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Environmental Performance of China's Industrial System Considering Technological Heterogeneity and Interaction

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Abstract: The industrial sector, the backbone of China's economic development, is a key field that requires environmental management. The purpose of this study is to propose an improved data envelopment analysis (DEA) model to analyze the performance of provincial industrial systems (ISs) from 2011 to 2020 in China. To comprehensively characterize the operational framework of ISs, this study proposes an improved meta-frontier network DEA model. Unlike the existing models, the one proposed in this study not only considers the technical heterogeneity of ISs, but also reflects the interaction between IS subsystems. The empirical analysis yields valuable research findings. First, the overall environmental performance of Chinese ISs is generally low, with an average performance of 0.50, showing a U-shaped trend during the study period. Furthermore, significant regional differences are observed in the environmental performance of Chinese ISs. Second, the average performance of the production subsystem is 0.75, while the average performance of the pollution control subsystem (PTS) is 0.44. The low performance of the PTS pulls down the overall performance of Chinese ISs. Third, the technological level of Chinese ISs is low, with about 50% improvement potential. Finally, targeted suggestions to promote the green development of ISs are proposed on the basis of the empirical results.

Keywords: industrial system; technological heterogeneity; interaction; DEA model

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1. Introduction

Since the implementation of the reform and opening up policy, China's economy has achieved leapfrog development, making it the second-largest economy in the world [1]. In 2020, China's GDP reached CNY 10.16 billion, with a total energy consumption of 4.98 billion tons of standard coal. The consumption of fossil energy, however, generates large amounts of pollutants. The China 2021 Statistical Yearbook reported that the country emitted 3.18 million tons of sulfur dioxide, 11.82 million tons of nitrogen oxides, and 6.13 million tons of particulate matter in 2020. The crude economic development mode is unsustainable [2]. Given that the industrial sector is the main contributor to China's economy and to the country's energy consumption and pollution emissions [3], improving industrial environmental performance is critical to promoting sustainable economic development in the country. Therefore, conducting a scientific and objective evaluation of the performance of China's industrial systems (ISs) is important.

Scholars have widely adopted data envelopment analysis (DEA) models to evaluate the environmental performance of ISs [4]. However, traditional DEA models only consider initial inputs and final outputs, while the internal structures of decision-making units (DMUs) are ignored [5,6]. Thus, scholars have proposed network DEA models to address this problem. For example, Zhang et al. [7] and Li et al. [8] divided ISs into the production subsystem (PS) and pollution treatment subsystem (PTS) to analyze their overall performance and individual subsystem performances. However, existing studies have ignored the interaction between the two subsystems. In addition, production technology heterogeneity exists between ISs due to differences in geographical location and level of economic development. Therefore, the evaluation results that ignore heterogeneity and interaction relations will be inconsistent with reality [9,10].

The purpose of the current study is to propose a DEA model to evaluate and analyze the performance of the IS with two subsystems. The research object of this study includes 27 provincial ISs in China. Given the data availability, this study collects the panel data of these ISs in China from 2011 to 2020. Specifically, this study explores the following issues: (1) how to build a performance model for an IS with two subsystems, (2) the characteristics of the performance of China's provincial ISs and their subsystems, and (3) the process by which inefficient ISs can improve performance.

To address the aforementioned issues, this study first constructs a new two-stage network DEA model by considering the technological heterogeneity between ISs and the interaction between subsystems. Then, the proposed model is applied to evaluate the performance of China's provincial ISs from 2011 to 2020. Next, the technological gap, management potential (MP), and technical potential (TP) of the ISs are analyzed. Finally, targeted improvement measures to improve the performance of the ISs are proposed.

The theoretical contributions of this study are as follows. First, pollutants (e.g., solid waste) in the production stage of real ISs can be converted into recyclable resources after treatment in the pollution treatment stage. The recycled resources are then reused for production. To address this reality, this study decomposes the IS into the production and pollution treatment subsystems and considers the interaction between them. Second, previous studies assessing regional industrial performance in China have often ignored heterogeneity. To address this problem, the meta-frontier analysis framework is introduced into the DEA model and an innovative two-stage network DEA model is proposed. The model can effectively consider the existing production technology heterogeneity among ISs in the process of performance evaluation.

The practical contributions of this paper are as follows. First, in previous studies, scholars have generally concluded that China's IS performance has been improving year by year and the performance of eastern China is higher than that of central and western China [7,11,12]. However, this study finds that, overall, China's IS performance shows a U-shaped change in the study period and that the central region of China has the highest industrial system performance. Second, this study finds that PS performances in the eastern, central, and western regions have convergent characteristics, while PTS performance has U-shaped characteristics similar to IS performance. Therefore, the results further validate the existence of regional differences in IS performance in China. Finally, this study proposes recommendations to promote IS performance improvement from both technical and managerial perspectives.

The rest of the paper is organized as follows. Section 2 reviews the main literature relevant to this work. Section 3 proposes an environmental performance model that considers technological heterogeneity and interaction. Section 4 provides an empirical analysis of China's inter-provincial ISs. Finally, Section 5 summarizes the main conclusions.

2. Literature Review

2.1. Environmental Efficiency Assessment

DEA, as a nonparametric model that does not require the assumption of a production function in advance, has been widely used in efficiency assessment [13]. Liu et al. [14] reviewed the application of DEA between 1978 and 2010 and found that DEA methods have been gaining popularity among scholars. Emrouznejad and Yang [15] reviewed the application of DEA in different fields between 1978 and 2016 and found that DEA has been widely used in the energy and environment fields. For example, Shah et al. [16] evaluated the energy efficiency and productivity of South Asian countries using the slack-based model (SBM) and the Malmquist index method. Their results show that energy efficiency in South Asian countries still has potential for improvement. Vlontzos et al. [17] evaluated the environmental efficiency of European Union (EU) member states using a non-radial DEA model and found that the low level of technology is the main factor of environmental inefficiency in some countries. Chen and Jia [12] measured the environmental efficiency of China's regional industries through the undesired output SBM. The results reveal significant regional differences in the environmental efficiency of Chinese industries. Wu et al. [18] used an improved DEA model to measure China's regional environmental efficiency and conducted a dynamic evaluation of environmental total factor productivity through the Malmquist index. They found that China's overall carbon emission efficiency is still in an inefficient state, with the eastern region being the most efficient and the western region being the least efficient. Piao et al. [19] proposed three DEA models by considering the disposability of undesired outputs. They also combined the Malmquist–Luenberger (ML) index to evaluate China's environmental efficiency. Their results suggest that the technological progress is the primary driver of environmental efficiency.

Some scholars have considered technical heterogeneity when evaluating regional environmental efficiency. For instance, Li and Lin [20] introduced a meta-frontier analysis framework into DEA to measure China's energy and carbon emission efficiency. Chen and Zhou [21] applied a non-radial DEA model and meta-frontier ML index to evaluate the eco-efficiency of urban agglomerations in China. The authors concluded that the increase in the technology gap has led to the broadened eco-efficiency gap between urban agglomerations. Ma et al. [22] analyzed the environmental efficiency of Chinese cities using a meta-frontier DEA model. Their empirical results reveal that Chinese coastal cities outperform central and western cities, and the efficiency of large and mega cities is higher than that of medium and small cities. Wang et al. [23] analyzed the energy efficiency of the Chinese steel industry using a meta-frontier analysis framework and revealed the existence of spatial technical heterogeneity in the Chinese steel industry. Li et al. [24] conducted a dynamic evaluation of environmental efficiency in China through a meta-frontier dynamic DEA model and found that Chinese high-income cities perform well. Meanwhile, Ding et al. [25] investigated the environmental efficiency of Chinese urban agglomerations based on a nonparametric meta-frontier approach and reported that the eastern and southern coastal regions of China are more efficient compared with other regions.

2.2. Application of Two-Stage DEA Model in ISs

The industrial sector is a major source of pollution emissions; thus, industrial environmental performance has attracted extensive academic attention. Scholars have widely used two-stage DEA models to measure the environmental performance of ISs. For example, Wu et al. [13] constructed a two-stage model with shared inputs to evaluate the energy efficiency and environmental pollution control efficiency of ISs in China. The results show that the energy efficiency of the IS outperforms the environmental pollution control efficiency. Li et al. [11] used a combination of a network SBM model and DEA window analysis to dynamically evaluate the environmental performance of the regional ISs in China. The authors divided regional ISs into production and pollutant treatment processes. The results show that the overall low performance of the regional ISs is caused by the inefficiency of their pollutant treatment sub-processes. Chen et al. [26] constructed a two-stage DEA model to evaluate the environmental efficiency of China's industrial water systems. Using the proposed model, which considers noncooperative and cooperative relationships in two subsystems, they found that noncooperative relationships hinder the sustainable development of industrial water systems. Chu et al. [27] formed an ecosystem of the regional production and pollution treatment systems in China and measured the eco-efficiency of the system using a network DEA model. The results show that the eco-efficiency of most Chinese regions still has a large potential for improvement. Shao et al. [28] proposed a network DEA model that is applicable to the environmental performance of ISs by decomposing them into production, wastewater treatment, and exhaust gas treatment phases. Their results show that the environmental performance of the Chinese industrial sector has gradually improved over the years. Wang and Feng [29] proposed a super-efficient network DEA approach to analyze the efficiency of the production stage and pollution control stage of Chinese ISs and found that Chinese ISs are inefficient as a whole. Qu et al. [30] applied an improved network DEA to assess the environmental sustainability performance of Chinese regions and reported that the eastern region of China is leading in sustainable development. Meanwhile, Liu et al. [31] constructed a two-stage DEA model with ratio output to evaluate the environmental efficiency of the Chinese industrial sector. Their results showed the gradual improvement of the environmental performance of the Chinese industrial sector throughout the years.

2.3. Literature Summary

The abovementioned works reveal that the study of the regional environment and the performance of ISs has received extensive attention from scholars. The scholars have analyzed regional IS performance from static and dynamic perspectives, and some have also considered the technological heterogeneity of ISs. The present study has two main differences from previous studies. First, this work refines the traditional internal structure of ISs by considering the interactions that exist in their internal subsystems based on practical considerations. Second, this study extends the traditional two-stage model to model the situation with production technology heterogeneity and subsystem interactions. Based on previous studies and the purpose of the current one, the following hypotheses are proposed:

Hypothesis 1: *Regional differences exist between China's provincial IS performance and subsystem performance.*

Hypothesis 2: *The performance of PTS is low and has a great impact on the overall performance of ISs in China.*

Hypothesis 3: *Significant technological gaps exist among regional ISs.*

3. Methodology

3.1. Group Frontier Model Considering Technical Heterogeneity and Interaction

This study considers N regional ISs, defined as DMU_n $(n = 1, \cdots, N)$. As shown in Figure 1, each IS contains two subsystems: PS and PTS. Figure 1 also shows an interaction between the two subsystems. In the PS, the inputs and desired outputs are denoted by x^f_{in} and y^f_{rn}, respectively, while the undesired outputs are denoted by w_{sn}. In the PTS, the undesired output w_{sn} of the PS is treated to obtain some recyclable resources $\overline{w}_{sn}$ and then returned to the PS. The other inputs in the PTS are x^s_{pn}, and the undesired output is y^s_{qn}.

All DMUs belong to K groups. The number of DMUs of the kth group is N^k, and then we have $\sum_{k=1}^{K} N^k = N$. Without a loss of generality, DMUs within the same group have the same or similar production technologies. For the DMU_o in group k, its group efficiency can be obtained by the following Model (1):

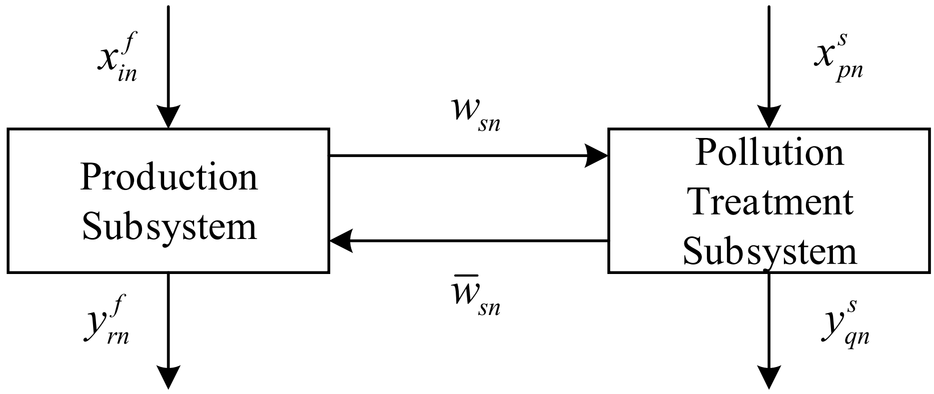

Figure 1. Internal structure of the regional IS.

$$
\begin{aligned}
\min e_o = & \frac{\frac{1}{3}[(1-\frac{1}{I}\sum_{i=1}^{I}\alpha_g^k)+(1-\frac{1}{P}\sum_{p=1}^{P}\sigma_p^k)+(1-\frac{1}{Q}\sum_{q=1}^{Q}\delta_q^k)]}{1+\frac{1}{R}\sum_{r=1}^{R}\beta_r^k} \\
s.t. & \sum_{n=1}^{N^k}\lambda_n^k x_{in}^f \le (1-\alpha_i^k)x_{io}^f, \quad i=1,2,\ldots,I, \\
& \sum_{n=1}^{N^k}\lambda_n^k y_{rn}^f \ge (1+\beta_r^k)\, y_{ro}^f, \quad r=1,2,\ldots,R, \\
& \sum_{n=1}^{N^k}\omega_n^k x_{pn}^s \le (1-\sigma_p^k)x_{po}^s, \quad p=1,2,\ldots,P, \\
& \sum_{n=1}^{N^k}\omega_n^k y_{qn}^s = (1-\delta_q^k)\, y_{qo}^s, \quad q=1,2,\ldots,Q, \\
& \sum_{n=1}^{N^k}\lambda_n^k w_{sn} = w_{so}, \quad s=1,2,\ldots,S, \\
& \sum_{n=1}^{N^k}\omega_n^k w_{sn} = w_{so}, \quad s=1,2,\ldots,S, \\
& \sum_{n=1}^{N^k}\lambda_n^k \overline{w}_{sn} = \overline{w}_{so}, \quad s=1,2,\ldots,S, \\
& \sum_{n=1}^{N^k}\omega_n^k \overline{w}_{sn} = \overline{w}_{so}, \quad s=1,2,\ldots,S, \\
& \lambda_n^k, \omega_n^k \ge 0, n=1,\ldots,N^k.
\end{aligned}
\tag{1}
$$

In the PS, α_i^k is the reduction ratio of inputs, and β_r^k is the increase ratio of expected outputs. In the PTS, σ_p^k is the reduction ratio of inputs, and δ_q^k is the reduction ratio of undesired outputs. In Model (1), λ_n^k is the weight of the PS, and ω_n^k is the weight of the PTS. The PT and PTS subsystems are linked through two intermediate indicators w_{sn} and $\overline{w}_{sn}$, where w_{sn} is the output and input of the PT subsystem as well as the input of the PTS subsystem, and similarly, $\overline{w}_{sn}$ is the output and input of the PTS subsystem as well as the input of the PT subsystem. Referring to Ding et al. [25], this study defines this link relationship as the interaction relationship between the two subsystems. The fifth to eighth constraints of Model (1) are used to reflect the interaction relationship between the two subsystems. Model (1) is a nonlinear programming model that can be converted into a linear model using the following steps.

Step 1: Let $\frac{1}{1+\frac{1}{R}\sum_{r=1}^{R}\beta_r^k} = t$, and then, Model (1) becomes Model (2).

$$
\begin{aligned}
&\min e_o = \tfrac{1}{3}[(1-\tfrac{1}{I}\sum_{i=1}^{I}\alpha_g^k)+(1-\tfrac{1}{P}\sum_{p=1}^{P}\sigma_p^k)+(1-\tfrac{1}{Q}\sum_{q=1}^{Q}\delta_q^k)] \\
&s.t. 1+\tfrac{1}{R}\sum_{r=1}^{R}\beta_r^k=\tfrac{1}{t}, \\
&\sum_{n=1}^{N^k}\lambda_n^k x_{in}^f \le (1-\alpha_i^k)x_{io}^f, \quad i=1,2,\ldots,I, \\
&\sum_{n=1}^{N^k}\lambda_n^k y_{rn}^f \ge (1+\beta_r^k)\, y_{ro}^f, \ \ r=1,2,\ldots,R, \\
&\sum_{n=1}^{N^k}\omega_n^k x_{pn}^s \le (1-\sigma_p^k)x_{po}^s, \quad p=1,2,\ldots,P, \\
&\sum_{n=1}^{N^k}\omega_n^k y_{qn}^s = (1-\delta_q^k)\, y_{qo}^s, \ \ q=1,2,\ldots,Q, \\
&\sum_{n=1}^{N^k}\lambda_n^k w_{sn} = w_{so}, \ \ s=1,2,\ldots,S, \\
&\sum_{n=1}^{N^k}\omega_n^k w_{sn} = w_{so}, \ \ s=1,2,\ldots,S, \\
&\sum_{n=1}^{N^k}\lambda_n^k \overline{w}_{sn} = \overline{w}_{so}, \ \ s=1,2,\ldots,S, \\
&\sum_{n=1}^{N^k}\omega_n^k \overline{w}_{sn} = \overline{w}_{so}, \ \ s=1,2,\ldots,S, \\
&\lambda_n^k, \omega_n^k \ge 0, n=1,\ldots,N^k.
\end{aligned} \tag{2}
$$

Step 2: Let $t\alpha_g^k=\overline{\alpha}_g^k$, $t\sigma_p^k=\overline{\sigma}_p^k$, $t\delta_q^k=\overline{\delta}_q^k$, $t\beta_r^k=\overline{\beta}_r^k$, $t\lambda_n^k=\overline{\lambda}_n^k$, and $t\omega_n^k=\overline{\omega}_n^k$; then, Model (2) can be converted into Model (3).

$$
\begin{aligned}
&\min e_o = t-\tfrac{1}{3I}\sum_{i=1}^{I}\overline{\alpha}_g^k-\tfrac{1}{3P}\sum_{p=1}^{P}\overline{\sigma}_p^k-\tfrac{1}{3Q}\sum_{q=1}^{Q}\overline{\delta}_q^k \\
&s.t.\ t+\tfrac{1}{R}\sum_{r=1}^{R}\overline{\beta}_r^k=1, \\
&\sum_{n=1}^{N^k}\overline{\lambda}_n^k x_{in}^f \le (t-\overline{\alpha}_i^k)x_{io}^f, \quad i=1,2,\ldots,I, \\
&\sum_{n=1}^{N^k}\overline{\lambda}_n^k y_{rn}^f \ge (t+\overline{\beta}_r^k)\, y_{ro}^f, \ \ r=1,2,\ldots,R, \\
&\sum_{n=1}^{N^k}\overline{\omega}_n^k x_{pn}^s \le (t-\overline{\sigma}_p^k)x_{po}^s, \quad p=1,2,\ldots,P, \\
&\sum_{n=1}^{N^k}\overline{\omega}_n^k y_{qn}^s = (t-\overline{\delta}_q^k)\, y_{qo}^s, \ \ q=1,2,\ldots,Q, \\
&\sum_{n=1}^{N^k}\overline{\lambda}_n^k w_{sn} = t w_{so}, \ \ s=1,2,\ldots,S, \\
&\sum_{n=1}^{N^k}\overline{\omega}_n^k w_{sn} = t w_{so}, \ \ s=1,2,\ldots,S, \\
&\sum_{n=1}^{N^k}\overline{\lambda}_n^k \overline{w}_{sn} = t\overline{w}_{so}, \ \ s=1,2,\ldots,S, \\
&\sum_{n=1}^{N^k}\overline{\omega}_n^k \overline{w}_{sn} = t\overline{w}_{so}, \ \ s=1,2,\ldots,S, \\
&\overline{\lambda}_n^k, \overline{\omega}_n^k \ge 0, n=1,\ldots,N^k.
\end{aligned} \tag{3}
$$

Step 3: Model (3) is solved to obtain the optimal solution $(\overline{\alpha}_g^{k*}, \overline{\sigma}_p^{k*}, \overline{\delta}_q^{k*}, \overline{\beta}_r^{k*}, \overline{\lambda}_n^{k*}, \overline{\omega}_n^{k*}, t)$. Then, the optimal solution of Model (2) is $\alpha_g^{k*} = \frac{\overline{\alpha}_g^{k*}}{t}$, $\sigma_p^{k*} = \frac{\overline{\sigma}_p^{k*}}{t}$, $\delta_q^{k*} = \frac{\overline{\delta}_q^{k*}}{t}$, $\beta_r^{k*} = \frac{\overline{\beta}_r^{k*}}{t}$, $\lambda_n^{k*} = \frac{\overline{\lambda}_n^{k*}}{t}$, and $\omega_n^{k*} = \frac{\overline{\omega}_n^{k}}{t}$.

According to the solution of the abovementioned models, we can calculate the efficiency value e_o^k of the DMU_o in the kth group, and its efficiency improvement potential under the group frontier is expressed as:

$$ep_o = 1 - e_o^k \tag{4}$$

If $1 > ep_o > 0$, the DMU_o is group-inefficient; if $ep_o = 0$ or $e_o^k = 1$, then the DMU_o is group-efficient.

3.2. Meta-Frontier Model Considering Technological Heterogeneity and Interaction

As mentioned previously, technological heterogeneity exists among regional ISs due to differences in resource endowments, economic development, and geographic conditions. Model (1) only considers all ISs with the same or similar technology levels. Based on meta-frontier theory, this section proposes a meta-frontier model that considers technological heterogeneity and interaction. According to the ideas of Sun et al. [32], Model (5) is proposed as follows:

$$\begin{aligned}
&\min E_o = \frac{\frac{1}{3}[(1-\frac{1}{I}\sum_{i=1}^{I}\alpha_g^m)+(1-\frac{1}{P}\sum_{p=1}^{P}\sigma_p^m)+(1-\frac{1}{Q}\sum_{q=1}^{Q}\delta_q^m)]}{1+\frac{1}{R}\sum_{r=1}^{R}\beta_r^m}\\
&s.t. \sum_{k=1}^{K}\sum_{n=1}^{N^k}\lambda_n^k x_{in}^f \le (1-\alpha_i^m)x_{io}^f, \quad i = 1,2,\ldots,I,\\
&\sum_{k=1}^{K}\sum_{n=1}^{N^k}\lambda_n^k y_{rn}^f \ge (1+\beta_r^m)\, y_{ro}^f, \quad r = 1,2,\ldots,R,\\
&\sum_{k=1}^{K}\sum_{n=1}^{N^k}\omega_n^k x_{pn}^s \le (1-\sigma_p^m)x_{po}^s, \quad p = 1,2,\ldots,P,\\
&\sum_{k=1}^{K}\sum_{n=1}^{N^k}\omega_n^k y_{qn}^s = (1-\delta_q^m)\, y_{qo}^s, \quad q = 1,2,\ldots,Q,\\
&\sum_{k=1}^{K}\sum_{n=1}^{N^k}\lambda_n^k w_{sn} = w_{so}, \quad s = 1,2,\ldots,S,\\
&\sum_{k=1}^{K}\sum_{n=1}^{N^k}\omega_n^k w_{sn} = w_{so}, \quad s = 1,2,\ldots,S,\\
&\sum_{k=1}^{K}\sum_{n=1}^{N^k}\lambda_n^k \overline{w}_{sn} = \overline{w}_{so}, \quad s = 1,2,\ldots,S,\\
&\sum_{k=1}^{K}\sum_{n=1}^{N^k}\omega_n^k \overline{w}_{sn} = \overline{w}_{so}, \quad s = 1,2,\ldots,S,\\
&\lambda_n^k, \omega_n^k \ge 0, n = 1,\ldots,N^k.
\end{aligned} \tag{5}$$

Compared with the frontier of Model (1), that of Model (5) is formed by the efficient DMUs among all groups' DMUs. In other words, the technology level represented by the meta-frontier is higher than that of the group frontier. Furthermore, Model (5) is nonlinear, and it can be transformed into the linear Model (6) through the abovementioned step.

$$
\begin{aligned}
&\min E_o = t - \tfrac{1}{3I}\sum_{i=1}^{I}\alpha_g^m - \tfrac{1}{3P}\sum_{p=1}^{P}\sigma_p^m - \tfrac{1}{3Q}\sum_{q=1}^{Q}\delta_q^m \\
&s.t.\ t + \tfrac{1}{R}\sum_{r=1}^{R}\overline{\beta}_r^m = 1, \\
&\quad \sum_{k=1}^{K}\sum_{n=1}^{N^k}\overline{\lambda}_n^k x_{in}^f \le (t - \overline{\alpha}_i^m)x_{io}^f,\quad i = 1,2,\ldots,I, \\
&\quad \sum_{k=1}^{K}\sum_{n=1}^{N^k}\overline{\lambda}_n^k y_{rn}^f \ge (t + \overline{\beta}_r^m)\, y_{ro}^f,\ \ r = 1,2,\ldots,R, \\
&\quad \sum_{k=1}^{K}\sum_{n=1}^{N^k}\overline{\omega}_n^k x_{pn}^s \le (t - \overline{\sigma}_p^m)x_{po}^s,\quad p = 1,2,\ldots,P, \\
&\quad \sum_{k=1}^{K}\sum_{n=1}^{N^k}\overline{\omega}_n^k y_{qn}^s = (t - \overline{\delta}_q^m)\, y_{qo}^s,\ \ q = 1,2,\ldots,Q, \\
&\quad \sum_{k=1}^{K}\sum_{n=1}^{N^k}\overline{\lambda}_n^k w_{sn} = t w_{so},\ \ s = 1,2,\ldots,S, \\
&\quad \sum_{k=1}^{K}\sum_{n=1}^{N^k}\overline{\omega}_n^k w_{sn} = t w_{so},\ \ s = 1,2,\ldots,S, \\
&\quad \sum_{k=1}^{K}\sum_{n=1}^{N^k}\overline{\lambda}_n^k \overline{w}_{sn} = t\overline{w}_{so},\ \ s = 1,2,\ldots,S, \\
&\quad \sum_{k=1}^{K}\sum_{n=1}^{N^k}\overline{\omega}_n^k \overline{w}_{sn} = t\overline{w}_{so},\ \ s = 1,2,\ldots,S, \\
&\quad \overline{\lambda}_n^k, \overline{\omega}_n^k \ge 0, n = 1,\ldots,N^k.
\end{aligned}
\tag{6}
$$

Model (6) can obtain the efficiency value E_o of the DMU_o under the meta-frontier, and its efficiency improvement potential under the meta-frontier is given by

$$EP_o = 1 - E_o \tag{7}$$

where $EP_o = 0$ indicates that the DMU_o is efficient in the meta-frontier; otherwise, the DMU_o is inefficient.

Based on the optimal solutions of Model (6), the following definitions are given.

Definition 1: The meta-frontier efficiency of the PS is given by

$$E_o^1 = \frac{1 - \frac{1}{I}\sum_{i=1}^{I}\alpha_g^m}{1 + \frac{1}{R}\sum_{r=1}^{R}\beta_r^m} \tag{8}$$

Definition 2: The meta-frontier efficiency of the PTS is given by

$$E_o^2 = \frac{1}{2}[(1 - \frac{1}{P}\sum_{p=1}^{P}\sigma_p^m) + (1 - \frac{1}{Q}\sum_{q=1}^{Q}\delta_q^m)] \tag{9}$$

If $E_o^1 = 1$ (or $E_o^2 = 1$), then the DMU_o is efficient in the PS (or in the PTS); otherwise, DMU_o is inefficient.

The technology gap ratio index (TGRI) under the two frontiers is defined as follows:

$$TGRI_o = \frac{E_o}{e_o} \tag{10}$$

This study further decomposes the potential improvement capabilities of DMU_o under meta-frontier technologies into MP and TP, which are defined as follows:

$$MP_o = ep_o = 1 - e_o \quad (11)$$

$$TP_o = EP_o - ep_o = (1 - E_o) - (1 - e_o) = e_o - E_o \quad (12)$$

4. Empirical Analysis

4.1. Samples and Variables

Given the data availability, this study collects the panel data of 27 provinces in China from 2011 to 2020. Three inputs are considered in the PS: (1) main business cost (CNY 100 million), (2) industrial energy consumption (10,000 t of standard coal), and (3) industrial labor (10,000 people). The desirable output in the PS is the total industrial output value (CNY 100 million). In the PTS, the input is industrial governance investment (CNY 100 million), and the output is the amount of industrial solid waste disposal (10,000 t). The intermediate outputs/inputs linking the two subsystems are the industrial solid waste emissions (10,000 t) and the comprehensive utilization of industrial solid waste (10,000 t). The data regarding the indicators came from the China Statistical Yearbook and China Industrial Statistical Yearbook. Their statistical descriptions are shown in Table 1.

Table 1. Statistical description.

References	Indicators	Mean	Maximum	Minimum	Standard Deviation
Inputs [11,28,33–35]	Main business cost	30,605.18	139,748.56	1226.80	31,071.37
	Industrial energy consumption	10,141.65	31,805.20	826.98	6935.62
	Industrial labor	184.47	1055.37	9.83	185.93
	Total industrial output value	8864.09	38,526.29	415.12	8018.60
	Industrial governance investment	21.79	141.23	0.05	21.55
Intermediate outputs/inputs [27,36,37]	Industrial solid waste emissions	11,499.16	52,037.00	333.00	10,038.43
	Comprehensive utilization of industrial solid waste	6811.29	25,230.00	193.00	5356.35
Outputs [11,28]	Industrial solid waste disposal	2742.06	27,402.00	6.00	4178.22

4.2. System Performance Analysis

Figure 2 shows the meta-frontier performance trends of ISs from 2011 to 2020, and the following findings can be drawn. First, China's overall regional IS performance is low and shows a U-shaped trend over time. Before 2015, China's IS performance declined over the years. After 2015, the IS performance increases with years. This finding differs from the findings of Zhang et al. [7] who found that the performance of ISs increased during the study period. The potential reasons for the U-shaped characteristic are as follows. Before 2015, China focused on economic development and industrialization while neglecting environmental protection. As a result, the IS performance of Chinese regions declined. After 2015, the Chinese government strengthened the control on energy conservation and emission reduction, which led to a turnaround in IS performance from a downward to an upward trend [38]. This situation also indicates that the Chinese government's environmental policies and measures have had a general enhancing effect on IS performance.

Second, although industrial development in central China has lagged behind that in the eastern region, the IS performance in the former is higher than that in the latter. This situation may be related to the transfer of Chinese industry-related industries to the central region of China. The central region of China has not only taken over the industry-related industries transferred from the eastern region but also absorbed the advanced experience and technology from the eastern region to avoid wasting resources. This situation makes the IS performance in the central region better than that in the eastern region. This finding, however, differs from the general findings of scholars, such as Li et al. [11] and Chen and Jia [12], who found that the IS performance in eastern China is significantly higher than that in central and western regions.

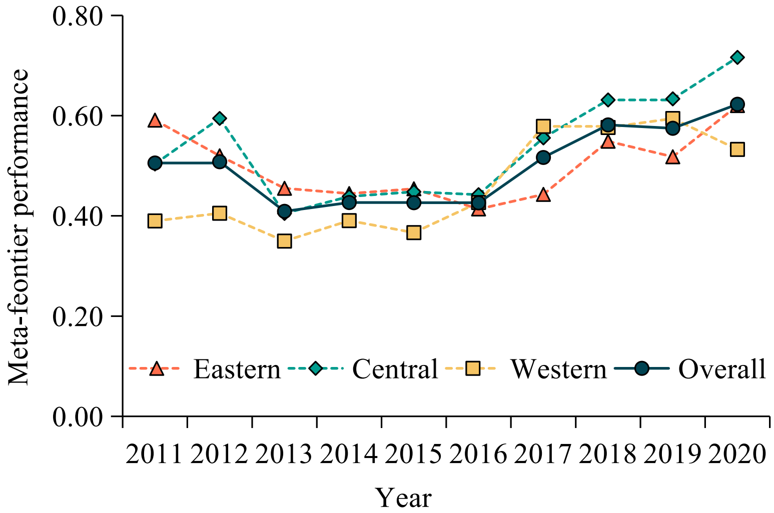

Figure 2. Meta-frontier performance of ISs.

Third, among the three regions, western China has the lowest IS performance. This finding indicates that economic development and ecological protection in this region are not coordinated. Thus, the western region should focus on industrial restructuring, optimizing the economic development model, and facilitating industrial performance improvement [39]. Figure 2 shows the convergent characteristics of IS performance in the eastern, central, and western regions of China. This result is due to the fact that China's industry-related industries are shifting from the developed eastern provinces to the central and western regions. This situation further contributes to the increase in industrial capacity in the central and western regions and promotes the convergence of IS performance across regions in China. This finding is also supported by Zhang et al. [40]. Overall, there are significant regional differences in the performance of ISs in China's eastern, central, and western regions, thus confirming Hypothesis 1.

Table 2 shows the average IS performance in each province from 2011 to 2020, and the following findings can be drawn. First, the three provinces with the highest IS performance are Anhui, Jiangxi, and Tianjin. Among them, Anhui ranks first with 0.79. Anhui is located on the edge of the Yangtze River Delta. Thus, Anhui has a geographical location advantage in taking over the industry-related industries transferred from developed provinces [41]. Second, the IS performance of all sample provinces is below 0.80, and 85.19% of the sample provinces have IS performance below 0.60. This finding indicates that, overall, China's IS development is ineffective. Third, the provinces with IS performance below 0.40 are Jilin, Xinjiang, Ningxia, and Gansu. The underdeveloped economies and insufficient investments made in environmental management in the four provinces have resulted in the low IS performances in these provinces [13]. The above findings are consistent with the findings of Wang and Feng [29], suggesting that the ISs in Chinese provinces still have a large potential for improvement.

4.3. Sub-Stage Performance Analysis

Figure 3 shows the meta-frontier performance trends of PS and PTS from 2011 to 2020. The following conclusions can be drawn from these findings. First, the overall PS performance in the eastern, central, and western regions of China has improved over the years, while the performance gap among the three regions decreases over the years. In particular, the PS performance in the eastern region is the highest. The eastern region of China has a better-developed economy and higher level of industrial production technology compared with other regions [29]. Therefore, the PS in eastern China performs the best. Second, the PTS performance in each region is very low, and the overall mean value does not exceed 0.60. However, the trend of the change in the PTS performance in each region during the study period is consistent with the trend of the IS performance. Thus, this result indirectly indicates that the PTS inefficiency is the main factor that pulls down the overall IS performance. This finding supports the validity of Hypothesis 2.

Table 2. Average value of IS performance in each province from 2011 to 2020.

Eastern				Central				Western			
Provinces	e_o	E_o	**TGRI**	**Provinces**	e_o	E_o	**TGRI**	**Provinces**	e_o	E_o	**TGRI**
Tianjin	0.72	0.71	0.97	Anhui	0.83	0.79	0.95	Chongqing	0.87	0.63	0.72
Shanghai	0.64	0.60	0.93	Jiangxi	0.76	0.72	0.95	Sichuan	0.65	0.58	0.89
Jiangsu	0.66	0.59	0.90	Hunan	0.54	0.52	0.98	Yunnan	0.69	0.53	0.75
Guangdong	0.64	0.54	0.85	Shanxi	0.68	0.52	0.77	Shaanxi	0.61	0.48	0.79
Liaoning	0.77	0.51	0.65	Hubei	0.52	0.51	0.99	Guizhou	0.63	0.44	0.70
Shandong	0.72	0.49	0.69	Heilongjiang	0.61	0.49	0.81	Xinjiang	0.53	0.38	0.71
Fujian	0.60	0.47	0.79	Henan	0.46	0.44	0.95	Ningxia	0.44	0.36	0.81
Hebei	0.72	0.44	0.60	Jilin	0.37	0.30	0.88	Gansu	0.36	0.30	0.82
Beijing	0.49	0.43	0.87								
Guangxi	0.68	0.40	0.57								
Hainan	0.61	0.34	0.57								
Mean	0.66	0.50	0.76	Mean	0.59	0.54	0.91	Mean	0.60	0.46	0.78
Overall mean	0.62	0.50	0.81								

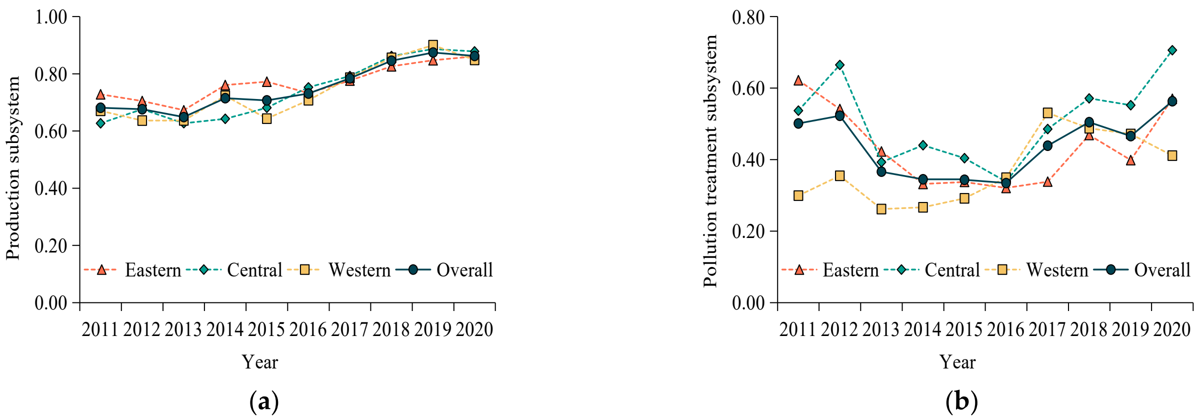

Figure 3. Meta-frontier performance in the production subsystem (**a**) and the pollution treatment subsystem (**b**).

Table 3 presents the average performance and ranking of PS and PTS in each province, and the following findings are obtained. First, the top five provinces in terms of PS performance are Shanghai, Shaanxi, Guangdong, Anhui, and Jiangsu, which have 0.95, 0.95, 0.90, 0.89, and 0.89, respectively. Shanghai, Guangdong, and Jiangsu are developed eastern provinces with mature industries and high levels of economic development, which contribute to their high PS performance. Meanwhile, Anhui and Shaanxi have taken over a large number of industry-related industries transferred from the developed eastern provinces; thus, they also have high industrial PS performance [42].

Second, the top five provinces in terms of PTS performance are Anhui, Jiangxi, Tianjin, Liaoning, and Sichuan, which have average performance rates of 0.80, 0.72, 0.66, 0.65, and 0.56, respectively. These data indicate that the PTS performance of Chinese provinces is generally low. Anhui's high PS and PTS performances can be attributed to the province's focus on the positive interaction between industrial development and environmental management. For example, Anhui has established comprehensive pollution management and trading systems and has regularly implemented environmental protection laws and regulations to increase the participation of all people in ecological environmental protection [43].

Table 3. Sub-stage performance of each province and its ranking.

Regions	Provinces	Production Stage	Regional Ranking	Overall Ranking	Pollution Treatment Stage	Regional Ranking	Overall Ranking
Eastern	Beijing	0.86	4	8	0.25	11	26
	Tianjin	0.86	5	10	0.66	1	3
	Hebei	0.66	8	19	0.43	5	11
	Shanghai	0.95	1	1	0.42	6	13
	Jiangsu	0.89	3	5	0.48	4	9
	Shandong	0.70	7	17	0.51	3	7
	Fujian	0.83	6	12	0.31	9	23
	Guangdong	0.90	2	3	0.37	8	19
	Guangxi	0.60	10	23	0.41	7	14
	Hainan	0.56	11	25	0.30	10	24
	Liaoning	0.64	9	21	0.65	2	4
	Mean	0.77	-	-	0.44	-	-
Central	Shanxi	0.84	3	11	0.40	7	16
	Jilin	0.44	8	27	0.44	4	10
	Heilongjiang	0.62	7	22	0.50	3	8
	Anhui	0.89	1	4	0.80	1	1
	Jiangxi	0.87	2	6	0.72	2	2
	Henan	0.69	6	18	0.37	8	18
	Hubei	0.79	5	14	0.41	6	15
	Hunan	0.80	4	13	0.42	5	12
	Mean	0.74	-	-	0.51	-	-
Western	Chongqing	0.86	3	9	0.53	2	6
	Sichuan	0.77	4	15	0.56	1	5
	Guizhou	0.74	5	16	0.34	4	20
	Yunnan	0.86	2	7	0.38	3	17
	Shaanxi	0.95	1	2	0.24	8	27
	Gansu	0.51	8	26	0.32	6	22
	Ningxia	0.65	6	20	0.28	7	25
	Xinjiang	0.59	7	24	0.33	5	21
	Mean	0.74	-	-	0.37	-	-
Overall mean		0.75	-	-	0.44	-	-

Third, the ranking results of the two subsystems reveal the imbalanced development of PS and PTS in most provinces. Thus, each province needs to improve either PS or PTS performance or both according to reality to enhance their overall IS performance.

4.4. TGRI Analysis

Figure 4 shows the trend of TGRI of Chinese ISs from 2011 to 2020, from which the following conclusions are obtained. First, the central region of China has the largest mean TGRI value, followed by the western region. The eastern region has the smallest mean TGRI value, which is 0.76. This finding confirms Hypothesis 3 and indicates a technological gap among ISs. Second, the average TGRI value of all regions in China is 0.81, and the TGRI value of each region has a relatively stable trend of fluctuation over time. Third, Yao et al. [44] found that the eastern region has the best technology level due to the advantage of economic level and development conditions. However, the current study obtained a different conclusion, that is, the technological level of ISs in the central regional provinces is close to the overall optimal technological level compared with those of the eastern and western regions.

4.5. Analysis of Performance Improvement Potential

In this section, the performance improvement potential of the ISs in each province is calculated by decomposing it into MP and TP. When MP or TP accounts for more than 30%, it is necessary to make corresponding countermeasures [45]. The following conclusions can be drawn from Table 4. First, all provinces must improve their management. In particular, current government regulations and production management of industrial enterprises require further improvements. Second, eastern China must enhance its management and technological levels. Input–output data show that Hebei, Shandong, Guangxi, Hainan, and Liaoning all have high energy consumption and industrial solid waste emissions. This situation reflects severe deficiencies in resource utilization technology in these provinces. Therefore, these provinces need to introduce high-tech talent and advanced technologies to improve their IS performance. Third, in the central region, Shanxi needs to further enhance its technology as well. Therefore, the lack of technology in Shanxi, as a province endowed with coal resources, leads to the underutilization of resources in industrial production. Fourth, in the western region, Chongqing, Guizhou, and Yunnan also need to further improve their industrial technology. Overall, the western region has the greatest potential for enhancement, followed by the eastern region and the central region, which has the least potential.

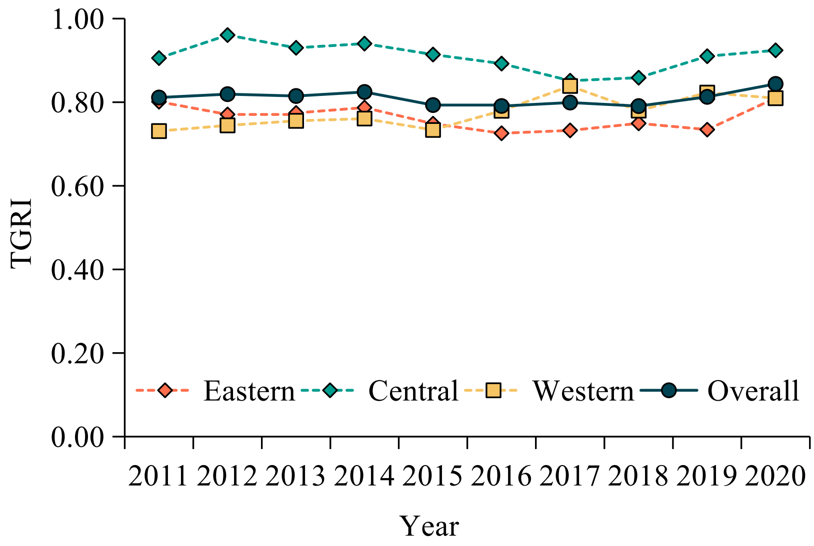

Figure 4. TGRI values of ISs in various regions.

Table 4. Decomposition of improvement potential and improvement strategy.

Regions	Provinces	Improvement Potential	MP		TP		Improvement Strategy	
			Mean	Proportion (%)	Mean	Proportion (%)	Management	Technology
Eastern	Beijing	0.57	0.51	89.02	0.06	10.98	√	
	Tianjin	0.29	0.28	94.22	0.02	5.78	√	
	Hebei	0.56	0.28	49.31	0.29	50.69	√	√
	Shanghai	0.40	0.36	89.95	0.04	10.05	√	
	Jiangsu	0.41	0.34	83.78	0.07	16.22	√	
	Shandong	0.51	0.28	55.28	0.23	44.72	√	√
	Fujian	0.53	0.40	76.71	0.12	23.29	√	
	Guangdong	0.46	0.36	78.36	0.10	21.64	√	
	Guangxi	0.60	0.32	52.75	0.29	47.25	√	√
	Hainan	0.66	0.39	59.71	0.27	40.29	√	√
	Liaoning	0.49	0.23	47.57	0.26	52.43	√	√
	Mean	0.50	0.34	68.47	0.16	31.53	√	√

Table 4. *Cont.*

Regions	Provinces	Improvement Potential	MP		TP		Improvement Strategy	
			Mean	Proportion (%)	Mean	Proportion (%)	Management	Technology
Central	Shanxi	0.48	0.32	65.91	0.16	34.09	√	√
	Jilin	0.70	0.63	90.83	0.06	9.17	√	
	Heilongjiang	0.51	0.39	76.84	0.12	23.16	√	
	Anhui	0.21	0.17	82.14	0.04	17.86	√	
	Jiangxi	0.28	0.24	85.28	0.04	14.72	√	
	Hainan	0.56	0.54	95.95	0.02	4.05	√	
	Hubei	0.49	0.48	99.18	0.00	0.82	√	
	Hunan	0.48	0.46	97.63	0.01	2.37	√	
	Mean	0.46	0.41	87.49	0.06	12.51	√	
Western	Chongqing	0.37	0.13	34.44	0.24	65.56	√	√
	Sichuan	0.42	0.35	84.56	0.06	15.44	√	
	Guizhou	0.56	0.37	65.24	0.20	34.76	√	√
	Yunnan	0.47	0.31	65.10	0.17	34.90	√	√
	Shaanxi	0.52	0.39	74.60	0.13	25.40	√	
	Gansu	0.70	0.64	90.96	0.06	9.04	√	
	Ningxia	0.64	0.56	87.74	0.08	12.26	√	
	Xinjiang	0.62	0.47	75.94	0.15	24.06	√	
	Mean	0.54	0.40	74.61	0.14	25.39	√	
Overall mean		0.50	0.38	75.65	0.12	24.35	√	

5. Conclusions and Recommendations

This study first divides ISs into two subsystems: PS and PTS. Then, an improved two-stage network DEA model is proposed, which considers the production technology heterogeneity among ISs and the interaction between subsystems. Finally, the performance of the inter-provincial IS in China is evaluated using the proposed model. The empirical analysis yields some valuable conclusions. First, China's overall industrial performance is low and shows a U-shaped trend over time during the study period. The provinces with IS performance of less than 0.60 account for 85.19% of the total. Second, significant regional differences in IS performance are found. In particular, this study finds that the central region has the highest performance, followed by the eastern and the western region, which has the lowest. The IS performance trend changes over the study period are generally consistent across regions. Third, the average IS performance of all provinces improves year after year. However, the average PTS performance of all provinces is below 0.45, which is the main factor that pulls down the overall IS performance of Chinese provinces. Fourth, China's overall TGRI does not fluctuate significantly over time, and its trend is relatively stable. Fifth, all provinces must improve their management level, and most of them still need to consider enhancing and strengthening their technological levels.

This study provides the following suggestions based on the aforementioned empirical results.

First, the overall performance of China's ISs is low and reveals significant regional differences. The central government must therefore consider guiding industrial transformation and upgrading to build low-carbon green ISs. For example, the central government can incentivize energy reduction and emission reduction in energy-intensive industrial enterprises by means of green development funding [46].

Second, PTS inefficiencies pull down the overall performance of China's ISs. Therefore, the provincial administration of each region should invest more on pollution control of the ISs, especially in eastern China, in which the economic and environmental benefits of industrial production should be balanced. In addition, all provincial administrations must strengthen the exchange and cooperation of management experience and technological development to promote overall IS performance in China.

Third, the results show that all sample provinces must improve their management levels. Local environmental protection departments need to further strengthen environmental monitoring to force enterprises to improve their investments in environmental management, which in turn can enhance IS performance. For example, protection departments can increase the penalties for non-compliant companies [47].

Fourth, industrial enterprises should focus on the improvement of pollution management capabilities, such as strengthening research on and development of emission reduction technologies, eliminating old equipment with high energy consumption, and introducing advanced green production lines [48].

This study can be further extended. For example, based on the carbon peaking and carbon neutral requirements, the model proposed in this study can be used to analyze the regional inter-provincial carbon reduction potential in China. In addition, given the relevance of environmental protection, the degrees of importance of PTS and PS differ. Thus, the model in this study can be further improved to consider the game relationship between PTS and PS.

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