from Bank of America Merrill Lynch forecasts unprecedented growth in electricity demand in the United States, expecting a compound annual growth rate of 2.8% from 2023 to 2030. Although countries worldwide advocate for the transition to clean energy for electricity production, the surging demand means that clean energy sources cannot meet current needs in the short term, leaving coal power as the dominant source. Consequently, finding effective strategies to improve the environmental performance (EP) of the energy market remains an urgent issue to address (Zeng et al., 2023).

In this context, the evaluation of EP in the energy market has garnered significant academic attention. Our review of existing literature reveals that scholars primarily focus on two aspects: (1) the impact of various policy implementations on the EP of the power industry (Bigerna et al., 2020). Some studies argue that regulatory measures can inhibit production efficiency and lead to heterogeneous effects across different regions (Tang et al., 2023). Conversely, other scholars contend that policy constraints can significantly drive reforms within the power industry, ultimately enhancing EP (Sueyoshi and Goto, 2013). (2) EP evaluations of the power industry from a macro perspective (Long et al., 2018). Currently, few studies have addressed the EP evaluation of power enterprises and the mechanisms influencing their performance from a micro perspective. Given that power enterprises are primarily responsible for energy production, exploring EP at this level can effectively guide the energy industry toward achieving green and high-quality development. Therefore, we aim to advance research in this area.

In China, energy combustion accounts for approximately 88% of its CEs, with the electricity market alone contributing about 41% of emissions from the energy sector. Therefore, improving EP in the electricity market is crucial for the sustainable development of the energy sector. According to the latest report from the IEA, China is currently the world's largest electricity consumer, with average annual energy demand exceeding a quarter of global demand (Fan et al., 2019). Given the variability in production capacities among different power enterprises, we selected 15 power companies in eastern China, where the power industry is relatively advanced, as the focus of our study. These enterprises consume more than 10,000 tons of standard coal annually or produce over 26,000 tons of CEs, collectively representing more than one-third of the region’s power production, making them highly representative for our analysis.

Considering the differences in technical capabilities and production scales among various power enterprises, we propose our first research question: (1) Is there heterogeneity in the EP of different power enterprises? To investigate this, we employ an improved non-radial directional distance function (NDDF) approach to analyze the historical production data of 15 power enterprises in China from 2016 to 2020. Our findings reveal significant disparities in EP across these enterprises, with notable fluctuations in efficiency values at different stages. However, the underlying causes of this heterogeneity in EP and the factors influencing changes at various stages remain unclear. Therefore, we present the second research question: (2) What mechanisms drive efficiency heterogeneity and fluctuations in different power enterprises?

This study significantly contributes to both theoretical frameworks and management practices. From a theoretical perspective, we introduce several innovations in environmental production technology: (1) To address the limitations of the radial directional distance functions (DDF) model, which may overestimate efficiency due to non-zero relaxation (Fukuyama and Weber, 2009), we employ an NDDF method that integrates relaxation into the efficiency measurement. (2) Previous practices that imposed equal constraints on undesirable outputs in measuring the efficiency of decision-making units (DMUs) can lead to misleading conclusions (Chen, 2014). We address this by utilizing inequality constraints, which enable the incorporation of Pareto-Koopman efficiency into our analysis. Furthermore, we developed an environmental production technology model that employs non-uniform emission reduction factors, accounting for the heterogeneity in emission reduction technologies among different DMUs, thereby strengthening our theoretical foundation. (3) Numerous classical approaches exist for exploring heterogeneity in the literature (Bigerna et al., 2020). To facilitate temporal comparisons and effectively address issues of infeasibility, we adopted a global frontier analysis approach, which serves as a benchmarking technique for all DMUs. This method allows for the construction of a best practice frontier based on comprehensive observations. These innovations enhance the robustness and applicability of environmental production technology models, offering a detailed understanding of the ecological efficiency of various DMUs.

In terms of management practice, previous studies on the power industry have largely focused on macro perspectives, emphasizing regional development heterogeneity (Li et al., 2024). While these conclusions inform government departments regarding macro allocation, they do not directly guide production decision-making at the enterprise level. Our analysis, based on actual production data from 15 power enterprises, offers actionable insights for enterprise-level production decisions. Additionally, the annual standard coal consumption of these enterprises exceeds 10,000 tons, effectively representing the development of the power industry in eastern China. Thus, our findings can guide not only the power industry in China but also serve as a reference for similarly scaled power enterprises globally.

2. Literature review

In this section, we systematically review two categories of literature pertinent to this study: (1) EP measurement of power enterprises, and (2) Aapplications of the

Malmquist Productivity Index(MPI). These two types of literature offer valuable insights that inform the foundation of this research.

EP measurement

Due to rapid economic development and a continuous increase in energy demand, power enterprises remain a primary source of energy supply in China. The energy produced by these facilities predominantly relies on fossil fuels, resulting in substantial CEs (Pan et al., 2024). Globally, countries have set the goal of limiting the average temperature increase to below 2° C compared to pre-industrial levels, with efforts to restrict the rise to within 1.5° C. This underscores the urgent need to enhance EP in the energy sector.

Wang et al. (2017) employed a validity measurement approach based on Data envelopment analysis(DEA) to evaluate the EP of power enterprises in China, using an efficiency index to demonstrate changes in EP. Wu et al. (2019) developed a novel DEA method to assess the EP of different power enterprises, revealing that nearly half of these companies require significant improvement in their performance. Fang et al. (2022) investigated the development efficiency of power enterprises within China's energy markets, analysing factors such as energy, economy, and environment. Zhu et al. (2022) utilized network DEA alongside the non-parametric production DEA method to evaluate the developmental efficiency of China's energy sector, offering recommendations for effective industry transformation. Li et al. (2022) focused on power enterprises in China, proposing a two-stage DEA method to assess energy production and utilization efficiency. Li et al. (2023) investigated the EP of different power enterprises in China by employing a fixed total pollutant framework, combining advanced DEA with an efficiency index to explore the underlying impact mechanisms.

Existing research on the performance of power enterprises has yielded substantial results, introducing a range of classical methods such as the DDF model and the application of equilibrium constraints on undesirable outputs. In this study, we propose an NDDF model and employ unequal constraints on undesirable outputs to mitigate the inaccuracies in efficiency measurement associated with previous methodologies. Furthermore, we will utilize a GNMI to facilitate efficiency comparisons among all

DMUs across different stages. This enhancement will provide business managers and researchers with a more nuanced understanding of the environmental efficiency of various DMUs.

Study of the MPI

MPI is a valuable tool for evaluating and comparing the production efficiency of DMUs over various time periods. By comprehensively considering the effects of technological progress and environmental factors, it enables managers to analyze production efficiency in depth, making it widely applicable in fields such as environmental and economic decision-making (Simar et al., 2002; Simar et al., 2011). For instance, Ali et al. (2016) introduced a global MPI capable of addressing adverse factors in DEA to measure the productivity and efficiency decomposition of different manufacturing industries in China across multiple years. Wang et al. (2024) constructed a MPI index based on an adjusted epsilon measure to assess the total factor productivity (TFP) of heavily polluting listed enterprises in China. Additionally, Song et al. (2018) proposed an EP evaluation model utilizing the Ray relaxation metric, analyzing the EP and energy consumption of various regions in China in conjunction with the TFP.

To address the limitations of the traditional MPI method, some scholars have proposed revisions. For example, Du et al. (2018) developed an improved MPI based on a new directional distance function (DDF) to resolve the infeasibility issues associated with the traditional MPI. This method evaluates the TFP of China from a macro perspective and assesses the EP of Chinese automobile manufacturers from a micro perspective. Aparicio et al. (2021) built an efficiency measurement model based on the DDF that accommodates non-proportional changes in input and output combinations with variable returns to scale(VRS), applying this model to measure the productivity of various types of schools in EU countries. Bansal et al. (2022) introduced dynamic MPI and dynamic sequential MPI indices to assess productivity changes in dynamic network production structures, applying these methods to evaluate productivity across different banks in India. Yu et al. (2023) established a MPI index for a two-stage dynamic production system, verifying dynamic changes in productivity within the airline sector and its various stages. Du et al. (2023) proposed a new MPI method that combines meta-frontier DEA with a cost minimization function to evaluate TFP and efficiency decomposition in different urban water supply industries.

This study employs the global MPI to measure TFP, technical efficiency(TE), and scale efficiency(SE) of 15 power enterprises in eastern China from 2016 to 2020. It provides a reference for power industry managers to analyze resource utilization efficiency in the production process, inform policy decisions, and promote the industry's green transformation. Additionally, this methodology allows us to explore the mechanisms affecting productivity in power enterprises from a micro perspective, assisting managers in making more informed management decisions.

3. Methodology

3.1 DEA with undesired outputs

The Chinese Institute of Ecological and Environmental Sciences(CIEES) provided us with input and output data for 15 power enterprises between 2016 and 2020. For each power enterprise, three production inputs, namely installed capacity (C), unit running time (H) and standard coal consumption (E), were converted into a single desired output—power generation capacity (Y)—and one undesired output—CE. Undesired outputs differ from desired outputs in that the DMUs (in this case, the power enterprises) does not want to increase these outputs, but rather reduce them. While the quality of coal used in the different power enterprise varies, for the calculation of the EP of the power enterprise (*see Section 4.1*), a standardised coal quality was applied.

Most DEA models focus on evaluating the EP of a DMU during a single time period. However, when assessing multi-period data, it is essential that the EP of different power enterprises remains comparable across the various time periods. This can be achieved by employing a global DEA technique (Oh, 2010) where all observations belong to the same production possibility set (PPS). Moreover, when modelling a realistic production process for power enterprises, where the DMU_0 produces both desired and undesired outputs, the environmental production technology can be defined as follows:

$$PPS=\{(C,H,E,Y,CO2):\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}\,C_{jt} \le C_o, \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}\,H_{jt} \le H_o, \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}\,E_{jt} \le E_o, \sum_{j=1}^{n}Y_j\lambda_{jt} \ge Y_o\,, \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}\,CO2_{jt} = CO2_o, \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt} = 1, \lambda_{jt} \ge 0, j = 1,2,\cdots,n, t = 1,2,\cdots,T\} \tag{P1}$$

In the above PPS (P1), both the null-jointness assumption (A1) and the weak disposability assumption (A2) of the desired and undesired outputs are valid. The null-jointness assumption implies that producing desired outputs inevitably results in the production of undesired outputs, while the weak disposability assumption indicates that a decrease in undesired outputs is inevitably accompanied by a decrease in desired outputs. The two assumptions are as follows:

(A1) Null-jointness assumption:

$$(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{0}) \in PPS \Rightarrow \boldsymbol{Y} = \boldsymbol{0}_s.$$

(A2) Weak disposability assumption:

$$(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{B}) \in PPS \Rightarrow (\boldsymbol{X},\lambda\boldsymbol{Y},\lambda\boldsymbol{B}) \in PPS, \forall\lambda \in [0,1].$$

where $\boldsymbol{X},\boldsymbol{Y}$ and $\boldsymbol{B}$ represent inputs, and the desired and undesired outputs, respectively, while subscript *s* is the dimension of the desired outputs. The uniform abatement factor employed in the PPS (P1), which represents the heterogeneous power generation and pollution treatment capacities of the TPPs, fails to accurately capture the heterogeneity in weak disposability between the desired and undesired outputs of the different power enterprises. Following Kuosmanen (2005), we revised the environmental production technology under the assumption that the VRS characterises the non-uniform abatement factors across the power enterprises and ensures the comparison of EP across multiple periods. The specific formula used is as follows:

$$PPS=\{(C,H,E,Y,CO2):\ \sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt}+\mu_{jt})C_{jt} \le C_o, \sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt}+\mu_{jt})H_{jt} \le H_o, \sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt}+\mu_{jt})\,E_{jt} \le E_o, \sum_{j=1}^{n}Y_j\lambda_{jt} \ge Y_o\,, \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}\,CO2_{jt} = CO2_o, \sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt}+\mu_{jt}) = 1, \lambda_{jt},\mu_{jt} \ge 0, j = 1,2,\cdots,n, t = 1,2,\cdots,T\} \tag{P2}$$

where λ_{jt} and μ_{jt} are weighting variables used for linearisation and construction of the convex combination of the evaluated DMU$_0$. However, PPS (P2) may violate the

Pareto-Koopmans environmental dominance. Here, the Pareto-Koopmans environmental dominance is defined as follows: for a given $(\boldsymbol{X}_o,\boldsymbol{Y}_o,\boldsymbol{B}_o) \in PPS$, if there does not exist another solution $(\widehat{\boldsymbol{X}_o},\widehat{\boldsymbol{Y}_o},\widehat{\boldsymbol{B}_o}) \in PPS$ such that $\widehat{\boldsymbol{X}_o} \leqq \boldsymbol{X}_o$, $\widehat{\boldsymbol{Y}_o} \geqq \boldsymbol{Y}_o$, $\widehat{\boldsymbol{B}_o} \leqq \boldsymbol{B}_o$, then $(\boldsymbol{X}_o,\boldsymbol{Y}_o,\boldsymbol{B}_o)$ is considered a Pareto-Koopmans environmentally dominant solution of the PPS. Here, "≦" denotes component-wise inequality.

It is worth noting that the Pareto-Koopmans environmental dominance is similar to the Pareto-Koopmans efficiency (Cooper et al., 2007, pp. 45–46). Therefore, in the undesirable output constraints in the PPS (P2), the "=" constraints were replaced with "≤" constraints to reformulate the PPS (P3). This implies that not only does the modified PPS satisfy the Pareto-Koopmans environmental dominance but also that the undesirable outputs can be improved independently of desirable outputs (Ji et al., 2021; Leleu, 2013; Sun et al., 2017). The modified Pareto-Koopmans environmental production technology is as follows:

$$PPS = \{ (C,H,E,Y,CO2): \sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt}+\mu_{jt})C_{jt} \le C_o, \sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt}+\mu_{jt})H_{jt} \le H_o, \sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt}+\mu_{jt})\,E_{jt} \le E_o, \sum_{j=1}^{n} Y_j\lambda_{jt} \ge Y_o, \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}\,CO2_{jt} \le CO2_o, \sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt}+\mu_{jt}) = 1, \lambda_{jt},\mu_{jt} \ge 0, j = 1,2,\cdots,n, t = 1,2,\cdots,T\} \tag{P3}$$

Following Chambers et al. (1996), to calculate the environmental inefficiency of TPPo, a DDF model was constructed based on the Pareto-Koopmans environmental production technology under the VRS assumption as follows:

$$\begin{aligned}
\vec{D}(x_0,y_0,b_0,\boldsymbol{g}) = \quad & \max\ \beta \\
\text{s.t.} \quad & \sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt}+\mu_{jt})C_{jt} \le C_o + \beta g_C, \\
& \sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt}+\mu_{jt})H_{jt} \le H_o + \beta g_H, \\
& \sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt}+\mu_{jt})\,E_{jt} \le E_o + \beta g_E, \qquad (1) \\
& \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}\,Y_{jt} \ge Y_o + \beta g_Y,
\end{aligned}$$

$$\sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}\, CO2_{jt} \le CO2_o + \beta g_{CO2},$$

$$\sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt} + \mu_{jt}) = 1,$$

$$\beta \ge 0, \lambda_{jt}, \mu_{jt} \ge 0, j = 1,2,\cdots,n, t = 1,2,\cdots,T$$

where $\boldsymbol{g} = (g_C, g_H, g_E, g_Y, g_{CO2})$ denotes the direction vectors for reducing inputs, expanding desirable outputs and expanding undesirable outputs, and β represents the supremum of the inputs contraction proportion, desirable outputs expansion proportion and undesirable outputs expansion proportion. In this study, we set $(g_C, g_H, g_E, g_Y, g_{CO2})$= $(-C, -H, -E, Y, -CO2)$ according to Färe and Grosskopf (2004). When $\beta_o = 0$, TPPo is the Pareto-Koopmans environmental efficient in the direction $\boldsymbol{g}$, whereas if $\beta_o > 0$, TPPo is the Pareto-Koopmans environmental inefficient.

Notwithstanding this, the radial DDF described above assumes that the inputs, desired outputs and undesired outputs scale in the same proportion. This assumption could result in biased efficiency estimates when slack items are non-zero. The NDDF model relaxes this assumption, allowing for non-uniform proportions of input reduction, expansion of desired outputs and reduction in undesired outputs (Lin & Guan, 2023; Zhang et al., 2020; Zhou et al., 2012). This relaxation addresses the issue of slack bias, thus improving the accuracy of the efficiency assessment. Therefore, based on the Pareto-Koopmans environmental production technology, we define the NDDF model as follows:

$$\vec{D}(x_0, y_0, b_0, g) = \max\ w_C\beta_C + w_H\beta_H + w_E\beta_E + w_Y\beta_Y + w_{CO2}\beta_{CO2}$$

s.t.

$$\begin{aligned}
&\sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt} + \mu_{jt})C_{jt} \le C_o - \beta_C g_C,\\
&\sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt} + \mu_{jt})H_{jt} \le H_o - \beta_H g_H,\\
&\sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt} + \mu_{jt})\, E_{jt} \le E_o - \beta_E g_E, \qquad (2)\\
&\sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}\, Y_{jt} \ge Y_o + \beta_Y g_Y,\\
&\sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}\, CO2_{jt} \le CO2_o - \beta_{CO2} g_{CO2},\\
&\sum_{t=1}^{T}\sum_{j=1}^{n}(\lambda_{jt} + \mu_{jt}) = 1,
\end{aligned}$$

$$\beta_C, \beta_H, \beta_E, \beta_Y, \beta_{CO2} \geq 0, \lambda_{jt}, \mu_{jt} \geq 0, j = 1,2,\cdots,n, t = 1,2,\cdots,T$$

where $(w_C, w_H, w_E, w_Y, w_{CO2})$ represents the normalised weight parameter of each input, desired output and undesired output. Here, the normalised weight parameter is set at $(w_C, w_H, w_E, w_Y, w_{CO2})=(\frac{1}{9},\frac{1}{9},\frac{1}{9},\frac{1}{3},\frac{1}{3})$ in this study with reference to Barros et al. (2012) and Zhou et al. (2012). In this study, the normalised weight parameters are set at $(w_C, w_H, w_E, w_Y, w_{CO2})=(\frac{1}{9},\frac{1}{9},\frac{1}{9},\frac{1}{3},\frac{1}{3})$ with reference to Barros et al. (2012) and Zhou et al. (2012). By solving the equation (2), the optimal solution $\beta^* = ({\beta_{C,jt}}^*, {\beta_{H,jt}}^*, {\beta_{E,jt}}^*, {\beta_{Y,jt}}^*, {\beta_{CO2,jt}}^*)^T$ can be obtained. With reference to Zhou et al. (2012), the unified Pareto-Koopmans environmental efficiency index (*UEEI*) of the TPPs can be defined as follows:

$$UEEI_{jt} = \frac{1-\frac{1}{4}({\beta_{C,jt}}^*+{\beta_{H,jt}}^*+{\beta_{E,jt}}^*+{\beta_{CO2,jt}}^*)}{1+{\beta_{Y,jt}}^*},\ j = 1,2,\cdots,n, t = 1,2,\cdots,T \tag{3}$$

The larger the *UEEI* score (*UEEI*$\in (0,1]$), the higher the unified Pareto-Koopmans environmental efficiency.

Theorem 1. *UPEE* is the Pareto-Koopmans environmental measure.

Proof. If *UPEE*($\boldsymbol{X}_o$, $\boldsymbol{Y}_o$, $\boldsymbol{B}_o$)=1. Assume that there exists another solution $(\widehat{\boldsymbol{X}_o}, \widehat{\boldsymbol{Y}_o}, \widehat{\boldsymbol{B}_o}) \in PPS$(P3), where $(\widehat{\boldsymbol{X}_o}, \widehat{\boldsymbol{Y}_o}, \widehat{\boldsymbol{B}_o}) \neq (\boldsymbol{X}_o, \boldsymbol{Y}_o, \boldsymbol{B}_o)$, with $\widehat{\boldsymbol{X}_o} \leqq \boldsymbol{X}_o$, $\widehat{\boldsymbol{Y}_o} \geqq \boldsymbol{Y}_o$ and $\widehat{\boldsymbol{B}_o} \leqq \boldsymbol{B}_o$. According to the equation (2) and the equation (3), we can deduce that *UPEE*($\boldsymbol{X}_o$,$\boldsymbol{Y}_o$,$\boldsymbol{B}_o$)<1. Therefore, the original assumption is not valid. This implies that for a given solution $(\boldsymbol{X}_o, \boldsymbol{Y}_o, \boldsymbol{B}_o) \in PPS$(P3) where *UPEE*($\boldsymbol{X}_o$,$\boldsymbol{Y}_o$,$\boldsymbol{B}_o$)=1, there exists no other solution $(\widehat{\boldsymbol{X}_o}, \widehat{\boldsymbol{Y}_o}, \widehat{\boldsymbol{B}_o}) \in PPS$ such that $(\widehat{\boldsymbol{X}_o}, \widehat{\boldsymbol{Y}_o}, \widehat{\boldsymbol{B}_o}) \neq (\boldsymbol{X}_o, \boldsymbol{Y}_o, \boldsymbol{B}_o)$, $\widehat{\boldsymbol{X}_o} \leqq \boldsymbol{X}_o$, $\widehat{\boldsymbol{Y}_o} \geqq \boldsymbol{Y}_o$ and $\widehat{\boldsymbol{B}_o} \leqq \boldsymbol{B}_o$. If there exists no other solution $(\widehat{\boldsymbol{X}_o}, \widehat{\boldsymbol{Y}_o}, \widehat{\boldsymbol{B}_o}) \in PPS$(P3), where $(\widehat{\boldsymbol{X}_o}, \widehat{\boldsymbol{Y}_o}, \widehat{\boldsymbol{B}_o}) \neq (\boldsymbol{X}_o, \boldsymbol{Y}_o, \boldsymbol{B}_o)$, with $\widehat{\boldsymbol{X}_o} \leqq \boldsymbol{X}_o$, $\widehat{\boldsymbol{Y}_o} \geqq \boldsymbol{Y}_o$ and $\widehat{\boldsymbol{B}_o} \leqq \boldsymbol{B}_o$, then according to the equation (2) and the equation (3), we can deduce that *UPEE*($\boldsymbol{X}_o$,$\boldsymbol{Y}_o$,$\boldsymbol{B}_o$)=1. In summary, we conclude that *UPEE*($\boldsymbol{X}_o$,$\boldsymbol{Y}_o$,$\boldsymbol{B}_o$)=1 if it is non-dominated in the PPS (P3), that is *TPP*($\boldsymbol{X}_o$, $\boldsymbol{Y}_o$, $\boldsymbol{B}_o$) is the Pareto-Koopmans environmentally efficient.

3.2 Global Non-radial Malmquist-Luenberger Productivity Index (GNMI)

According to Emrouznejad and Yang (2016), we propose a GNML index of UEEI based on the contemporaneous, and global production technologies as follows:

$$
\begin{aligned}
GNML_v^G(X^t,Y^t,B^t,X^{t+1},Y^{t+1},B^{t+1}) &= \frac{1+D_v^G(X^t,Y^t,B^t)}{1+D_v^G(X^{t+1},Y^{t+1},B^{t+1})} \times \frac{SE^{t+1}(X^{t+1},Y^{t+1},B^{t+1})}{SE^t(X^t,Y^t,B^t)} \\
&= \frac{1+D_v^t(X^t,Y^t,B^t)}{1+D_v^{t+1}(X^{t+1},Y^{t+1},B^{t+1})} \\
&\times [\frac{(1+D_v^G(X^t,Y^t,B^t))/(1+D_v^t(X^t,Y^t,B^t))}{(1+D_v^G(X^{t+1},Y^{t+1},B^{t+1}))/(1+D_v^{t+1}(X^{t+1},Y^{t+1},B^{t+1}))}] \\
&\times \frac{SE^{t+1}(X^{t+1},Y^{t+1},B^{t+1})}{SE^t(X^t,Y^t,B^t)} \\
&= \frac{PTE^{t+1}}{PTE^t} \times \frac{BPG_{t+1}^{t,t+1}}{BPG_t^{t,t+1}} \times \frac{SE^{t+1}(X^{t+1},Y^{t+1},B^{t+1})}{SE^t(X^t,Y^t,B^t)} \\
&= PEC^{t,t+1} \times BPC^{t,t+1} \times SCH^{t,t+1}
\end{aligned}
$$

where subscript 'v' denotes VRS assumption on technology, subscript 'c' denotes CRS assumption on technology and superscript 'G' denotes the global technology. Where contemporaneous benchmark technology is calculated as $D_v^t(X^t,Y^t,B^t)$, $D_v^{t+1}(X^{t+1},Y^{t+1},B^{t+1})$ and abbreviated PTE^t, PTE^{t+1}. $PTE^t = \frac{1}{1+D_v^t(X^t,Y^t,B^t)}$, and $PEC^{t,t+1} = \frac{PTE^{t+1}}{PTE^t}$ denotes the pure technical efficiency (PTE) in period t and the pure efficiency change (PEC) in period t to t+1. PEC measures the pure efficiency change between the time t and t+1. When PEC > (<)1, it means the DMU in period t+1 catches up (lags behind) relatively to the contemporaneous benchmark technology frontier. $BPC_t^{t,t+1} = \frac{1}{(1+D_v^G(X^t,Y^t,B^t))/(1+D_v^t(X^t,Y^t,B^t))}$ denotes the best practice gap ratio between the contemporaneous technology frontier and global technology frontier. Thus $BPC^{t,t+1} = \frac{BPG_{t+1}^{t,t+1}}{BPG_t^{t,t+1}}$ denotes the best practice gap change, which measures technical change between two time period t and t+1. When a BPC >(<)1 implies that the contemporaneous technology frontier is moving closer or faraway(>(<)1) from the global technology frontier. Variable SE^t means the scale efficiency on global benchmark in period t and $SE^t(X^t, Y^t, B^t) = (1 + D_v^G(X^t, Y^t, B^t))/(1 + D_c^G(X^t, Y^t, B^t))$. Variable $SCH^{t,t+1} = \frac{SE^{t+1}(X^{t+1}, Y^{t+1}, B^{t+1})}{SE^t(X^t, Y^t, B^t)}$ denotes the scale efficiency changes (SCH) .

4. Variable selection and data description

4.1 Variable selection

Among the existing studies on performance evaluation in the energy industry and power enterprises, several scholars have conducted in-depth discussions on constructing indicator systems for EP evaluation (Zha et al., 2016; Wang et al., 2018; Hadi-Vencheh et al., 2024; Pan et al., 2024), which provide valuable references for this research.

Through a review of the literature and interviews with staff from various power enterprises, we selected installed capacity(C), Unit Running Time (H), and coal consumption(E) as input indicators; Power generation capacity(Y) as the expected output indicator; and CO_2 emissions(CEs) as the indicator for undesirable output. See Table 1 for the meanings of indicators.

Table 1 Definition of different indicators

Inputs Indicator	
C	Installed capacity of all units in a power enterprise, measured in MW.
H	Cumulative working time of all units in a power enterprise in one year, measured in hours.
E	Standard coal consumed by power enterprises in one year, measured in tons.
Desirable output	
Y	Electricity produced by a power enterprise in one year, measured in MWh.
Undesirable output	
CEs	Carbon dioxide emitted by the production of power enterprises in one year, measured in tons.

4.2 Data description

This study focuses on the EP of various power enterprises. To facilitate this analysis, we obtained production and operational data for all major emitters within the jurisdiction of CIEES for the period from 2016 to 2020. The key emission power enterprises included in our study are those with annual standard CEs exceeding 10,000 tons (*i.e., noting that different power plants utilize varying coal qualities, which are converted to standard coal for calculations*) or CEs exceeding 26,000 tons. This criterion not only meets our research needs but also ensures strong representativeness. The study period spans five years; however, due to incomplete CEs records for some power enterprises in 2016 and 2017, we excluded this data and finalized our sample to 15 power enterprises. Descriptive statistics for the relevant indicators are presented in Table 2.

Table 2 Descriptive statistics

Year	Variable	Obs	Mean	Min	Max	Std. dev.
2016	C	15	655	300	1000	185
	H	15	7176	4679	8068	926
	E	15	1039642	274370	1657932	304085
	Y	15	3508483	861972	6158256	1148656
	CEs	15	3425097	784226	8989990	1824485
2017	C	15	655	300	1000	185
	H	15	6123	2386	8429	1552
	E	15	874677	151875	1409701	340864
	Y	15	2838627	467658	5121302	1288647
	CEs	15	2453408	442853	4231000	975654
2018	C	15	655	300	1000	185
	H	15	7106	6103	8494	650
	E	15	948356	476812	1534678	262410
	Y	15	3331557	1513700	6118286	1139051
	CEs	15	2987195	1352663	5324916	971524
2019	C	15	655	300	1000	185
	H	15	7251	5787	12836	1666
	E	15	945001	473438	1650646	288433
	Y	15	3257651	1511239	5855435	1099566
	CEs	15	3195587	1707448	5953109	1086180
2020	C	15	655	300	1000	185
	H	15	6734	2816	12265	2135
	E	15	848472	338098	1329783	263077
	Y	15	2963762	1058717	4992040	1016156
	CEs	15	2353416	947312	3666054	724691

5. Results

In this section, we calculate the EP for 15 DMUs(*i.e., power enterprises*), from 2016 to 2020 based on the model presented in Section 3. We compare the heterogeneity of the EP values among different DMUs and analyze the evolution of overall efficiency in the power industry across the years. Additionally, we explore the mechanisms influencing the efficiency values of power enterprises.

5.1 EP results

Table 3 presents the EP results for 15 DMUs from 2016 to 2020. The overall EP of these DMUs during this five-year period remains low, at only 0.7757, indicating that none have reached an effective state. The highest EP was recorded by DMU*aq*, with a value of 0.9618, while DMU*ciz* exhibited the lowest performance at only 0.6572. Column (6) displays the average EP for the 15 DMUs over the past five years, revealing that 10 DMUs (66.7%) fell below the overall average, highlighting significant room for improvement in the EP of the power industry in eastern China.

Further analysis shows that the overall EP of the 15 DMUs fluctuated between 2016 and 2020, with values of 0.7903, 0.7637, 0.7832, 0.7502, and 0.7910, respectively, indicating clear cyclical variations (*i.e., a decline followed by a rise, then another decline followed by a rise*). Notably, only DMU*wh* displayed a consistent upward trend in EP throughout this period, while the efficiency values of the remaining DMUs exhibited fluctuations. This instability suggests that the development of the power industry in the region remains uncertain, and relevant management entities should consider implementing unified standards to regulate the operations of power enterprises.

Additionally, the overall EP of the 15 DMUs decreased by 2.66% between 2016 and 2017. Analysis revealed that 7 DMUs (46.7%) experienced a decline in performance, with DMU*hn* and DMU*ciz* showing decreases exceeding 15%. Conversely, between 2017 and 2018, the overall EP increased by 1.95%, with 7 DMUs (46.7%) demonstrating improvements; notably, DMU*tl* saw an increase of nearly 30%. However, between 2018 and 2019, EP declined for 12 DMUs (80%), except for DMU*hn*, DMU*la*, and DMU*wh*, with DMU*bb* experiencing a decline of over 20%.

Finally, the overall EP of the 15 DMUs increased by 4.08% between 2019 and

2020, representing the largest improvement in the past five years. Further analysis indicated that 11 DMUs (73.3%) showed upward trends, with 5 DMUs (33.3%) increasing by more than 10%. Nonetheless, some DMUs, such as DMU*bz*, experienced significant declines. This aligns with previous findings, underscoring the necessity for a unified management policy to standardize production management within power enterprises.

Table 3 EP results from 2016 to 2020

	2016	2017	2018	2019	2020	Ave
	(1)	(2)	(3)	(4)	(5)	(6)
DMU_{hf}	0.7932	0.7319	0.7206	0.7023	0.7737	0.7443
DMU_{hb}	0.6575	0.6715	0.7534	0.7492	0.8172	0.7298
DMU_{bz}	0.9328	0.9349	0.8711	0.8642	0.6108	0.8428
DMU_{sz}	0.7322	0.7175	0.8176	0.7603	0.7588	0.7573
DMU_{bb}	1	1	0.8237	0.5926	0.7401	0.8313
DMU_{fy}	0.7089	0.7871	0.7996	0.7313	0.7121	0.7478
DMU_{hn}	0.8609	0.6836	0.6574	0.7958	0.6351	0.7266
DMU_{cuz}	0.9081	1	0.7282	0.6796	0.8849	0.8402
DMU_{la}	0.8080	0.8162	0.7936	0.8309	0.9089	0.8315
DMU_{mas}	0.7628	0.7553	0.7348	0.7194	0.7701	0.7485
DMU_{wh}	0.6393	0.7050	0.7920	0.8024	0.8264	0.7530
DMU_{xc}	0.7234	0.7361	0.7769	0.7572	0.7995	0.7586
DMU_{tl}	0.5717	0.5127	0.8032	0.7473	0.8900	0.7050
DMU_{ciz}	0.7559	0.4804	0.6759	0.6357	0.7380	0.6572
DMU_{aq}	1	0.9239	1	0.8851	1	0.9618
Ave	0.7903	0.7637	0.7832	0.7502	0.7910	0.7757

Comparison between different DMUs

Fig.1 presents the average EP results for different DMUs from 2016 to 2020. The overall EP of the power industry in eastern China during this five-year period is 77.57%, indicating a noticeable gap from an effective state. Further analysis reveals that only one DMU (6.7%) has EP values between 60% and 70%, while 9 DMUs (60%) fall within the range of 70% to 80%. Additionally, 4 DMUs (26.7%) have EP values between 80% and 90%, and only one DMU (6.7%) exceeds 90%. The fact that most power enterprises have performance ratings below 80% underscores the need for substantial improvements in the overall development of the power industry.

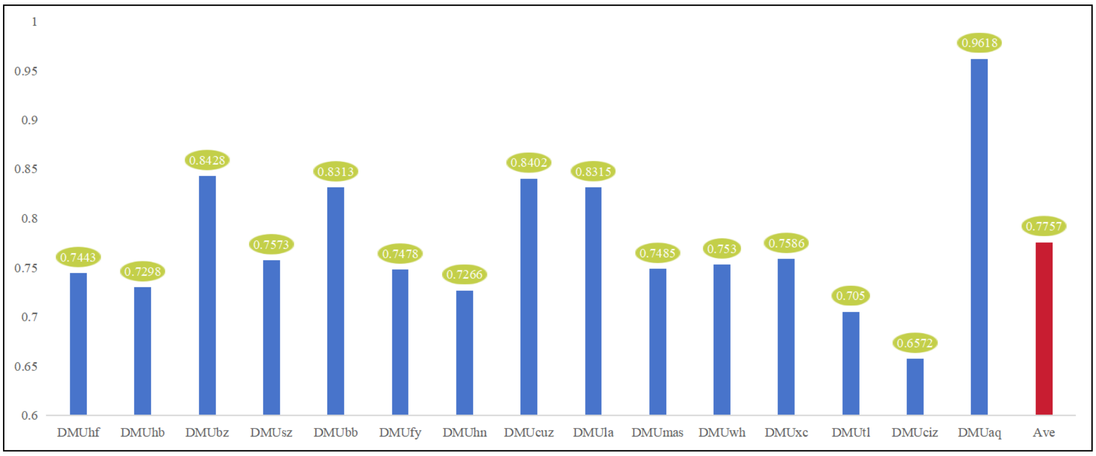

Fig.1 EP of different DMUs from 2016 to 2020

In 2016, the DMU*tl* exhibited the lowest EP, with an efficiency value of only 57.17%. In contrast, DMU*bb* and DMU*aq* achieved the highest efficiency values, both reaching an effective state (*i.e., efficiency value of 1*). As indicated in Table 3, the overall EP of the 15 DMUs was 79.03%. Furthermore, as shown in Fig.2, 8 DMUs (53.3%) fell below the annual average performance, while only 2 DMUs (13.3%) attained an efficiency value of 1.

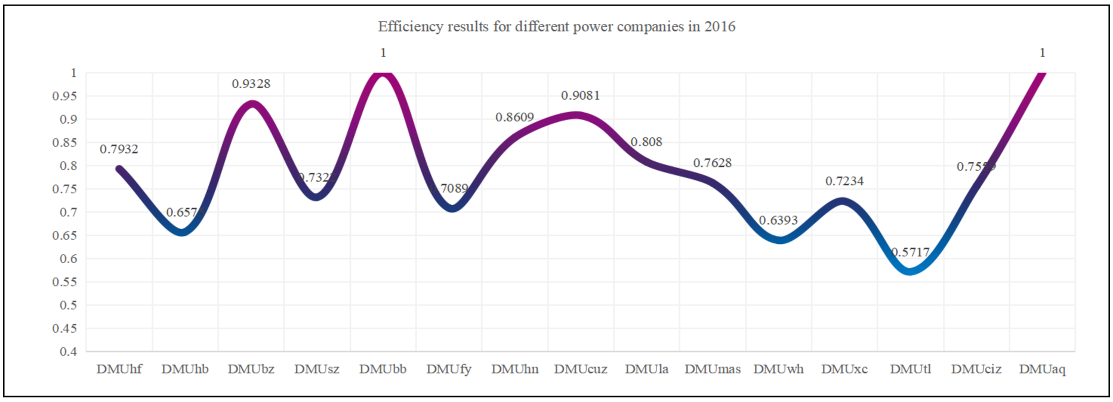

Fig.2 EP of different DMUs in 2016

In 2017, DMU*ciz* exhibited the worst EP, with an efficiency value of only 48.04%, representing a 27.55% decrease compared to 2016. This decline may be attributed to factors such as endogenous production decision-making or technological development issues. Conversely, DMU*bb* and DMU*cuz* demonstrated the highest EP, both achieving an effective state (*i.e., efficiency value of 1*). Notably, DMU*bb* has maintained this effective status for two consecutive years, suggesting that its internal factors, such as management decision-making and technical capabilities, are relatively sound. According to Table 3, the overall EP of the 15 DMUs was 76.37%. Furthermore, as indicated in Fig.3, 9 DMUs (60%) fell below the annual average performance, with only 2 DMUs (13.3%) achieving an efficiency value of 1.

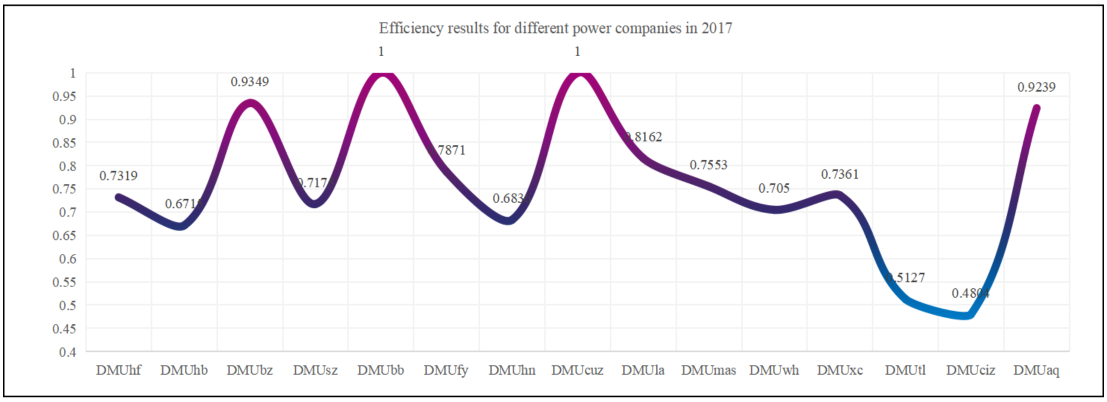

Fig.3 EP of different DMUs in 2017

In 2018, DMU*hn* exhibited the lowest EP, with an efficiency value of only 65.74%. This represents a significant improvement of 17.7% compared to the lowest performance recorded in 2017, indicating an overall enhancement in the EP of the power industry. However, some individual DMUs experienced slight declines. DMU*aq* achieved the highest EP, reaching an effective state (*i.e., efficiency value of 1*), although the number of DMUs attaining this effective status decreased compared to 2016 and 2017. According to Table 3, the overall EP of the 15 DMUs was 78.32%. Furthermore, as shown in Fig.3, 11 DMUs (73.3%) fell below the annual average performance, with only one DMU (6.7%) achieving an efficiency value of 1.

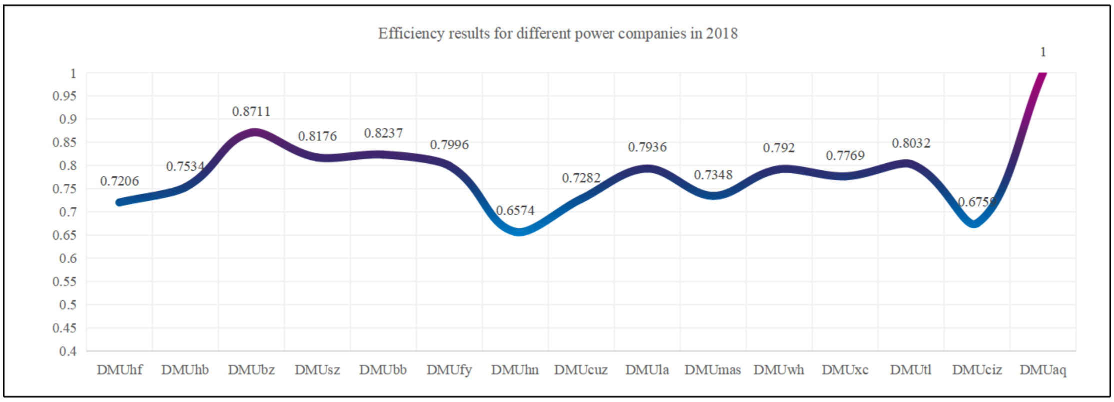

Fig.4 EP of different DMUs in 2018

In 2019, DMU*bb* recorded the lowest EP at only 59.26%, a decline of 23.11% compared to the same period in 2018. This fluctuation underscores the significant variability in EP among power enterprises over time, highlighting the need for improved production management. The highest EP was achieved by DMU*aq*, with an efficiency value of 88.51%, which is 11.49% lower than the best performance of the previous three years (which was 1). Notably, no enterprise reached an effective state of EP, indicating a significant decline in the overall performance of the power industry that year. According to Table 3, the overall EP of the 15 DMUs was 75.02%, marking the worst performance in the past five years. Additionally, as shown in Fig.3, 8 DMUs (53.3%) had EP below the annual average, with none achieving effective performance.

In 2020, DMU*bz* recorded the lowest EP at 61.08%, a decrease of 26.03% compared to 2019. The highest EP was again observed in DMU*aq*, which reached an effective state. As indicated in Table 3, the overall EP of the 15 DMUs improved to 79.10%, representing the best performance of the power industry over the past five years.

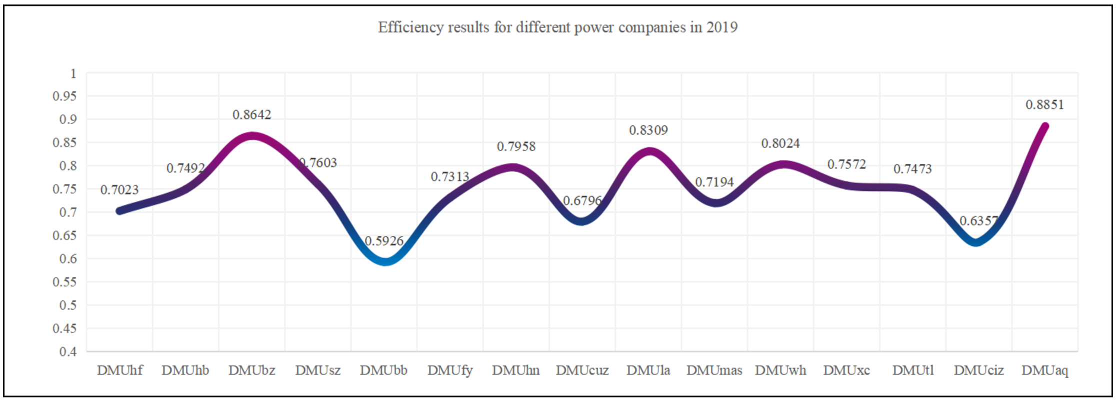

Fig.5 EP of different DMUs in 2019

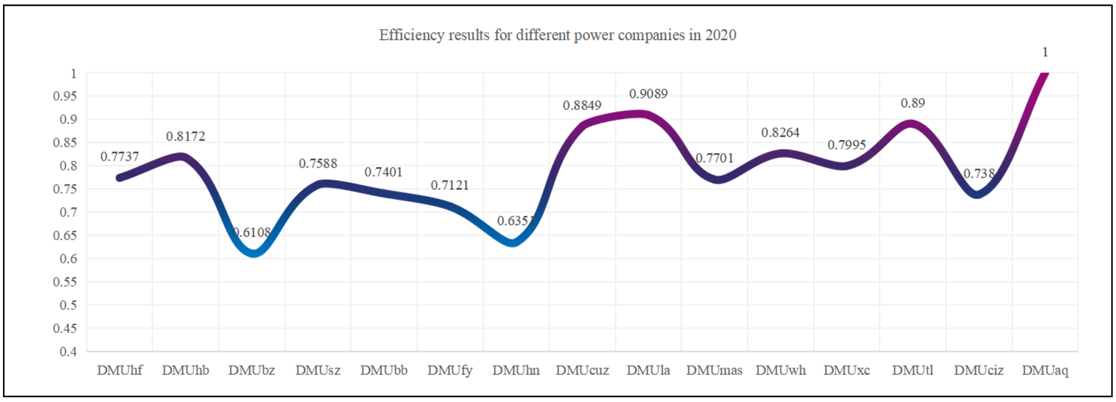

Fig.6 EP of different DMUs in 2020

Comparative analysis of Fig.2 to 5 reveals significant heterogeneity in the EP of different power enterprises. For instance, DMU*aq* consistently achieved an overall EP level exceeding 96% over the past five years, reaching an effective state in three of those years. Conversely, while DMU*wh*'s overall performance remains modest, it has shown remarkable growth, increasing by over 18.71% annually from 63.93% in 2016 to 82.64% in 2020. In contrast, other DMUs have experienced serious declines; DMU*bb*'s performance dropped from an effective state of 1 in 2016 to 74.01% in 2020, a decrease of more than 25%. Similarly, DMU*ciz* saw a reduction of 27.55% in its performance between 2016 and 2017. These findings highlight the overall low development level of EP in the power industry and indicate that individual enterprises have considerable room for improvement regarding factors such as production decision-making and technological advancement.

5.2 GNMI analysis

Based on the analysis in Section 5.1, we subdivide the research period into distinct stages according to the year and further investigate the factors influencing the production efficiency of the power industry in eastern China over the past five years. The results are illustrated in Fig.7. Overall, the GNMI for eastern China's power industry increased from 0.9999 to 1.0571, indicating a continuous improvement in overall productivity and a trend toward high-quality development within the industry. Additionally, the BPC rose from 1.0008 to 1.0492, signifying substantial efforts to control undesirable outputs, such as CEs, with an accelerating trend in progress. Furthermore, both TE and SE of the power industry improved by approximately 5%.

Examining specific stages, from 2016 to 2018, the overall GNMI of the power industry in eastern China increased slightly from 0.9999 to 1.0028, accompanied by improvements in TE, best practice gap, and SE. However, from 2017 to 2019, the GNMI, TE, BPC, and SE all declined, with GNMI falling from 1.0028 to 0.9729 (*i.e., decrease of 2.99%)*, TEC from 1.0061 to 0.9761 (*i.e., decrease of 3*%), BPC shifting from 1.0052 to 0.9699 (*i.e., decrease of 3.53%*), and SE decreasing from 1.0101 to 0.9680 (*i.e., decrease of 4.21%*). This suggests a significant decline in BPC, TEC, and SEC during this period, alongside a notable increase in CEs.

Between 2018 and 2020, the GNMI rose from 0.9729 to 1.0571, reflecting a substantial increase in the overall productivity of the power industry. Our analysis indicates that TE and SE increased by 7.89% and 8.99%, respectively, contributing to the overall productivity enhancement. Additionally, the BPC improved from 0.9699 to 1.0492 (*i.e., increase of 7.93%*), further demonstrating the industry's intensified efforts to manage CEs. In conclusion, we find that TE and SE significantly impact the productivity of the power industry.

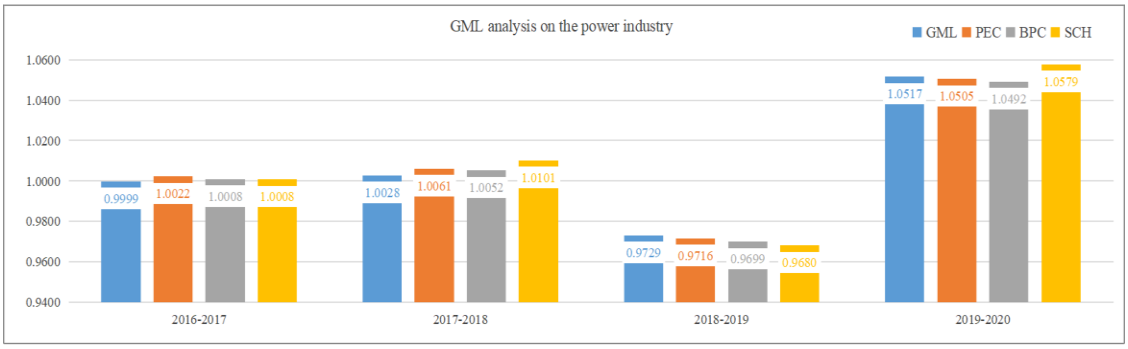

Fig.7 Power industry GNMI results from 2016 to 2020

Comparison between different DMUs

Building on the previous analysis, we further examine the productivity changes across different DMUs over the past five years. Notably, 73.3% of DMUs experienced productivity improvements, indicating overall progress in the power industry's development. Among these, DMU*wh* exhibited the largest increase in the GNMI at 5.16%. Conversely, 26.7% of DMUs saw declines in productivity, with DMU*bz* recording the most significant drop at 3.78%. Among the 4 DMUs with decreased productivity, two experienced simultaneous declines in both PEC and SEC while one DMU showed a decline in PEC and another in SCH. This suggests that both TEC and , SEC significantly impact the productivity of the power industry.

Additionally, within the 15 DMUs analyzed, PEC grew for 10 DMUs (66.7%), with DMU*wh* showing the largest increase at 5.78%. Our analysis further revealed that the GNMI improved for 9 of the 10 DMUs with PEC growth, reinforcing our earlier findings that PEC plays a crucial role in enhancing productivity. Thus, it is advisable for regulators and industry stakeholders to invest more in technological advancements to boost EP.

Moreover, 9 DMUs (60%) experienced growth in BPC, although the rate of increase was slow, underscoring the need for sustained efforts to manage CE within the power sector. Additionally, SEC increased in 5 DMUs (33.3%), with productivity rising in four of them, highlighting the importance of SEC for achieving high-quality development in the industry. Enterprise managers should make informed production decisions and engage in reasonable investment practices to avoid inefficiencies stemming from resource wastage.

Table 4 GNMI variation from 2016 to 2020

	GNMI	PEC	BPC	SEC
DMU_{hf}	0.9950	0.9859	1.0096	1.0034
DMU_{hb}	1.0279	1.0269	1.0028	1.0007
DMU_{bz}	0.9622	1.0066	0.9881	0.9708
DMU_{sz}	1.0112	1.0188	1.0017	0.9926
DMU_{bb}	0.9748	0.9898	0.9982	0.9873
DMU_{fy}	1.0042	1.0094	1.0031	0.9925
DMU_{hn}	0.9731	0.9774	1.0012	0.9992
DMU_{cuz}	1.0064	1	0.9984	1.0092
DMU_{la}	1.0112	1.0108	0.9986	1.0021
DMU_{mas}	1.0032	1.0025	1.0024	0.9984
DMU_{wh}	1.0516	1.0578	0.9989	0.9983
DMU_{xc}	1.0289	1.0323	1	0.9975
DMU_{tl}	1.0421	1.0003	1.0095	1.0368
DMU_{ciz}	1.0078	1.0213	1.0041	0.9883
DMU_{aq}	1.0029	1	1.0026	1

6. Conclusion

This paper utilizes an improved NDDF model and the GNMI to analyze the EP of 15 power enterprises in eastern China from 2016 to 2020, as well as the underlying mechanisms influencing their impact. The findings are as follows: (1) The overall EP of the power industry in eastern China remains low, with approximately 66.7% of the companies underperforming relative to the industry average; (2) The development of EP within the sector is unstable, characterized by significant fluctuations among certain enterprises; thus, a unified standard is necessary to regulate EP across the industry; (3) Although there has been an improvement in the overall EP of the power sector, the growth rate is sluggish, necessitating ongoing efforts to mitigate CEs; (4) TE and SE have a substantial impact on the productivity of the power industry.

Furthermore, based on these conclusions, we explore potential causes affecting the

EP of China's power industry and offer relevant policy recommendations. This study focuses on specific power enterprises in eastern China. Future research could investigate the EP of power companies in various countries or regions to conduct a heterogeneity analysis. Additionally, while the power sector represents a significant portion of the energy market, it encompasses numerous components, warranting further examination of the EP across different energy sectors to provide valuable insights for promoting green and high-quality development in the energy field.

Ethical approval

This research does not contain any studies with human participants or animals performed by any of the authors.

Declaration of competing interest

All authors declare that they have no conflicts of interest.

Data availability

Data are available from the authors upon request.

Declaration of generative AI in scientific writing

We did not use generative AI nor AI-assisted technologies during the writing process.

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