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Comprehensive performance evaluation of coordinated development of industrial economy and its air pollution control

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A R T I C L E I N F O

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A B S T R A C T

Exploring coordinated pathways that can promote not only the sustainable development of the industrial economy but also air quality is of great significance for the prevention and control of air pollution in China. Currently, the joint development pathways of the industrial economy-environment nexus remain unclear and poorly evaluated. In this study, we proposed a comprehensive performance evaluation combining objective and subjective weighting to identify industrial enterprises' economic-environment nexus benefits. It would be one of the most important steps to explore the coordinated pathways. Based on data envelopment analysis (DEA), the proposed method integrated with the index integration was used to evaluate the comprehensive performances of 41 industrial sectors in China's 13th five-year plan (2016–2020). Evaluation results showed that the comprehensive performances of the economy-environment nexus of the industrial sectors varied significantly, with the five-year average comprehensive technical efficiency (TE) of 0.11–1. Overall, the best two performances were realized by the industries of equipment manufacturing and living consumption, whereas the worst one belonged to the industry of bulk raw materials, with average comprehensive TE values of 0.50, 0.43, and 0.19, respectively. The results of the quantitative evaluation were consistent with those of the qualitative analysis in terms of the developmental status of the industrial sectors. According to the analyses of pure technical efficiency and scale effect, the proposed method identified the industrial sectors with the highest developmental value and with the highest need to control air pollution. Compared with those of the original DEA model, the results of the proposed method showed pronounced differences in terms of the performances of industrial sectors with high energy consumption and high particulate matter (PM) emissions and with low energy consumption and low PM emissions. The proposed evaluation method combining the weighting was suitable for identifying the comprehensive performance of the industrial economy-environment nexus and provides the basis for the prevention and control of air pollution.

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1. Introduction

In recent years, air quality in China has been improving continuously, but with plenty of room for further improvement. In 2021, in 339 major cities, the average number of days with good air quality reached 87.5%, 64.3% of which met the air quality standards [1]. However, there remains a large degree of spatiotemporal imbalance in air quality across China. For example, the number of days with good air quality was 67.2% in the Beijing-Tianjin-Hebei region and its surrounding areas and 70.2% in the Fen-Wei plain. Some cities still suffer from severe or even worse pollution in winter. In the recently revised Global Air Quality Guidelines (2021) (AQG-2021), the World Health Organization further lowered the average annual target value of fine particulate matter ($PM_{2.5}$) to 5 μg/m^3 [2]. Relative to AQG-2021, the ambient air quality standards in China are considered relaxed. Thus, there remains plenty of room for air quality improvement in China.

The direct cause of air pollution is that pollutant discharge exceeds the atmospheric carrying capacity [3]. Therefore, the continuous reduction of air pollutant emissions remains a fundamental way to improve air quality. According to the source apportionment results for atmospheric particulates, industrial enterprises are an important contributor. $PM_{2.5}$ apportionment results of major cities in China issued by the State departments, such as Beijing [4], Tianjin [5], Nanjing [6], Hangzhou [7], Shanghai [8], and Guangzhou [9], revealed that the contribution ratio of industrial sectors to ambient $PM_{2.5}$ varied between 12% and 30%. Previous studies have also pointed out that industrial sectors exert a significant influence on air quality. For example, it reviewed more than 200 studies of source apportionment since 1986 and pointed out that industry is the largest contributor to ambient PM2.5 in the northern, northeastern, and central regions of China during 2007–2016, with an average contribution ratio of 22.2–28.7% [10]. In the east, south, northwest, and southwest regions of China, the industry is also the main contributor with an average ratio of 12.9–17.2%. And it was estimated from more than 400 studies of source apportionment during 2014–2019 that industrial sectors are the global main contributor to ambient $PM_{2.5}$ with an average ratio of 17% [11].

In the coupled industrial process of production and pollution control, the coordinated development pathways of the industrial economy-environment nexus remain unclear. Performance evaluation may play an important role in solving this problem. It should be one of the most important steps to promote the coordinated development of the industrial economy and its air pollution control. Performance evaluation has widely been applied in the field of environmental quality. The indicator of pollutant emission per unit output value was used to evaluate the pollutant control performances of industrial enterprises and emphasized the importance of performance evaluation as an effective method to integrate and quantify their economic and environmental benefits [12]. Overall, all methods of performance evaluation include the following three key procedures: the development of an indicator system and its weighting and performance [13]. Some examples of common methods of performance evaluation include the analytic hierarchy process [14], the entropy method [15], and fuzzy comprehensive evaluation [16]. Data envelopment analysis (DEA) is one of the performance evaluations most extensively used in industry [17, 18], agriculture [19,20], transportation [21,22], energy [23,24], and environment [25,26]. According to the search results in the core collection database of the Web of Science (Fig. S1), the numbers of publications using DEA to carry out environmental performance evaluation were on the rise and reached 3,921 in 2022 and exceeded those obtained using other methods.

DEA is commonly used to estimate production efficiency in various fields but faces a prominent issue when applied to air pollution control as it is an objective weighting method. In other words, it assigns weights to indicators solely based on the characteristics of data without consideration of the actual weight preference, which may lead to inconsistency between the weighting results of indicators and their actual importance. For example, under different spatiotemporal conditions, air pollutants with a greater impact on ambient air quality should get a greater weight, whereas those with a smaller impact on ambient air quality should get a smaller weight. In most places in China, the impact of particulate matter (PM) on ambient air quality is significantly greater than that of SO_2. For the original DEA model, all input and output indicators are regarded as equally important, as also stated by many studies [27–29]. Therefore, how integrating DEA with subjective preferences to combine subjective and objective weighting remains an important issue facing the application of the DEA model to air pollution control.

To this end, this study aimed to integrate the DEA and index integration methods to combine the subjective and objective weighting for developing a comprehensive performance evaluation of the industrial economy-environment nexus and apply it to 41 industrial sectors in China according to the 13th five-year plan (2016–2020). In addition, this study explored the applicability of this method in terms of guiding industrial development and quantifying its comprehensive performance. The proposed method and results of this study can provide insights into promoting the coordinated development of the industrial economy and its air pollution control across China.

2. Materials and methods

2.1. DEA model

Based on linear programming according to multiple input and output indices, DEA is a method used to evaluate the relative effectiveness of comparable decision-making units (DMUs). Its evaluation result is essentially the production efficiency of DMU; namely, the ratio of output (weighted sum) to input (weighted sum), which has the same connotation as the comprehensive performance of the economy-environment nexus examined in this study. DEA uses various environmental and economic factors as input and output indicators, respectively, and quantifies the degree of match between input and output as well as the degree of collaboration between the industrial economy and environmental protection. Compared with other performance evaluations, the DEA model has several unique advantages. First, when the production efficiency of multiple inputs and multiple outputs is evaluated, DEA bases indicators on the input-output relationship and does not need to establish a complex indicator system. Second, there is no need for the DEA to estimate or assume the form of the production function in advance, thereby avoiding the influence of various subjective factors. Finally, DEA has a diversification function in that, in addition to measuring the production efficiency (i.e., performance) of a DMU, it can extract abundant information, such as pure technical efficiency (PTE), scale effect (SE), productivity change, and technological progress.

The earliest DEA model was the CCR-DEA model proposed by Chames and Copper [30]. In the following 45 years, the CCR-DEA model paved the way for a variety of derivative models with various functions according to the needs of applications, including the super-efficiency model [31], directional distance function (DDF) [32], network DEA model [33], and slack-based measure model (SBM-DEA) [34]. In this study, the SBM-DEA model with an undesired output was selected as the data processing module and expressed as follows [34]:

$$\min \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} S_i^- / x_{ik}}{1 + \frac{1}{q}\sum_{r=1}^{q} S_r^+ / y_{rk}} \tag{1}$$

$$s.t.\ X\lambda + S^- = x_k \tag{2}$$

$$Y\lambda - S^+ = y_k \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{4}$$

$$\lambda, S^-, S^+ \geq 0 \tag{5}$$

$$i = 1, 2 \ldots, m; r = 1, 2 \ldots, q; j = 1, 2 \ldots, n \tag{6}$$

where ρ is the comprehensive performance of DMU; *n* DMUs to be measured are denoted as DMUj (j = 1, 2 … *n*); DMU to be measured is denoted as DMUk; each DMU has *m* inputs denoted as xi (i = 1, 2 … m); *q* outputs are denoted as *yr* (r = 1, 2 … q); and S^-, S^+, and S^{b-} are the relaxation variables of input, desirable output, and undesirable output, respectively.

In the development process of the DEA model, the following three indicators were proposed: comprehensive technical efficiency (TE), pure technical efficiency (PTE), and scale effect (SE) [35]. Both TE and PTE reflected the comprehensive performance of the economic-environment nexus, of which TE may be more indicative. As a comprehensive performance indicator of DMU, TE was defined as the ratio of the weighted sum of output to that of input, whereas PTE referred to technical efficiency after the effect of the scale was excluded; i.e., the technical efficiency estimated by placing all DMUs at the same scale. The TE, PTE, and SE values ranged from 0 to 1. When the value reached 1, the technology is deemed effective. The relationship among them was expressed as TE = PTE × SE, where TE was estimated from Eqs. (1)–(3) and 5–6), while PTE was calculated from Eqs. (1)–(6).

2.2. Development of indicator system

This study established an indicator system for evaluating the comprehensive benefits of the economy-environment nexus of industrial sectors. The proposed system aimed to guide the industry to invest less resources and energy, emit fewer pollutants, and produce higher economic benefits; namely, low input, high output, and less pollution. Based on this goal, this study referred to Song et al. [36], Wu et al. [28], and Wang and Feng [37] and used fixed asset investment, energy consumption, and employment as the input indicators. Industrial output was considered an indicator of desirable output, whereas pollutant emission was the indicator of undesirable output. The categories of atmospheric pollutants include SO2, NOx, and particulate matter (PM). The above indicators together constituted the input-output system of the industry, covering all kinds of input factors involved in industrial generation and output factors that we pay attention to. Among them, industrial output value, fixed asset investment, and employment represented the economic benefits, whereas energy consumption and pollutant emissions represented the environmental benefits. It should be pointed out that the industrial output in this study is the gross industrial output value, rather than the industrial added value. Gross industrial product is the total value of all the products that have been produced by various industrial sectors. Industrial added value is the industrial output value after deducting the cost of raw materials, which is more accurately used to represent the economic benefits of enterprises. If the data are available, the use of industrial added value as an indicator of desirable output is more recommended. Since the added value data of various industrial sectors in China cannot be obtained in this study, only gross industrial output value is taken as an example to demonstrate the application of the performance evaluation method.

2.3. Index integration method

Previous studies on the DEA model have not often considered the difference in the relative importance of indicators and treated them as equally important in the performance evaluation process. This process may strengthen the secondary indicators and weaken the influence of the primary indicators on the results in the process of assigning weights. Therefore, to strengthen the primary indicators and weaken the secondary indicators, this study proposed to use the index integration method to combine subjective and objective weighting for the performance evaluation. This method mainly refers to the evaluation method of complex DEA systems by Ma et al. [38]. The study of Ma et al. [38] was not used for industrial air pollution prevention, but his ideas inspired us. This method was divided into three steps. First, all the indicators were treated as first-level indicators and divided into the three categories of input, desirable output, and undesirable output. Second, in each category, initial weights and sums were calculated based on the importance of each level of indicators, the second-level indicators in this study. Finally, each second-level indicator was inputted into the DEA model for the final performance estimation. The initial weights required for the integration of each first-level indicator could be derived from AHP, an expert-knowledge method, or other methods that could reflect the relative importance of indicators. Thus, all the indicators could fully be taken into account, while the primary and secondary status of each indicator could be reflected to avoid underestimating the primary indicators or overestimating the secondary indicators, thus making the results more comprehensive and objective. Eventually, the integration of subjective and objective weighting based on the DEA model was realized.

For example, in this study, fixed asset investment, energy consumption, and employment numbers were regarded as the first-level inputs. SO_2, NO_x, and PM emissions were the first-level undesirable outputs, while the industrial output value was the first-level desired output. The second-level input, second-level undesired outputs, and second-level desirable outputs were estimated by the following Eqs. 7–10:

$$\text{Second-level input} = a \times (\text{fixed asset investment}) + b \times (\text{energy consumption}) + c \times (\text{employment number}) \tag{7}$$

$$\text{Second-level undesirable output} = e \times (SO_2 \text{ emissions}) + f \times (NO_x \text{ emissions}) + g \times (\text{PM emissions}) \tag{8}$$

$$\text{Second-level desirable output} = \text{industrial output} \tag{9}$$

$$a + b + c = 1 \text{ and } e + f + g = 1 \tag{10}$$

The second-level input, second-level undesired outputs, and second-level desirable outputs synthesized by each first-level indicator were then incorporated into DEA. When there are many first-level indicators, multiple second-level indicators may exist. The initial weights required for the integration of first-level indicators, such as a, b, c, d, e, f, and g, can be derived from AHP, the Delphi method, or any other method that can reasonably reflect the relative importance of the indicators.

In this study, the initial weights of SO_2, NO_x, and PM were assigned based on the impacts of SO_2, NO_2, and coarse particulate matter (PM_{10}) on ambient air quality in China, according to the calculation method of air quality sub-index in "Technical Regulations on Ambient Air Quality Index (on trial) (HJ 633–2012)". The annual air quality sub-index of each pollutant (SO_2, NO_2, and PM_{10}) was calculated based on the concentration-monitoring data of 337 major cities in China. The proportions of the air quality sub-index of SO_2, NO_2, and PM_{10} in the total index were taken as the initial weights of SO_2, NO_x, and PM (Table 1). The following two assumptions were adopted in this procedure: (1) although, according to "HJ 633–2012," the calculation method of air quality sub-index is only used for 1-h and 24-h time scales, this study used this method for annual-scale estimation, ignoring possible errors; and (2) the air quality sub-index of NO_2 and PM_{10} could approximately represent the impacts of industrial NO_x and PM pollutants on the air quality.

For the three inputs of energy consumption, fixed asset investment, and employment number, the estimation process of weight coefficients, such as AHP and the Delphi method, was temporarily omitted, and their combined weights were preliminarily assigned as 0.5, 0.35, and 0.15, respectively, through qualitative analysis. Since energy consumption is directly related to pollutant discharge, it is of great significance to air pollution control. In the context of carbon peak and carbon neutrality, reducing fossil fuel consumption is essential to reducing pollution and carbon emissions. Therefore, energy consumption was the most important of the three indicators. Fixed-asset investment and industrial output represented the main economic cost and benefit of the industry, respectively, and were secondary to energy consumption. Employment exerted a relatively small impact on economic and environmental benefits, thus carrying the least importance.

Since the index integration method needs to carry out the weighted summation of multiple indexes when it is used, but each index has different dimensions and orders of magnitude, it is necessary to normalize the original data. Various normalization methods may have different influences on the evaluation results. There is no universally effective normalization method. Different normalization methods can be tested to select the one whose results are most consistent with reality, to limit the uncertain influence of normalization on results. In this paper, the Min-max normalization method was used to convert each index into a value between 10 and 100. The specific normalization algorithms of each input index x and output index y are as follows (equations (11) and (12)). The x and y respectively represent the original input and output indicators, while x' and y' respectively represent normalized input and output

Table 1
The results of the initial weights of undesirable output (air pollutants).

Year	Average annual concentration[a]			Air quality sub-index			Initial weight result		
	SO_2	NO_2	PM_{10}	SO_2	NO_2	PM_{10}	SO_2	NO_x	PM
2016	22	30	82	22	37.5	66	0.17	0.3	0.53
2017	18	31	75	18	38.75	62.5	0.15	0.33	0.52
2018	14	29	71	14	36.25	60.5	0.13	0.33	0.54
2019	11	27	63	11	33.75	56.5	0.11	0.33	0.56
2020	10	24	56	10	30	53	0.11	0.32	0.57

[a] The data from the "Bulletin of Ecological Environment Quality" of the Ministry of Ecology and Environment of China.

indicators.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \times 90 + 10 \tag{11}$$

$$y' = \frac{y - y_{min}}{y_{max} - y_{min}} \times 90 + 10 \tag{12}$$

2.4. Data source

The data on fixed asset investment, energy consumption, and industrial output in industrial sectors during the 13th five-year plan (2016–2020) were obtained from the China Statistical Yearbook for 2016–2020. Employment data were gathered from the China Population and Employment Statistical Yearbook. Pollutant emission data on SO_2, NO_x, and PM were collected from China Environmental Statistical Yearbook. Since this study mainly explored the role of performance evaluation in guiding the prevention and control of industrial air pollution and the price changes during the 13th five-year plan were relatively small, an equivalent conversion of industrial output value was not carried out.

3. Results and discussion

3.1. Qualitative analysis of the development status of industrial sectors

According to "Industrial Classification for National Economic Activities (GB/T4754-2017)", industries involved in pollutant discharge were divided into 41 sectors according to the following broad categories: mining, manufacturing, electricity, heat, gas, and water generation and supply. Table 2 lists the classification names and identifications (IDs) of the 41 industrial sectors in China.

During the 13th five-year plan, the development level of China's industrial sectors represented by the indicators and their growth rate is shown in Fig. 1 and Fig. S2, respectively. Due to their large number, to summarize their characteristics and draw conclusions, the sectors were divided into the following five categories based on the focus of the study: (a) equipment manufacturing, (b) bulk raw materials, (c) living consumption, (d) mining, and (e) other industries. The production resources of fixed asset investment, energy consumption, and employment were concentrated in the industries of equipment manufacturing and bulk raw materials. In 2020, fixed asset investment and employment in the industry of equipment manufacturing accounted for 36% and 42% of the national total, respectively. Fixed asset investment, energy consumption, and employment in the industry of bulk raw materials accounted for 29%, 76%, and 20% of the national total, respectively. These two industries are the pillars of China's industrial economy, with the outputs of the industries of equipment manufacturing and bulk raw materials accounting for 39% and 26% of the national total, respectively. The shares of the resources in living consumption, mining, and other industries were relatively low.

Overall, the industrial sectors of equipment manufacturing yielded higher technology and higher value-added products, such as computer communication equipment (S34), automobile manufacturing (S31), and electromechanical equipment (S33), with its high contribution to industrial output maintaining a strong growth trend in recent years. During the 13th five-year plan, the industrial output of equipment manufacturing grew by 19.36%, whereas the growth rates of bulk raw materials, living consumption, and mining were 5.29%, −1.38%, and −8.15%, respectively. The industry of equipment manufacturing had a relatively low energy demand. In

Table 2
Classification of industrial sectors in China.

Sector ID	Sector name	Sector ID	Sector name
S1	Coal mining and washing	S22	Pharmaceutical manufacturing
S2	Oil and gas extraction	S23	Chemical fiber manufacturing
S3	Ferrous metal mining	S24	Rubber and plastic products
S4	Non-ferrous metals mining	S25	Non-metallic mineral products
S5	Non-metallic mining industry	S26	Ferrous metal smelting and rolling
S6	Mining professional and ancillary activities	S27	Non-ferrous metal smelting and rolling
S7	Other mining	S28	Metal products industry
S8	Agricultural and sideline food processing	S29	General equipment manufacturing
S9	Food manufacturing	S30	Special equipment manufacturing
S10	Alcoholic beverage and tea manufacturing	S31	Automobile manufacturing industry
S11	Tobacco manufacturing	S32	Non-road transport equipment
S12	Textile	S33	Electromechanical equipment
S13	Textile and garment	S34	Computer communication equipment
S14	Leather and fur products	S35	Instrumentation manufacturing
S15	Wood processing	S36	Other manufacturing
S16	Furniture manufacturing	S37	Waste resources utilization
S17	Papermaking	S38	Mechanical equipment repair
S18	Printing and recording media reproduction	S39	Electricity and heat production
S19	Cultural, sports, and entertainment articles	S40	Gas production
S20	Oil and coal processing	S41	Water production
S21	Chemical industry		

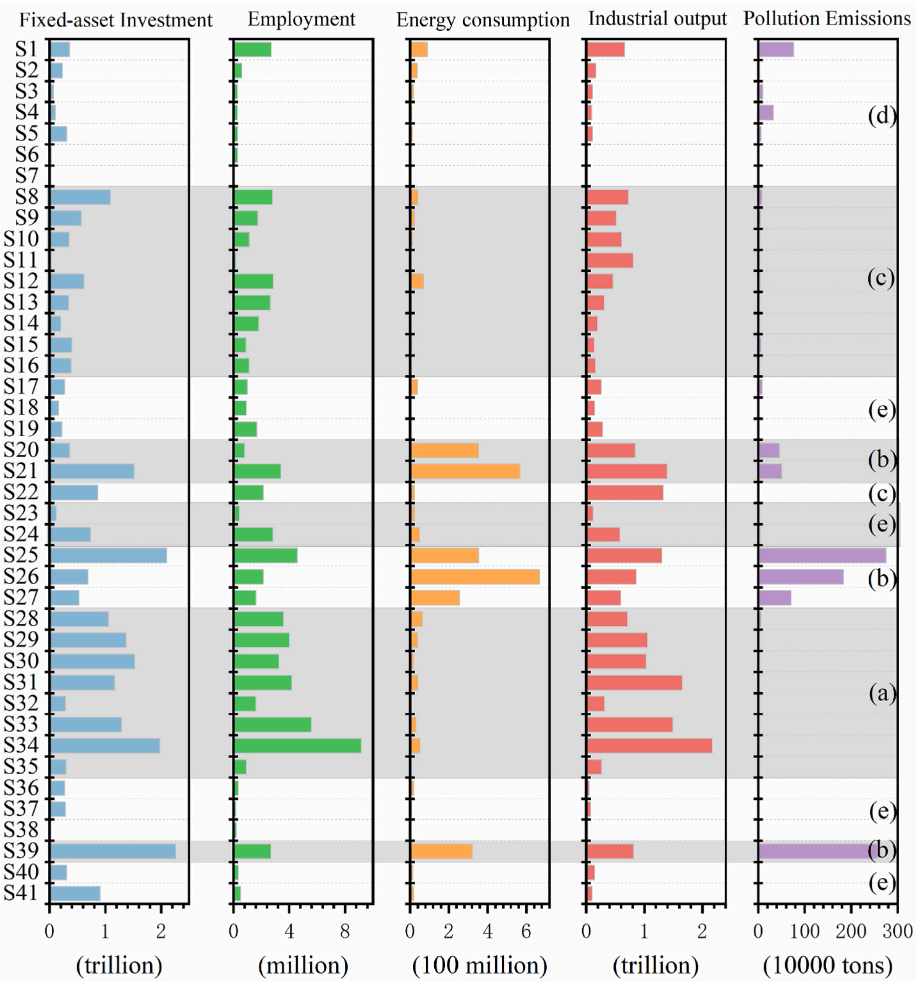

Fig. 1. The development levels of China's industrial sectors at the end of the 13th five-year plan (up to 2020): (a) equipment manufacturing, (b) bulk raw materials, (c) living consumption, (d) mining, and (e) other industries.

recent years, under the trend of replacing coal with natural gas, electricity, and other clean energy, the consumption of coal, natural gas, and other primary energy dropped significantly, with the emissions of the pollutants declining. Overall, in terms of energy consumption and pollutant emissions per unit output value, the industry of equipment manufacturing performed well. In 2020, energy consumption per unit output value of the industrial sectors of equipment manufacturing ranged from 0.1 to 0.9 tons of standard coal/10,000 RMB (an average of 0.63), slightly worse than that of the industry of living consumption (an average of 0.41) and significantly better than that of the industries of bulk raw materials (an average of 4.50) and mining (an average of 20.84). The pollutant emissions per unit output value of the industry of equipment manufacturing ranged from 0.89 to 54.54 tons/100 million RMB (an average of 12.35), slightly worse than that of the industry of living consumption (an average of 17.14) and significantly better than that of the industries of bulk raw materials (an average of 249.18) and mining (an average of 124.45).

In the industry of bulk raw materials, essential to the normal production and living of society, steel, cement, glass, non-ferrous metals, petrochemical products, and chemical products covered a broad application market, with a high scale of output value. Since the production process of these industrial sectors required a large quantity of primary energy, such as coal and natural gas, to provide heat, the emissions of SO_2, NO_x, PM, and other pollutants from these sectors accounted for a very high proportion of the national total.

The industrial sectors of living consumption had relatively low technical thresholds and low value-added products but a large consumption demand. Some of their production processes required high temperatures, which consumed a moderate quantity of energy. Therefore, the output value of the industry of living consumption remained at a medium or high level, while its pollutant emission was at a medium or low level.

Given the resources and energy consumed by the industrial sectors and their industrial outputs and pollutant emissions, preliminary qualitative evaluations could be conducted for the industries. The industry of equipment manufacturing exhibited the highest comprehensive performance, which was consistent with the evaluation class of low input, high output, and less pollution, whereas the industry of living consumption ranked in the middle. As the focus of industrial air pollution control, the comprehensive performance of the industry of bulk raw materials remained relatively poor.

3.2. Quantitative results of comprehensive performance evaluation of industrial sectors

Based on the development of the industrial sectors in China during the 13th five-year plan, the applicability of the DEA method to the comprehensive performance evaluation was explored quantitatively. The results of the comprehensive performance evaluation of the industrial sectors over the study period are presented in Table 3.

(1) Evaluation results of comprehensive technical efficiency (TE)

The performance evaluation results showed two characteristics. First, there was a large gap among the comprehensive TEs of the industrial sectors, with the five-year average TE varying between 0.11 and 1. Second, the overall performance results of the industry of equipment manufacturing were best, followed by the industry of living consumption, whereas those of the industries of mining and bulk raw materials were worst. The average annual TEs of the four categories of industries are shown in Fig. 2, with their five-year average TEs being ranked as follows: equipment manufacturing (0.50) > living consumption (0.43) > mining (0.20) > bulk raw materials (0.19).

In the industry of equipment manufacturing, the TE values of computer communication equipment (S34), automobile manufacturing (S31), and electromechanical equipment (S33) ranked in the top four every year. The industrial sectors of computer communication equipment (S34) and automobile manufacturing (S31) maintained a TE value of 1, regardless of the year of the study period, indicating that they were among the most valuable industrial sectors in China. The TE values of both general equipment (S29)

Table 3
The results of the comprehensive performance evaluation of the industrial sectors in terms of technical efficiency (TE) according to the 13th five-year plan.

Industrial sectors	2016	2017	2018	2019	2020	Mean	Ranking
Tobacco manufacturing	1	1	1	1	1	1	1
Computer communication equipment	1	1	1	1	1	1	1
Automobile manufacturing industry	1	1	1	0.93	1	0.99	3
Pharmaceutical manufacturing	0.78	0.91	1	1	0.97	0.93	4
Electromechanical equipment	0.81	0.82	0.73	0.73	0.82	0.78	5
Alcoholic beverage and tea manufacturing	0.45	0.45	0.44	0.45	0.44	0.45	6
General equipment manufacturing	0.44	0.45	0.31	0.33	0.46	0.40	7
Special equipment manufacturing	0.39	0.41	0.30	0.32	0.46	0.38	8
Food manufacturing	0.37	0.34	0.29	0.31	0.30	0.32	9
Agricultural and sideline food processing	0.42	0.37	0.26	0.27	0.27	0.32	10
Oil and coal processing	0.36	0.35	0.32	0.25	0.21	0.30	11
Coal mining and washing	0.26	0.36	0.33	0.29	0.26	0.30	12
Non-road transport equipment	0.33	0.30	0.23	0.27	0.27	0.28	13
Instrumentation manufacturing	0.29	0.30	0.26	0.24	0.26	0.27	14
Cultural, sports, and entertainment articles	0.30	0.29	0.25	0.26	0.27	0.27	15
Rubber and plastic products	0.31	0.29	0.23	0.24	0.26	0.27	16
Textile and garment	0.30	0.27	0.24	0.22	0.23	0.25	17
Metal products industry	0.28	0.25	0.20	0.21	0.25	0.24	18
Textile	0.29	0.25	0.20	0.20	0.22	0.23	19
Chemical industry	0.26	0.26	0.23	0.19	0.19	0.23	20
Oil and gas extraction	0.16	0.22	0.30	0.27	0.19	0.23	21
Leather and fur products	0.25	0.24	0.21	0.21	0.21	0.22	22
Papermaking	0.22	0.23	0.20	0.21	0.22	0.22	23
Printing and recording media reproduction	0.23	0.23	0.20	0.20	0.21	0.21	24
Chemical fiber manufacturing	0.21	0.21	0.19	0.20	0.20	0.20	25
Non-ferrous metals mining	0.21	0.22	0.20	0.19	0.19	0.20	26
Ferrous metal mining	0.22	0.20	0.18	0.19	0.20	0.20	27
The non-ferrous metal smelting and rolling	0.23	0.21	0.16	0.17	0.17	0.19	28
Gas production	0.19	0.19	0.18	0.19	0.19	0.19	29
Furniture manufacturing	0.21	0.20	0.16	0.17	0.18	0.18	30
Mechanical equipment repair	0.18	0.18	0.17	0.18	0.19	0.18	31
Non-metallic mining industry	0.19	0.18	0.16	0.16	0.17	0.17	32
Wood processing	0.21	0.19	0.14	0.15	0.16	0.17	33
Other mining	0.17	0.17	0.16	0.16	0.17	0.16	34
Waste resources utilization	0.18	0.17	0.15	0.15	0.16	0.16	35
Mining professional and ancillary activities	0.15	0.16	0.16	0.16	0.17	0.16	36
Non-metallic mineral products	0.18	0.17	0.14	0.16	0.16	0.16	37
Ferrous metal smelting and rolling	0.14	0.16	0.15	0.13	0.12	0.14	38
Other manufacturing	0.15	0.14	0.12	0.13	0.14	0.14	39
Water production	0.12	0.12	0.11	0.11	0.10	0.11	40
Electricity and heat production	0.12	0.10	0.10	0.12	0.11	0.11	41

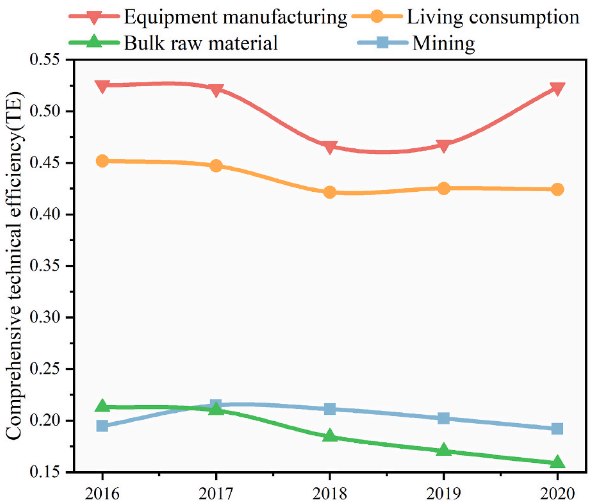

Fig. 2. The average comprehensive technical efficiency (TE) of the four major categories of industries according to the 13th five-year plan.

and special equipment (S30) ranked 7th–9th over the years, while those of non-road transportation equipment (S32), instrumentation manufacturing (S35), and metal products (S28) ranked 10th–25th. Overall, as analyzed in Section 3.1, the industry of equipment manufacturing yielded high technology and high value-added products, which best fit the evaluation class of low input, high output, and less pollution, thus exhibiting a highly comprehensive performance according to the evaluation system proposed in this study.

In the industry of living consumption, tobacco manufacturing (S11) was technologically efficient (TE = 1) over the study period, featuring low cost, high added-value, and low emissions, followed by pharmaceutical manufacturing (S22), which also yielded relatively high technology and high value-added products. As the industrial output value substantially increased on an annual basis, the TE value of pharmaceutical manufacturing (S22) gradually rose from 0.78 in 2016 (ranking 5th) to 0.97–1 in 2018–2020. The TE values of alcoholic beverage and tea manufacturing (S10), food manufacturing (S9), and agricultural and sideline processing (S8) ranked 6th–15th in the past years, whereas those of textile and garment (S13) and leather and fur products (S14) ranked 15th–23rd.

The industry of bulk raw materials mainly provides all kinds of basic raw materials and energy products for the Chinese industry. As its overall production process involved high temperatures, it led to high energy consumption and pollutant emissions, thus belonging to the typical evaluation class of industry with high pollution and high energy consumption. Its industrial sectors had a certain scale of industrial output, high energy consumption, and high pollutant emissions per unit output. According to the results of the comprehensive performance evaluation during the study period, the TE value of oil and coal processing (S20) ranked 8th–15th, whereas all the other industries ranked poorly. In particular, the three sectors of non-metallic products (S25), ferrous metal smelting and rolling (S26), and electricity and heat production (S39) resulted in the highest emission of the pollutants, with TE < 0.3 rankings 33rd–41st.

Overall, the ranking of the TE values of all the industrial sectors of mining was concentrated between the 30th and 40th, mainly because the output value was low and accompanied by a certain degree of energy consumption and pollutant emissions, in particular,

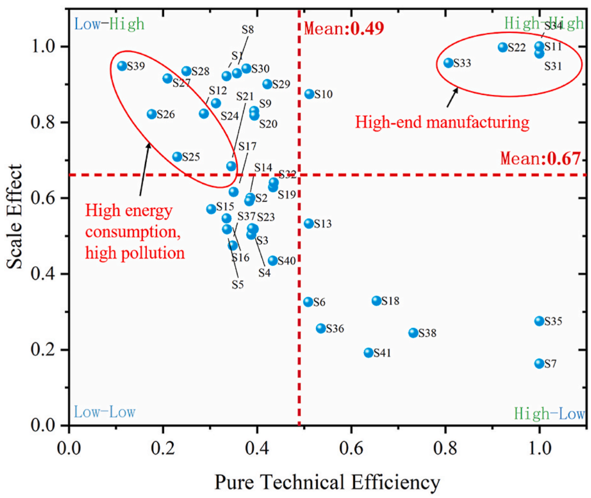

Fig. 3. Distributions of average pure technical efficiency (PTE) and scale effect (SE) of the industrial sectors in China during the 13th five-year plan.

PM.

(2) Evaluation results of pure technical efficiency (PTE) and scale effect (SE)

Based on the average PTE and SE levels, all the industrial sectors were grouped into the following four categories (Fig. 3):

High PTE-high SE: In this group, tobacco manufacturing (S11), automobile manufacturing (S31), and computer communication equipment (S34) were most prominent, followed by alcoholic beverage and tea manufacturing (S10), pharmaceutical manufacturing (S22), and electromechanical equipment (S33). Overall, these sectors belonged to high-end manufacturing with higher technology or profit margins (e.g., alcohol and tobacco manufacturing) and with higher added-value products. In terms of the specific input-output indicators, the above sectors showed higher output values, lower energy consumption, and lower pollutant emissions and belonged to the industries of equipment manufacturing and living consumption.

High PTE-low SE: This group primarily included mining activities (S6), textiles and garments (S13), printing (S18), and instrumentation manufacturing (S35). The production scale of these sectors was relatively small, and the indicators of industrial output value, pollutant emissions, and energy consumption were not outstanding. These sectors with high PTE but low SE values resulted in low TE values but exhibited high potential and value of the development. An appropriate expansion of the production scale in these sectors can be considered to achieve greater expected returns.

Low PTE-high SE: This group mainly included coal mining and washing (S1), oil and coal processing (S20), chemicals (S21), non-metallic mineral products (S25), ferrous metal smelting and rolling (S26), non-ferrous metal smelting and rolling (S27), general equipment manufacturing (S29), special equipment manufacturing (S30), and electricity and heat production (S39). All the industrial sectors of bulk raw materials were included, with the lowest overall PTE value. Their low TE, low PTE, and high SE values pointed to

Table 4
The results of the comprehensive performance evaluation of the industrial sectors before and after index condensation in 2019.

Sectors	Original DEA		Combined weighting		Efficiency difference	Ranking difference
	TE	Ranking	TE	Ranking		
Tobacco manufacturing	1	1	1	1	0	0
Pharmaceutical manufacturing	1	1	1	1	0	0
Computer communication equipment	1	1	1	1	0	0
Instrumentation manufacturing	1	1	0.24	16	−0.76	15↓
Other mining	1	1	0.16	33	−0.84	32↓
Textile and garment	0.60	6	0.22	18	−0.38	12↓
Printing and recording media reproduction	0.33	7	0.20	22	−0.13	15↓
Mechanical equipment repair	0.26	8	0.18	29	−0.08	21↓
Water production	0.20	9	0.11	41	−0.09	32↓
Automobile manufacturing industry	0.18	10	0.93	4	0.74	↑6
Cultural, sports, and entertainment articles	0.17	11	0.26	14	0.09	3↓
Non-road transport equipment	0.16	12	0.27	13	0.11	1↓
Special equipment manufacturing	0.13	13	0.32	8	0.19	↑5
General equipment manufacturing	0.08	14	0.33	7	0.24	↑7
Gas production	0.07	15	0.19	27	0.12	12↓
Oil and coal processing	0.06	16	0.25	15	0.19	↑1
Alcoholic beverage and tea manufacturing	0.06	17	0.45	6	0.39	↑11
Electromechanical equipment	0.05	18	0.73	5	0.68	↑13
Oil and gas extraction	0.04	19	0.27	12	0.23	↑7
Food manufacturing	0.03	20	0.31	9	0.28	↑11
Leather and fur products	0.03	21	0.21	20	0.18	↑1
Furniture manufacturing	0.03	22	0.17	31	0.14	9↓
Coal mining and washing	0.02	23	0.29	10	0.26	↑13
The ferrous metal smelting and rolling	0.02	24	0.13	39	0.10	15↓
Agricultural and sideline food processing	0.02	25	0.27	11	0.25	↑14
Chemical industry	0.02	26	0.19	25	0.17	↑1
Waste resources utilization	0.02	27	0.15	36	0.13	9↓
Ferrous metal mining	0.02	28	0.19	26	0.17	↑2
Non-ferrous metals mining	0.02	29	0.19	28	0.17	↑1
The non-ferrous metal smelting and rolling	0.02	30	0.17	30	0.15	0
Chemical fiber manufacturing	0.02	31	0.20	24	0.18	↑7
Non-metallic mining industry	0.02	32	0.16	34	0.14	2↓
Rubber and plastic products	0.02	33	0.24	17	0.22	↑16
Non-metallic mineral products	0.02	34	0.16	35	0.14	1↓
Papermaking	0.02	35	0.21	21	0.19	↑14
Metal products industry	0.02	36	0.21	19	0.20	↑17
Electricity and heat production	0.01	37	0.12	40	0.10	3↓
Wood processing	0.01	38	0.15	37	0.13	↑1
Textile	0.01	39	0.20	23	0.19	↑16
Other manufacturing	0.01	40	0.13	38	0.12	↑2
Mining professional and ancillary activities	0.01	41	0.16	32	0.16	↑9

the low PTE as the main reason for the low TE. If the basic role of these sectors in the industrial chain was not considered, their development value was not as good as that of the high PTE sectors. Overall, these sectors caused large production scales, high energy consumption, and pollutant emissions, the focus of industrial governance. Therefore, these sectors were the focus of industrial air pollution control, in particular, considering energy conservation, emission reduction, innovative technology, and other measures to improve PTE.

Low PTE-low SE: This cluster mainly included oil and gas extraction (S2), ferrous metal mining (S3), non-ferrous metal mining (S4), non-metallic mining (S5), wood processing (S15), and furniture manufacturing (S16). These sectors led to a relatively small production scale and low industrial output and were accompanied by a certain degree of pollutant emissions and resource and energy inputs. Without consideration of the basic role of these sectors in the industrial chain, their current development value and potential remained relatively low. This group also deserved special attention in terms of industrial air pollution control but may receive less attention than the group of low PTE-high SE due to its relatively low energy consumption and low pollutant emissions.

Overall, the quantitative results of the comprehensive performance evaluation of each industrial sector were consistent with the results of the qualitative analysis of the developmental status of each sector in Section 3.1. The industry of equipment manufacturing, as represented by computer communication equipment (S34), electromechanical equipment (S33), and automobile manufacturing (S31), yielded the best performance, which best described the characteristics of high-end manufacturing with high technology, high-added value, low pollution, and low emission. The industry of living consumption, as represented by tobacco manufacturing (S11) and pharmaceutical manufacturing (S22), benefited from China's broad consumer market and social development and led to a relatively large industrial output value, with its comprehensive performance being second only to that of the equipment manufacturing industry. Overall, all the industrial sectors of bulk raw materials belonged to the typical evaluation class of industry with high pollution and high energy consumption and were best described as the group of low TE, low PTE, and high SE, the focus of industrial air pollution control. Therefore, in the future industrial development of bulk raw materials, much effort should be made to improve its comprehensive performance through energy saving, emission reduction, innovative technology, and other measures. The results of this study were consistent with those of Yang et al. [39] and Wang et al. [40]. In their focus on industrial waste gas control in China, the total factor efficiency and eco-efficiency of the industries of electrical and mechanical equipment manufacturing, computer communication, and tobacco products were found to be better, whereas those of the industries of metal and non-metal products (e.g., ferrous metal, non-ferrous metal, and non-metallic mineral products) and chemicals remained generally poor.

3.3. Verification of the combined weighting

In this study, the index integration method was adopted to combine the subjective and objective weighting for the performance evaluation based on the DEA model. The rationality and necessity of the index integration method were verified by comparing the obtained results with those of the original SBM-DEA model. The data in 2019 with the most prominent difference in the results were selected as an example. The comparison results are presented in Table 4. The results of the index integration method significantly differed from the original model results, with the efficiency and ranking of many industrial sectors exhibiting a great degree of rise and fall. The sectors with significant changes in efficiency and ranking are shown in Fig. 4. Their characteristics were summarized below.

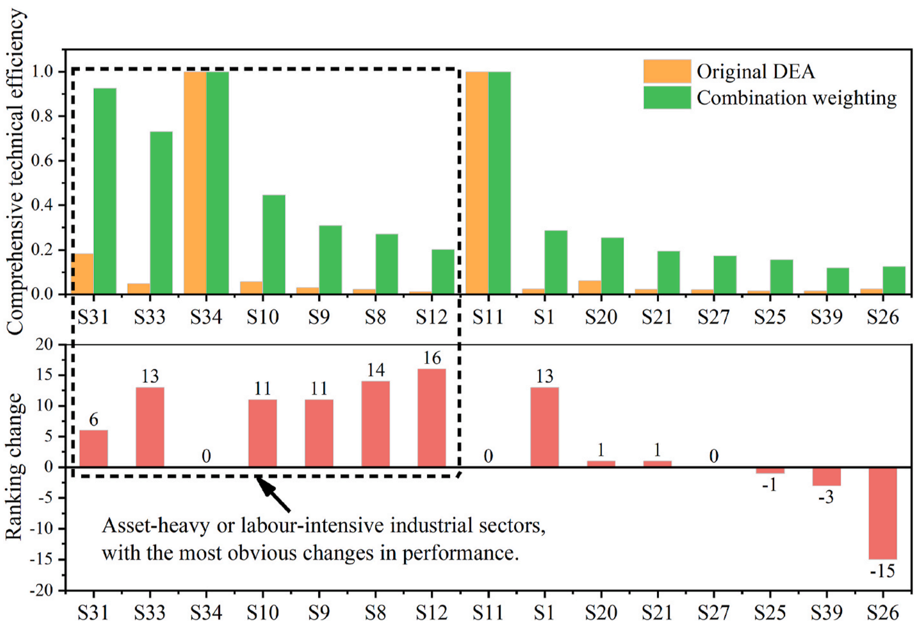

Fig. 4. Industrial sectors with a significant change in efficiency and ranking.

(1) The effective industrial sectors (TE = 1) in the original DEA model results included tobacco manufacturing (S11), pharmaceutical manufacturing (S22), computer communication equipment (S34), instrumentation manufacturing (S35), and other mining (S7). The TE values of the other industrial sectors ranged from 0.01 to 0.60. The index integration method resulted in only three effective industrial sectors: tobacco manufacturing (S11), computer communication equipment (S34), and pharmaceutical manufacturing (S22). The TE values of the other industrial sectors ranged from 0.11 to 0.93.
(2) The TE values and ranking of the industries of equipment manufacturing and living consumption significantly rose by 0.24–0.74 and 6–14, respectively, including automobile manufacturing (S31), electromechanical equipment (S33), alcoholic beverage and tea manufacturing (S10), food manufacturing (S9), agricultural and sideline food processing (S8), and general equipment manufacturing (S29).
(3) The TE value of the industry of bulk raw materials improved, but its ranking remained the same or decreased. The ranking of oil and coal processing (S20), chemicals (S21), non-ferrous metal smelting and rolling (S27), and non-metallic mineral products (S25) remained the same, whereas the ranking of electricity and heat production (S39) and ferrous metal smelting and rolling (S26) significantly dropped 3 and 15 places, respectively.

The index integration method exhibited the above characteristics compared with the original model results since it adjusted the relative weights between the input indicators and undesired output indicators. For example, due to the high fixed assets investment and the large number of employments, some industrial sectors of equipment manufacturing and living consumption, such as automobile manufacturing (S31), electromechanical equipment (S33), alcoholic beverage and tea manufacturing (S10), and food manufacturing (S9), yielded low performance in the original model results. This study weakened the weights of fixed assets and labor force and strengthened the weight of energy consumption through combined weighting. Therefore, the comprehensive performance of these industrial sectors improved significantly. The strengthened weight of energy consumption and the adjusted relative weight of the three pollutants (the increased weight of PM emissions) caused the ranking of the industrial sectors of bulk raw materials, such as electricity and heat production (S39) and ferrous metal smelting and rolling (S26) to fall significantly.

The combined weighting of the performance evaluation proposed in this study aimed to provide technical support for precise control over industrial air pollution by comprehensively examining industrial economic and environmental benefits. Compared with the original model results, the evaluation results after the index integration showed that the performance ranking of the industrial sectors with low energy consumption, high output, and less pollution improved, whereas the efficiency ranking of the industries with high energy consumption and high pollution declined. Therefore, the combined weighting based on the DEA model established by the index integration method solved the issue that the DEA model assigned indicator weights entirely based on the characteristics of data, and thus, became more in line to promote precise control over industrial air pollution.

4. Conclusion

Evaluating the industrial economic and environmental benefits was the primary procedure to explore the coordinated development pathways of the industrial economy and its air pollution control. This study proposed a combined subjective and objective weighting for the performance evaluation. In the development of this method, based on the DEA, the index integration method was further integrated to solve the problem that weight preference was not considered in current performance evaluation studies. Fixed asset investment, energy consumption, employment number, industrial output value, and pollutant emissions that represent the economic and environmental benefits of industrial enterprises were selected to construct indicator systems. The performance evaluation of the 41 industrial sectors in the 13th five-year plan was conducted as a case, to verify the rationality and effectiveness of its application in providing technical support for the coordinated development of the industrial economy and its air pollution control. The main conclusions reached were as follows:

(1) The proposed method yielded the quantitative results of the comprehensive performance evaluation of the economy-environment nexus of each industrial sector.

The quantitative evaluation results were consistent with the qualitative analysis results of the development status of the industrial sectors, which in turn verified the rationality and feasibility of the proposed method. The industries of equipment manufacturing and living consumption led to the highest performance, whereas the industry of bulk raw materials caused the worst performance, with their five-year average comprehensive performances being estimated at 0.50, 0.43, and 0.19, respectively.

(2) Based on the combined analyses of TE, PTE, and SE of the industrial sectors, where to specifically emphasize industrial air pollution control was further clarified.

The group of high PTE-high SE yielded the most development value, such as tobacco manufacturing, computer communication equipment, and automobile manufacturing. The groups of low PTE-high SE and low PTE-low SE were the focus of industrial air pollution control. The group of low PTE resulted in a lower level of economic output under the same energy consumption and pollutant emission level. In particular, the industrial sectors with large production scales, such as electricity and heat production, ferrous metal smelting and rolling, and non-metallic mineral products, exhibited relatively large potential for energy conservation and emission reduction.

(3) By comparing the evaluation results before and after the index integration method, the necessity of applying combined weighting to the prevention and control of air pollution was verified.

After the index integration method was adopted, the overall TE values and ranking of the industrial sectors with high energy consumption and high PM emissions fell in varying degrees, whereas those of the industrial sectors with low energy consumption and low PM emission rose. The index integration method solved the issue that the DEA model assigned indicators weights entirely based on the characteristics of the data, and thus, realized the purpose of flexibly carrying out performance evaluation according to the focus of air pollution control, more in line with the needs of air pollution control.

(4) There was still optimization space for the indicator system.

The indicator system needed to fully and accurately evaluate the economic and environmental benefits of each industrial sector. If the data were available, it was suggested to use "industrial added value" instead of "gross industrial output value" used in this study, which was more suitable to represent the economic benefits of the industrial sector. Meanwhile, this study only took each industrial sector as an example, and the data used were all statistical data from industrial enterprises above the designated size. In the future, the method in this study needs to be accurately applied to different regions such as provinces, cities, and counties, as well as large, medium, and small enterprises of different sizes. Then, the indicator system needs to be adjusted accordingly, which is exactly the direction of the following research.

Author contribution statement

Tingkun Li: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Yufen Zhang, Xiaohui Bi, Jianhui Wu, Yinchang Feng: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Mingyang Chen, Bin Luo: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

Data included in article/supp. material/referenced in article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e17442.

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