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# Carbon emission factor decomposition and carbon peak prediction based on multi-objective decision and information fusion processing

Chunxue Shi and Xiwen Feng\*

\*Correspondence:  
TopJo2361@163.com  
College of Energy  
and Mining Engineering,  
Shandong University  
of Science and Technology,  
Qingdao 266590, Shandong,  
China

## Abstract

Global warming caused by excessive carbon dioxide emissions has seriously threatened the sustainable development of human society. How to reduce carbon dioxide emissions has become a common problem faced by the international community. This article aims to study the decomposition of carbon emission factors and the prediction of carbon peaks from the perspective of multi-objective decision-making and information fusion processing. The sample collection method and statistical analysis method are used to collect samples and simplify the algorithm. A collection experiment of carbon emission factors based on the industry of City A is designed. The experimental data collection takes into account the conversion of coal and oil products into standard coal and carbon dioxide the resulting emissions impact. The experimental results in this paper show that the simulated and real values of my country's petroleum carbon emissions have both increased from 2000 to 2015, and the decline will be controlled in 2017. Both the simulated value and the real value of my country's coal carbon emissions have been on the rise from 2000 to 2015, and the decline will be controlled in 2017. The carbon emissions of coal are far greater than those of petroleum. The research on carbon emission factor decomposition and carbon peak prediction based on multi-objective decision-making and information fusion processing has been completed well. The research results can be used for industrial carbon emission factor decomposition and carbon peak prediction in other cities across the country.

**Keywords:** Multi-objective decision-making, Information fusion processing, Carbon emission factor decomposition, Carbon peak prediction research

## 1 Introduction

In recent decades, with the accelerated melting of the two-level glaciers and the increasing sea level, the environmental damage caused by global warming has become a global issue of general concern to the international community today, and curbing the further warming of the global climate has become a problem for mankind. The common challenges faced by society in this century. The factors that cause climate change are both natural and man-made. However, the large amount of greenhouse

gases such as CO<sub>2</sub> emitted into the atmosphere by human beings in the process of social and economic development is the main cause of global warming. The Intergovernmental Panel on Climate Change (IPCC) in its global climate change assessment report released in 2013 believes that global warming is unquestionable, and that climate warming is even more severe than previously expected, with more than 95%. The certainty that climate change is caused by human activities. Global warming has produced a series of abnormal climate problems, which have put tremendous pressure on ecological security, food security, water resources security, etc., which has made the ecological environment on which we depend for survival increasingly deteriorating, and has seriously threatened the sustainable development of human society ability. According to the IPCC's Special Report on Emission Scenarios (SRES), global sea levels will rise by an average of 22–34 cm from 1990 to the 1980s. Some island countries in the Pacific will be submerged by then, and coastal metropolises such as New York and Shanghai are also facing the threat of being swallowed up by the sea.

My country is the largest developing country in the world. With the rapid development of industry and the large-scale use of coal-based fossil energy, my country has also become a major carbon emitter. According to statistics, in the early 1990s, my country's total fossil energy consumption became the second largest consumer after the USA. By 2010, my country surpassed the USA to become the world's largest energy consumer. According to data from the Oslo International Center for Climate and Environmental Research (CICERO), China's cumulative carbon dioxide emissions will reach 146.4 billion tons in 2016, surpassing the 146.2 billion tons in the USA, making it the first place. Therefore, my country plays a pivotal role in solving global climate problems and implementing emission reduction measures. The continuous development of social economy has driven the rapid development of the transportation industry, and at the same time, it has also increased the environmental pollution caused by energy consumption in transportation and industrial production. Therefore, it is difficult to reconcile the industrial development based on traditional technology and energy conservation and emission reduction contradiction. Only by comprehensively analyzing the characteristics of changes in carbon emissions in various industries in our country can we reduce my country's carbon emissions from the source and thereby alleviate the pressure on my country's carbon emissions.

In recent years, the problem of multiple objective optimization has gradually attracted the attention of researchers and has become a hot and difficult problem. Among them, how to make full use of effective information in existing knowledge to predict the dominance of individuals Relationship is the key issue. To address this difficulty, researchers have merged the ideas of data mining into evolutionary algorithms and merged them into the ideas of data mining. The process of finding the best solution in the field of decision making is in fact the process of data mining. Data mining refers to the use of computer methods, including technical and statistical knowledge, to obtain knowledge and information with potential use value from a large amount of noisy and ambiguous data information. Today, data mining technology has been widely used in the fields of artificial intelligence and experience, and is receiving more and more attention from researchers. However, the application of data

mining to evolutionary arithmetic to solve the flaws of evolutionary algorithms is still in its infancy [1]. In the early stages, it has great potential.

Zhou et al. used numerical analysis to analyze the driving factors of carbon emissions from energy consumption in industry and transportation, and discussed the measures taken by my country to reduce carbon emissions from energy consumption, but his research did not extend to other industries [2]. Dieye uses the LEAP model to predict the steel, building materials, chemical, non-ferrous, power, coal, and high-growth industries in Henan Province under five scenarios: the benchmark scenario, the industrial structure optimization scenario, the energy efficiency improvement scenario, the energy structure adjustment scenario, and the comprehensive scenario. Carbon emissions, the results show that the comprehensive scenario is the optimal development model for industrial carbon emissions peaking in Henan Province, and industrial carbon emissions will peak in 2025, with a peak of 517 million tons. However, he did not do further research on how to apply the province's industrial carbon emission model to the whole country [3]. Reynard D et al. studied the carbon dioxide emissions of China, the USA, Germany, and Switzerland through the time series GM model and on the basis of environmental ecological economics. Combined with the historical data of global carbon dioxide emissions in 2000, they obtained economic growth, population size; the process of urbanization promotes the increase of carbon dioxide emissions, so he added the influencing factor of urbanization rate in the STIRPAT prediction model to predict future carbon dioxide emissions. However, his research is quite limited. It does not distinguish the difference between developing countries and developed countries, and there is no set of general rules and experience summaries [4].

The innovations of this paper are: (1) the interval multi-objective optimization method is used to simplify the method of screening data samples, making the algorithm work easier. (2) Data collection is from 2000 to 2015, which is also the fifteen years of rapid development of my country's industrialization and modernization, which is symbolic. Based on this, it is more convincing to make carbon peak prediction research. (3) The introduction of the decoupling index model of industrial carbon emissions makes the content of the article more substantial and specific.

## **2 Method of carbon emission factor decomposition and carbon peak prediction based on multi-objective decision and information fusion processing**

### **2.1 Total industrial carbon emissions and carbon emissions intensity**

Industrial carbon emissions mainly come from the consumption of fossil energy [5]. Commonly used carbon emission accounting methods include actual measurement method [6], material balance algorithm and coefficient method [7]. The actual measurement method is to calculate the total carbon emissions by measuring the flow rate [8], velocity and concentration of the exhaust gas through the instruments and facilities recognized by the relevant departments. The material balance algorithm is based on the law of conservation of material [9], which quantitatively analyzes the amount of material used in the energy consumption process or the production process to calculate carbon emissions [10]. It is divided into a material balance algorithm based on the production department and a material balance algorithm based on carbon source energy [11]. The

coefficient method is divided into the coefficient method based on the production field and the coefficient method based on fossil energy [12]. The coefficient method based on the production field refers to the calculation of the total carbon emissions by calculating the average value of the carbon emissions produced by the production unit product or the unit energy consumption under the general technical and economic management conditions [13]. The coefficient method based on fossil energy obtains the carbon emission coefficient of various energy sources according to different countries or regions [14], different energy structures and technological levels, and the sum of the products of standard coal consumption and oxidation rate converted to various energy sources is the carbon emission Total amount [15]. Due to specific issues, it is difficult to obtain the energy consumption data of the counties and districts at the municipal level, and it is impossible to directly calculate the industrial carbon emissions of the counties and districts based on the coefficient method based on fossil energy [16]. Studies have shown that industrial added value is positively correlated with industrial carbon emissions [17]. Therefore, in this paper, according to the proportion of the industrial added value of each county in the city's industrial added value, the total industrial carbon emissions are proportionally allocated to obtain the industrial carbon emissions of each county [18].

## 2.2 Low-carbon economic theory

Since the 1990s, scholars have gradually paid attention to the issue of carbon dioxide emissions [19], trying to explore the relationship between economic development and carbon dioxide emissions by consulting relevant literature and empirical research [20]. With the deepening of research, scholars at home and abroad generally believe that economic growth plays a positive role in driving carbon dioxide emissions [21], and rapid economic growth has brought about continuous increases in carbon dioxide emissions [22]. Therefore, researchers must pay attention to the issue of carbon emission reduction while developing the economy and the theory of low-carbon economy came into being [23].

The concept of "low-carbon economy" first appeared in the energy white paper "The Future of Our Energy: Creating a Low-Carbon Economy" published in the United Kingdom [24]. The book states that economic development should focus on ecological and environmental protection, instead of using a large amount of energy consumption and carbon dioxide emissions. In exchange for economic growth [25], it is necessary to change the economic growth mode based on fossil fuels such as coal and use more clean energy such as solar energy, wind energy, and tidal energy. This economic growth model of "low energy consumption, low pollution, low emissions" and "high efficiency, high efficiency, and high efficiency" three lows and three highs has attracted global attention and attention.

Low-carbon economy is based on a variety of means such as technological progress, industrial transformation, institutional innovation, and new energy development to form a series of economic forms such as low-carbon industry, low-carbon life, low-carbon energy, low-carbon technology, and low-carbon development. Change the mode of economic development to obtain more economic output with less energy use and lower carbon dioxide emissions. The development of a low-carbon economy does not mean not developing or developing at the expense of the economy, but to achieve

a harmonious unity of economy, society, and ecology through a change in the concept of development [26].

From a policy perspective, although my country's current carbon intensity policy helps curb the growth of carbon emissions; it is far from enough to achieve the peak of carbon dioxide emissions. He Jiankun, deputy director of the National Committee of Experts on Climate Change, believes that in 2030, the target carbon intensity of a relative decline in GDP can be measured by the decline in China's carbon dioxide emissions. This is also determined by the characteristics of my country's current industrialization and urbanization, and now we are in during the period of sustained rapid economic growth, energy demand and carbon dioxide emissions will continue to grow for a long period of time. A relative decline in GDP is a necessary condition to ensure sustained and stable economic development, but carbon emission reduction policies need to be further strengthened. So as to vigorously promote the extensive promotion of energy conservation and emission reduction [27].

### 2.3 Overview of interval multi-objective optimization problems

The constrained optimization problem is expressed as Eq. (1):

$$\begin{aligned} Q : \min_x F(x) &= (f_m(x)), \quad m = 1, 2, \dots, z \\ \text{s.t. } g_j(x) &\geq a_j, \quad j = 1, 2, \dots, n \\ h_k(x) &= b_k, \quad k = 1, 2, \dots, n^* \\ x &= (x_1, \dots, x_q) \in X \subset R \end{aligned} \quad (1)$$

Among them, all the solutions that meet the constraints in the target space are called feasible solutions.

Formula (1) describes the general form of multi-objective optimization problems, and in engineering problems, optimization problems are all with ambiguity and uncertainty. In order to solve these problems, we have proposed some research methods. This method is called non-Deterministic mathematical methods.

The constrained interval multi-objective optimization problem is shown in the following Eqs. (2), (3), (4), (5):

$$Q : \min_x F(x, u) = (f_m(x, u)), \quad m = 1, 2, \dots, z \quad (2)$$

$X$  is the  $q$ -dimensional decision space:

$$\text{s.t. } g_j(x, u) \geq a_j = [a_j, \bar{a}_j], \quad j = 1, 2, \dots, n \quad (3)$$

$x$  is the  $q$ -dimensional decision vector:

$$h_k(x, u) \geq b_k = [b_k, \bar{b}_k], \quad k = 1, 2, \dots, n^* \quad (4)$$

Define  $x$ :

$$x = (x_1, \dots, x_q) \in X \subset R^q, x_i = [x_i, \bar{x}_i], \quad i = 1, 2, \dots, q \quad (5)$$

Define  $u$ :

$$u = (u_1, \dots, u_p) \subset R^p, u_l = [u_l, \overline{u_l}], \quad l = 1, 2, \dots, p \quad (6)$$

Among them, several important data can be functionalized to obtain formulas (7), (8), (9):

$$f_z(x) = \min_u f_z(x, u), \overline{f_z(x)} = \max_u f_z(x, u) \quad (7)$$

$$g_j(x) = \min_u g_j(x, u), \overline{g_j(x)} = \max_u g_j(x, u) \quad (8)$$

$$h_k(x) = \min_u h_k(x, u), \overline{h_k(x)} = \max_u h_k(x, u) \quad (9)$$

On this basis, Taylor expands to  $u$ :

$$\min_x F(x, u) = ((f_1(x), \overline{f_1(x)}), \dots, (f_2(x), \overline{f_2(x)})) \quad (10)$$

Processing in the formula:

$$\begin{aligned} f_i(x) &= f_i(x, u^c) - \sum_{l=1}^p \left| \frac{\partial f_i(x, u^c)}{\partial u_l} \right| u_l^r \\ \overline{f_i(x)} &= f_i(x, u^c) + \sum_{l=1}^p \left| \frac{\partial f_i(x, u^c)}{\partial u_l} \right| u_l^r \end{aligned} \quad (11)$$

We use the same approach to the constraint function:

$$\begin{aligned} g_j(x, u) &= [g_j(x), \overline{g_j(x)}] \\ h_k(x, u) &= [h_k(x), \overline{h_k(x)}] \end{aligned} \quad (12)$$

where:

$$\begin{aligned} p_j(x) &= p_j(x, u^c) - \sum_{l=1}^p \left| \frac{\partial p_j(x, u^c)}{\partial u_l} \right| u_l^r \\ \overline{p_j(x)} &= p_j(x, u^c) + \sum_{l=1}^p \left| \frac{\partial p_j(x, u^c)}{\partial u_l} \right| u_l^r \\ j_k(x) &= j_k(x, u^c) - \sum_{l=1}^p \left| \frac{\partial j_k(x, u^c)}{\partial u_l} \right| u_l^r \\ \overline{j_k(x)} &= j_k(x, u^c) + \sum_{l=1}^p \left| \frac{\partial j_k(x, u^c)}{\partial u_l} \right| u_l^r \end{aligned} \quad (13)$$

The Taylor series expansion is used to effectively reduce the amount of calculation. In summary, the interval multi-objective optimization problem formula (1) is organized into the standard form of the constrained multi-objective interval optimization problem. The algorithm simplification is completed, and the experiment is ready to begin.

**Table 1** Standard coal conversion factor and CO<sub>2</sub> emission factor of various energy sources

Total coal	Table coal factor	Unit	Emission factor	Unit
Raw coal	0.7143	Kgce/Kg	2.69	KgCO <sub>2</sub> /Kg
Coke	1.4286	Kgce/Kg	3.14	KgCO <sub>2</sub> /Kg
Washed coal	0.9000	Kgce/Kg	2.69	KgCO <sub>2</sub> /Kg
Briquette	0.9714	Kgce/Kg	2.69	KgCO <sub>2</sub> /Kg
Coke oven gas	0.5929	Kgce/M <sup>3</sup>	0.93	KgCO <sub>2</sub> /M <sup>3</sup>

**Table 2** Standard coal conversion factor and carbon dioxide emission factor for oil products

Total oil products	Table coal factor	Unit	Emission factor	Unit
Raw oil	1.1286	Kgce/Kg	3.07	KgCO <sub>2</sub> /Kg
Gasoline	1.4714	Kgce/Kg	3.02	KgCO <sub>2</sub> /Kg
Kerosene	1.4714	Kgce/Kg	3.10	KgCO <sub>2</sub> /Kg
Diesel oil	1.4571	Kgce/Kg	3.17	KgCO <sub>2</sub> /Kg
Fuel oil	1.4286	Kgce/Kg	3.24	KgCO <sub>2</sub> /Kg
Liquefied petroleum gas	1.7143	Kgce/Kg	3.17	KgCO <sub>2</sub> /Kg
Refinery dry gas	1.5714	Kgce/Kg	2.65	KgCO <sub>2</sub> /Kg

### 3 Methods/experimental section

#### 3.1 Data sources and model construction

The data used in this article comes from China Statistical Yearbook and China Energy Statistical Yearbook. The standard coal conversion coefficient of various energy sources adopts China GB/T 2589—2008 General Principles of Comprehensive Energy Consumption Calculation. The standard coal conversion coefficient here is calculated based on the average low calorific value of the energy. When the conversion coefficient of certain energy is when the interval is selected, the middle value of the interval is used as the conversion coefficient of the energy. The CO<sub>2</sub> emission coefficient adopts the IPCC standard, and it is assumed in the calculation that the carbon in the fuel is completely oxidized and burned. The standard coal conversion coefficients and carbon emission coefficients of various energy sources are shown in the following table.

Table 1 shows the conversion of coal products into standard coal and the carbon dioxide emission coefficient.

Table 2 shows the standard coal conversion factor and carbon dioxide emission factor of oil products.

This article takes the total consumption of raw coal, coke, clean coal, briquette and coke oven gas as the consumption of coal, and the total consumption of crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas and refinery dry gas As the consumption of oil, the consumption of natural gas is regarded as the consumption of natural gas. This article divides the end consumption of energy into three parts, namely the primary, secondary and tertiary industries. Among them, the primary industry includes agriculture, forestry, animal husbandry, fishery, and water conservancy, the secondary industry includes industry and construction, and the tertiary

industry includes transportation, storage and postal services, wholesale, retail and accommodation, and catering.

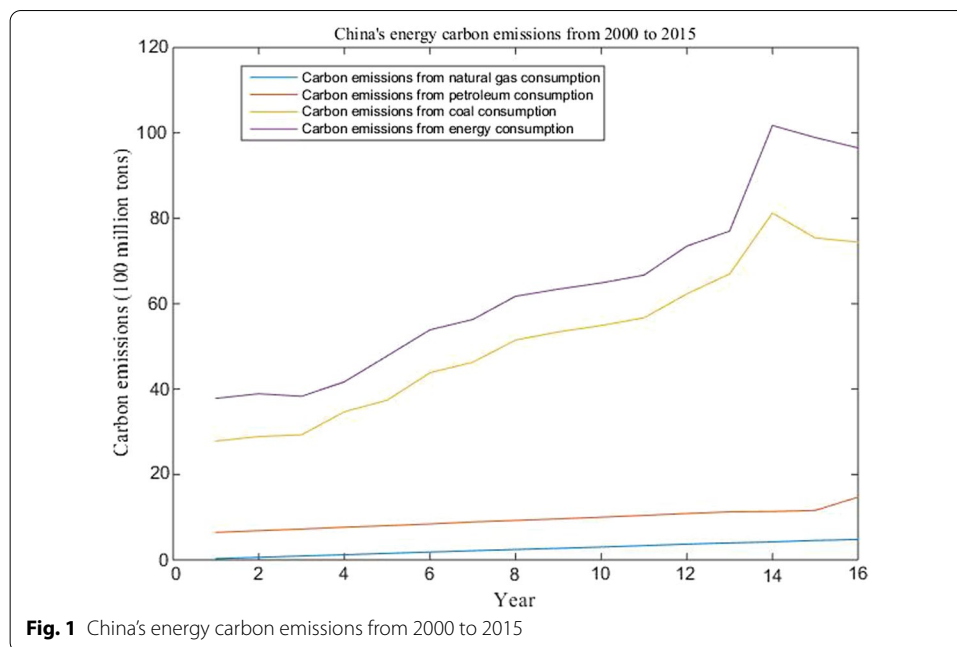
### 3.2 Change trend of carbon emissions

From 2000 to 2013, China's energy carbon emissions maintained rapid growth at an average annual rate of 8.6%. As of 2013, China's energy carbon emissions reached 103,5176 million tons. However, energy carbon emissions have declined in 2014 and 2015. This decline can be attributed to the decline in coal consumption caused by the government's reduction of coal production capacity. The increase in oil and natural gas consumption cannot compensate for the reduction in coal consumption. Vacancy. However, China's energy consumption is still rising. After reaching the lowest growth rate in 2015, the energy consumption growth rate in 2016 began to rise again. It is expected that the energy consumption growth rate in 2017 will be higher than that in 2016. The reduction of energy carbon emissions can be regarded as a short-term situation caused by the impact of the government's coal de-capacity policy. China's energy carbon emission peak has not arrived. As the effect of the de-capacity policy gradually weakens and the consumption of oil and natural gas continues to grow, China's energy carbon emissions will regain the momentum of growth. In terms of the contribution of the three energy sources to energy carbon emissions, the contribution of coal consumption to carbon emissions is the highest, with an average contribution of 80% over the past 16 years, followed by the contribution of oil consumption to carbon emissions, and the average contribution over the past 16 years. At 17%, the contribution of natural gas consumption to carbon emissions is the lowest, with an average contribution of 3% in 16 years; in terms of the changing trend of the contribution of the three energy sources to energy carbon emissions, the contribution of coal consumption to carbon emissions shows an increase first and then a decrease. The contribution of petroleum consumption carbon emissions shows a trend of first decreasing and then increasing, while the contribution of natural gas consumption carbon emissions presents a consistent growth trend. On the whole, the current coal carbon emissions basically determine energy carbon emissions, but this the degree of determination is gradually decreasing, and the influence of future oil and natural gas consumption on the development trend of energy carbon emissions will gradually increase. China's energy carbon emissions from 2000 to 2015 are shown in Fig. 1 below.

### 3.3 Determination of influencing factors

The STIRPAT model is further expanded according to the industrial status quo of the selected sample city A. The three indicators of population size, wealth, and technical level in the model are expanded into population indicators, wealth indicators, technical indicators, and structural indicators. Based on these four indicators, the influencing factors of city A's industrial carbon emissions are determined. Among them, (1) the population index is the total population. Due to the growth of urban population, the demand for energy is increasing, and energy consumption leads to the continuous increase of carbon emissions. Therefore, it is of practical significance to select the total population as the influencing factor of industrial carbon emissions in City A. (2) Wealth indicators choose labor productivity and industrialization rate. Rapid





economic development has led to an increase in energy demand. As a heavy industry base, industrial processes consume a lot of energy, which makes industrial carbon emissions increase sharply. Therefore, labor productivity and industrialization rate are selected. The factors are typical and representative; (3) technical indicators select industrial energy intensity and technical level. Industrial energy intensity refers to the energy consumed per unit of industrial added value. Industrial energy intensity is mainly affected by technology, especially equipment, equipment, and technological level. Therefore, the improvement and improvement of technical level have an impact on energy consumption per unit of industrial added value. Reduction plays a certain role, and then has an impact on industrial carbon emissions; the number of industrial and mining enterprise patent authorizations is a sign of the level of industrial technology, and also has a relationship with industrial carbon emissions, so the model uses the number of industrial and mining enterprise patent authorizations to represent the technical level; (4) structural indicators include industrial structure factors and energy structure factors. Three factors including industrial light and heavy structure, enterprise scale, and industrial energy structure are selected, respectively. Industrial light and heavy structure and enterprise scale can reflect the industrial characteristics of City A, and changes in the proportion of different types of energy consumption also have an important impact on industrial carbon emissions. The state and local governments encourage the use of clean energy, such as hydropower, solar energy, photovoltaics, etc., and use as little fossil energy as possible, such as coal, oil and other non-clean energy sources with large carbon emissions. At present, the industrial energy consumption structure of City A is still dominated by oil and coal. Compared with coal, the carbon emission coefficient of the two is much greater than that of oil. Therefore, this paper selects the proportion of coal consumption in primary energy consumption to reflect the impact of energy structure on industrial carbon

the impact of emissions. In order to more accurately reflect the relationship between various factors and industrial carbon emissions, the industrial added value was used to replace the total industrial output value of Lanzhou in the calculation process.

For uncertain optimization problems, one way of thinking is to first transform uncertain optimization problems into deterministic optimization problems through mathematical methods. Then solve it, but this method will lose some information in the process of solving; another way of thinking is to directly solve the uncertain optimization problem. This paper adopts the second method to directly solve the large number of uncertain factors in the analysis of industrial carbon emission factors using cloud computing to obtain the accuracy of the problem analysis.

In summary, this article decomposes the industrial carbon emission factors of City A into 8 items: total population, labor productivity, industrialization rate, industrial energy intensity, industrial energy structure, industrial light and heavy structure, enterprise scale, and technical level. The specific settings are shown in Table 3 shown.

### 3.4 Abbreviations

In order to be more detailed and complete in the selection of factors the technological level in the STIRPAT model is innovatively decomposed into two parts: Technical indicators and structural indicators taking into account the impact of technological progress industrial structure and energy structure factors on industrial carbon emissions

Where  $Y$  is the year,  $IC$  is the industrial carbon emissions,  $TP$  is the total population,  $LP$  is the labor productivity,  $IR$  is the industrialization rate,  $IEI$  is the industrial energy intensity,  $IES$  is the industrial energy structure,  $ILHS$  is the industrial light and heavy structure, and  $ES$  is the scale of the enterprise.  $TL$  stands for technical level. The values of various factors from 2002 to 2016 are shown in Table 4.

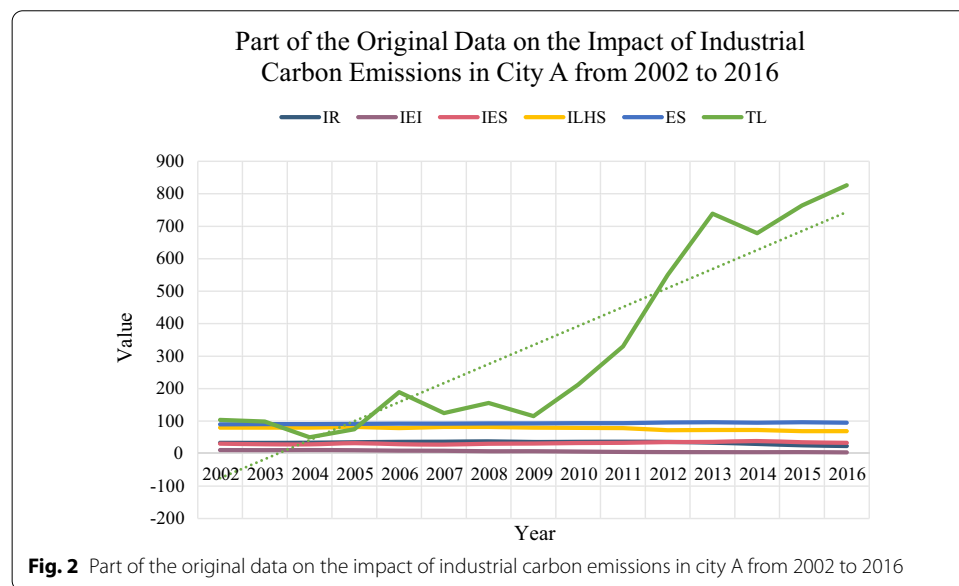
Figure 2 is made after statistics of some data as shown in the figure.

**Table 3** Setting of factors affecting industrial carbon emissions in city A

Variable	Definition	Unit
Industrial carbon emissions	CO <sub>2</sub> emissions from industrial energy consumption	Ten thousand tons
Population	Total people	Ten thousand people
Labor productivity	Industrial added value/number of employees	Yuan/per people
Industrialization rate	Industrial value Added/gross product	%
Industrial energy intensity	Industrial energy consumption/industrial added value	Tons of standard coal/ten thousand yuan
Industrial energy structure	Industrial coal consumption/industrial primary energy consumption	%
Industrial light and heavy structure	Heavy industry added value/industrial added value	%
Enterprise size	Value added of industrial enterprises above designated size/industrial added value	%
Technique level	Number of patents granted by industrial and mining enterprises	Item

**Table 4** Original data of the influencing factors of industrial carbon emissions in city A from 2002 to 2016

Y	IC	TP	LP	IR	IEI	IES	ILHS	ES	TL
2002	3054.04	300.95	45,695.44	33.14	10.82	30.54	80.00	90.03	104
2003	3342.33	300.95	51,085.09	33.02	10.56	28.70	80.00	90.47	99
2004	4057.96	304.36	59,468.09	33.52	10.86	28.41	80.00	90.47	50
2005	4595.00	308.11	75,892.82	34.87	10.36	32.04	81.79	91.75	75
2006	4648.19	311.74	87,190.33	36.16	9.03	28.90	78.66	91.99	189
2007	5198.72	313.64	98,232.27	36.56	8.70	27.70	81.88	92.55	125
2008	5132.90	319.28	130,816.41	37.63	7.17	30.27	81.77	93.00	156
2009	5396.55	322.28	133,043.13	35.77	7.26	30.87	79.90	93.04	115
2010	5527.97	323.59	154,019.61	36.27	6.15	32.53	78.90	93.39	212
2011	5761.18	323.54	203,740.36	36.52	5.15	33.19	78.50	93.61	330
2012	5809.36	323.30	221,687.03	35.95	4.57	35.41	71.82	95.69	550
2013	6102.89	321.52	240,771.64	33.60	4.43	35.98	72.34	96.60	739
2014	5817.97	321.43	232,682.07	29.70	4.26	38.60	72.53	95.07	679
2015	5398.90	321.90	205,863.79	25.53	4.45	34.92	69.23	96.25	764
2016	4379.41	324.23	182,673.37	23.27	3.71	33.12	68.73	95.29	826



## 4 Results and discussion section

### 4.1 History check

This paper uses coal consumption carbon emissions, petroleum consumption carbon emissions, natural gas consumption carbon emissions, cement production carbon emissions and total carbon emissions as test variables, and compares historical statistical data and simulated data from 2002 to 2016. The calculation error verifies the validity of China's peak carbon emission system model. The simulation verification results are as follows.

Table 5 shows the error statistics between the simulated and real carbon emissions of coal consumption.

**Table 5** Error statistics between simulated and true coal consumption carbon emissions

Year	Simulation value (ten thousand tons)	Real value (ten thousand tons)	Error (%)
2000	270,010.21	279,330.20	− 3.34
2001	285,180.75	286,133.53	− 0.33
2002	315,904.53	301,485.81	4.78
2003	360,402.90	357,522.19	0.81
2004	420,104.09	410,925.21	2.23
2005	464,456.00	459,013.58	1.19
2006	478,884.15	504,972.89	− 5.17
2007	528,155.38	539,976.21	− 2.19
2008	556,364.31	556,507.43	− 0.03
2009	570,110.56	585,683.73	− 2.66
2010	626,273.19	618,158.86	1.31
2011	693,441.84	678,965.23	2.13
2012	716,682.64	698,162.80	2.65
2013	875,968.30	840,269.01	4.25
2014	880,080.80	814,903.22	8.00
2015	785,253.48	785,999.46	− 0.09

**Table 6** Error statistics between simulated and real carbon emissions of petroleum consumption

Year	Simulation value (ten thousand tons)	Real value (ten thousand tons)	Error (%)
2000	71,514.74	68,788.03	3.96
2001	68,438.89	69,146.78	− 1.02
2002	72,707.30	73,038.82	− 0.45
2003	84,136.86	80,742.96	4.20
2004	93,574.57	93,142.78	0.46
2005	99,923.84	97,474.20	2.51
2006	104,082.87	104,468.86	− 0.37
2007	113,507.85	110,256.49	2.95
2008	114,493.57	115,008.15	− 0.45
2009	120,627.63	123,530.02	− 2.35
2010	132,694.93	138,906.11	− 4.47
2011	137,871.48	142,441.70	− 3.21
2012	151,070.48	151,231.61	− 0.11
2013	156,171.08	157,624.53	− 0.92
2014	168,584.69	167,003.18	0.98
2015	178,871.28	175,236.65	2.07

Table 6 shows the error statistics between the simulated and real carbon emissions of petroleum consumption.

Table 7 shows the error statistics between the simulated value and the true value of total carbon emissions:

It can be seen from the above three tables that the China peak carbon emission system dynamics model established on the Vensim software platform has a high prediction accuracy, and the average error between the simulated value and the true value of the total carbon emissions from 2000 to 2015 It is 1.90%, and the maximum error between

**Table 7** Error statistics between simulated and real carbon emissions

Year	Simulation value (ten thousand tons)	Real value (ten thousand tons)	Error (%)
2000	370,414.07	376,758.10	− 1.68
2001	385,110.10	387,057.64	− 0.50
2002	423,456.74	409,179.86	3.49
2003	485,565.39	479,299.32	1.31
2004	559,694.29	550,447.10	1.68
2005	616,555.48	608,396.22	1.34
2006	643,476.55	669,949.17	− 3.95
2007	709,960.90	718,736.23	− 1.22
2008	745,888.17	744,806.88	0.15
2009	776,688.74	792,899.81	− 2.04
2010	859,309.78	853,839.07	0.64
2011	944,009.53	931,814.62	1.31
2012	987,762.08	967,562.45	2.09
2013	1,161,451.46	1,129,526.82	2.83
2014	1,184,581.95	1,119,956.12	5.77
2015	1,099,435.84	1,095,476.56	0.36

the simulated value and the real value of all variables does not exceed 8%, which can pass the validity test of the system dynamics model. Therefore, the system dynamics model has a high degree of fit with China's carbon emission system, and can be used as a model for predicting the peak of China's carbon emission and its occurrence time later.

#### 4.2 Parameter setting

The specific settings of the economic growth rate scenario parameters are shown in Table 8 below.

The specific settings of the scenario parameters of the rate of change of the population are shown in Table 9 below.

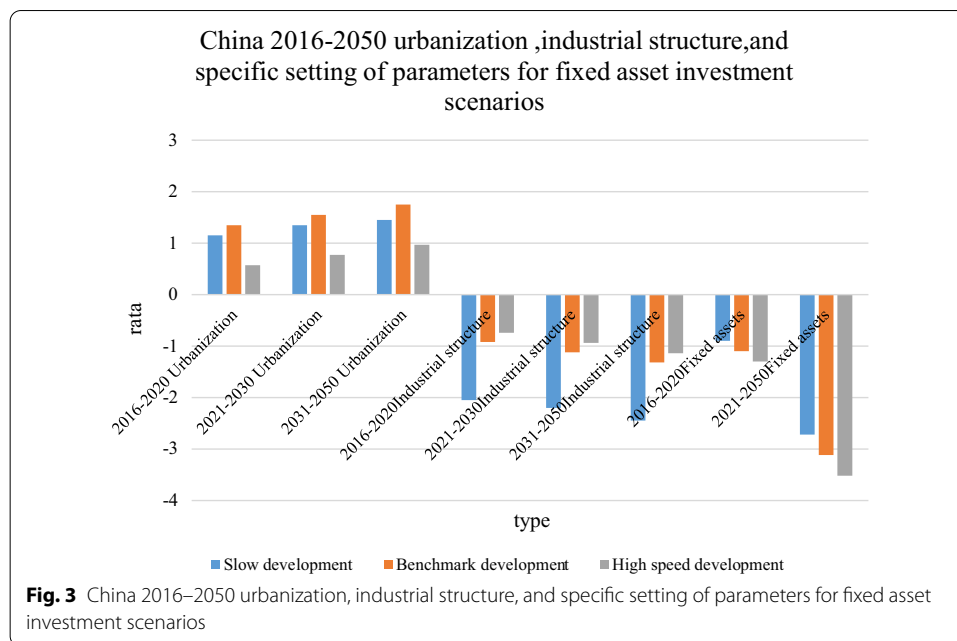
The specific settings of urbanization, industrial structure, and fixed asset investment scenario parameters are shown in Fig. 3 below.

**Table 8** China 2016–2050 economic growth rate scenario parameters

	2016–2020 (%)	2021–2025 (%)	2026–2030 (%)	2031–2050 (%)
Low-speed development scenario	6	5.3	4.3	4–2
Baseline development scenario	6.5	5.9	5.1	5–3
High-speed development scenario	7	6.5	5.9	6–4

**Table 9** China 2016–2050 population change rate scenario parameters

	2016–2020 (%)	2021–2030 (%)	2031–2050 (%)
Low-speed development scenario	0.602	0.159	− 0.311
Baseline development scenario	0.652	0.209	− 0.261
High-speed development scenario	0.702	0.259	− 0.211

**Table 10** The influence of evolutionary algebra G of different examples on algorithm performance

Optimization	Evolutionary algebra	E value	D value	C value
Q1	G = 20	0.2559	11.5577	0.3746
	G = 50	0.0164	11.5675	0.3655
	G = 100	0.1428	11.5760	0.3614
Q2	G = 20	0.2565	11.9861	0.2507
	G = 50	0.2268	11.9469	0.2468
	G = 100	0.1726	11.9528	0.2479
Q3	G = 20	0.3646	13.5155	0.3010
	G = 50	0.3079	14.5201	0.2744
	G = 100	0.2925	19.8167	0.2709

### 4.3 Algorithm parameter

For the first optimization problem and the second optimization problem, with the continuous increase of evolutionary algebra, the uniformity (E measure) and breadth (D measure) of Pareto's frontier continue to improve. At the same time, the convergence of the algorithm (C measure) is also getting better; for the second optimization problem, the E measure of the algorithm gradually becomes better with the increase of evolutionary algebra. Therefore, for the algorithm in this paper, with the increase of evolutionary algebra, the frontier performance of the algorithm Pareto is Gradually get better. Table 10 shows the influence of evolutionary algebra on algorithm measurement under different optimization problems.

Table 11 is the impact of algorithm performance.

To make a more detailed analysis of the results through the data, the D measure of the algorithm in this paper is better than the other two algorithms, but the difference is not much; for the multi-objective decision-making and information fusion processing

**Table 11** The influence of the number of individual cloud clusters pop in different calculation examples on the performance of the algorithm

Optimization	Evolutionary algebra	<i>E</i> value	<i>D</i> value	<i>C</i> value
Q1	Pop = 20	0.2459	11.5203	0.3963
	Pop = 40	0.1797	11.5698	0.3647
	Pop = 60	0.1438	11.5760	0.3614
Q2	Pop = 20	0.1726	11.9608	0.2364
	Pop = 40	0.3422	11.9569	0.2588
	Pop = 60	0.2534	11.9528	0.2479
Q3	Pop = 20	0.4900	19.2882	0.3038
	Pop = 40	0.3808	19.5188	0.2724
	Pop = 60	0.2925	19.8149	0.2709

optimization problem proposed in this paper, the *E* measure of the algorithm in this paper is better than the interval The particle swarm and interval NSGA-II algorithms get better performance indicators; the *E* measure of the algorithm in this paper is better than the other two algorithms. This shows that compared with the other two algorithms, the algorithm in this paper has an improvement in the *E*-measure for the optimization of multi-objective decision-making and information fusion processing.

#### 4.4 Decoupling index model of industrial carbon emissions

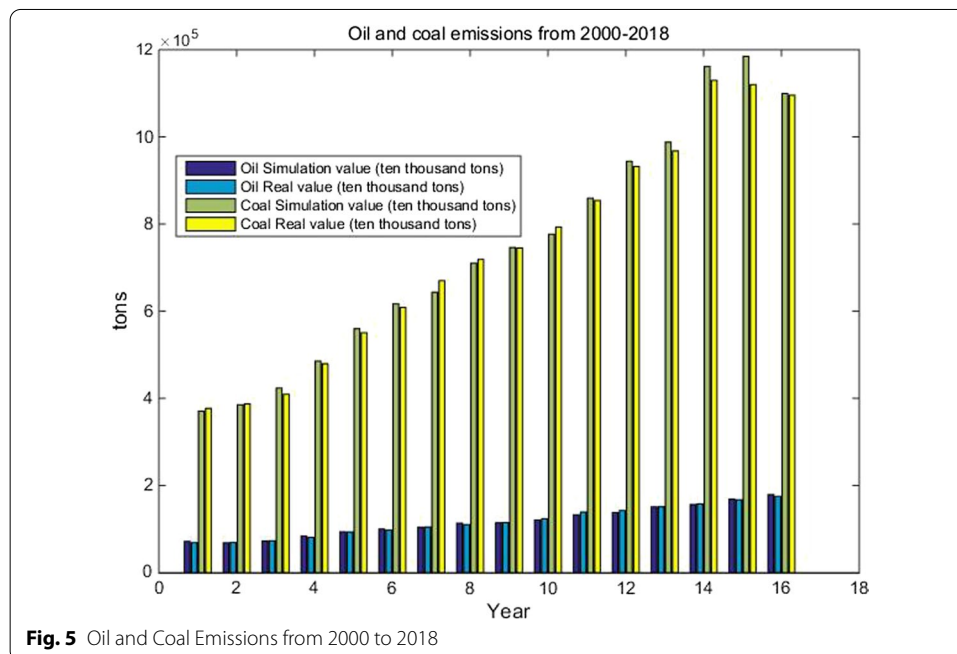
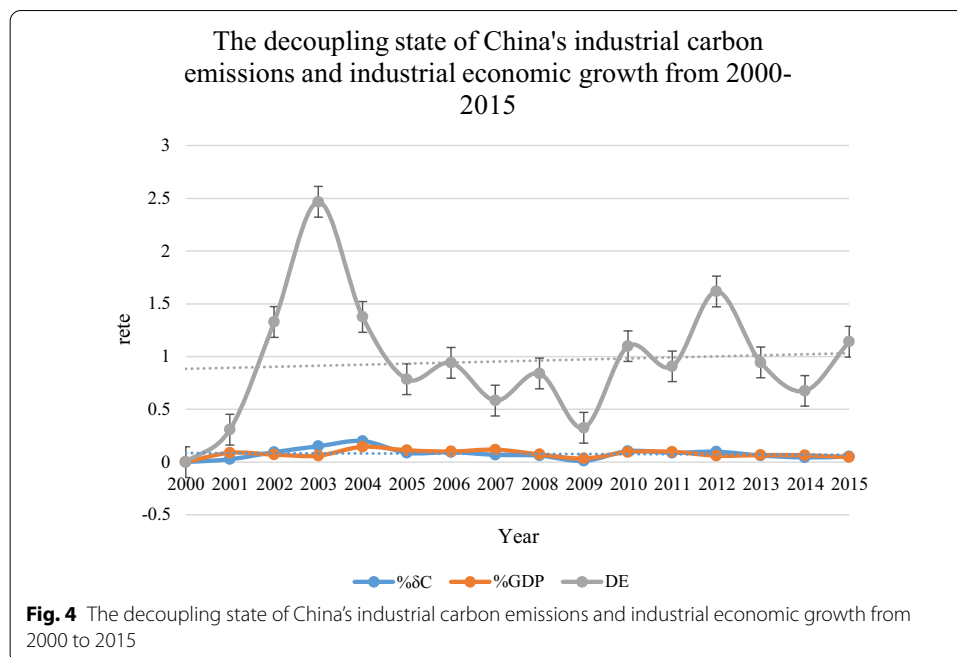
The term "decoupling" originated from the field of physics and used to explain that the relationship between two or more physical quantities that have a relationship no longer exists. Then the decoupling theory was first applied to the agricultural field by the OECD (Organization for Economic Cooperation and Development) and extended to the environmental field. In the environmental field, the OECD will use decoupling to measure the relationship between economic development and environmental pressure, and resource and energy consumption, in order to better study the relationship between economic development and environmental quality. Figure 4 shows the decoupling state of my country's industrial carbon emissions and industrial economic growth from 2000 to 2015.

The research on oil and coal emissions under this model is shown in Fig. 5.

It can be seen from the figure that the simulated and real values of my country's petroleum carbon emissions have both been on the rise from 2000 to 2015, and the decline will be controlled in 2017. Both the simulated value and the real value of my country's coal carbon emissions have been on the rise from 2000 to 2015, and the decline will be controlled in 2017. The carbon emissions of coal are far greater than those of petroleum.

## 5 Conclusions

Research and analysis show that the research on carbon emission factor decomposition and carbon peak prediction based on multi-objective decision-making and information fusion processing proposed in this paper is more comprehensive, intuitive, three-dimensional and more comprehensive than previous studies on carbon emission factor decomposition and carbon peak prediction intelligent. From the perspective of multi-objective decision-making, based on the related content of signal processing progress, this paper uses Taylor series



expansion method to summarize the interval multi-objective optimization problem and simplify the related algorithms. Taking city A as a sample, the research objects are taken from the carbon emissions from coal consumption, carbon emissions from petroleum consumption, carbon emissions from natural gas consumption, carbon emissions from cement production, and total carbon emissions from city A as test variables. Comprehensive data analysis to 2016. The research results show that the system dynamics model of China's peak



carbon emissions established on the Vensim software platform has high prediction accuracy. The average error between the simulated value and the true value of the total carbon emissions from 2000 to 2015 is 1.90%, and the maximum error between the simulated value and the real value of all variables does not exceed 8%, which can pass the validity test of the system dynamics model. The D measure of the algorithm in this paper is better than the other two algorithms, but the difference is not much; for the multi-objective decision-making and information fusion processing optimization problem proposed in this paper, the E measure of the algorithm in this paper is better than the interval. The particle swarm and interval NSGA-II algorithms get better performance indicators. The research on carbon emission factor decomposition and carbon peak prediction based on multi-objective decision-making and information fusion processing has been completed well. This article has some shortcomings in the following aspects: (1) the sample for this study is from the industrial city A, mainly using industrial data as the statistical model, and may not fully consider the impact of other industries on the decomposition of carbon emission factors. (2) The interval multi-objective optimization analysis algorithm introduced in this article is relatively complicated and not easy to promote. In the future research, programming technology can be used to turn the algorithm into a program that can be conveniently operated.

#### Abbreviations

IPCC: Intergovernmental Panel on Climate Change; SRES: Special Report on Emission Scenarios; CICERO: Oslo International Center for Climate and Environmental Research; OECD: Organization for Economic Cooperation and Development.

#### Authors' contributions

CS: Writing—editing data curation. XF: supervision; data analysis. Both authors read and approved the final manuscript.

#### Author Information

Chunxue Shi, was born in Shandong, Taian, P.R. China, in 1985. Now, she is a Ph.D. student of Shandong University of Science and Technology, P.R. China. She mainly involved in the research of logistics system simulation and optimization, big data system and resource economy.

Xiwen Feng, was born in Shandong, Qingdao, P.R. China, in 1963. He is a professor in Shandong University of Science and Technology. He has long been engaged in teaching and scientific research in industrial engineering and logistics and its applications, logistics system simulation and optimization, system decision theory and application, resource evaluation and analysis. He is a leader in system theory disciplines and an academic leader in resource economics and management at Shandong University of Science and Technology. He is also the head of the excellent course of logistics engineering.

#### Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

#### Availability of data and material

Data sharing does not apply to this article because no data set was generated or analyzed during the current research period.

#### Declarations

##### Ethics approval and consent to participate

This article is ethical, and this research has been agreed.

##### Consent for publication

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##### Competing interests

The authors declare that they have no competing interests.

Received: 28 June 2021 Accepted: 11 October 2021

Published online: 24 October 2021

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