



Carbon emission of China's power industry: driving factors and emission reduction path

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Abstract

The low-carbon development of power industry is the key to low-carbon development of the whole society. In order to determine appropriate and feasible emission reduction policies, it is necessary to identify the contribution of different drivers to the change of carbon emissions in China's power sector and to simulate the potential evolution trend of carbon emissions. This paper constructs LMDI model to analyze the driving factors of carbon emission changes in China's power industry from 2000 to 2018 and uses Monte Carlo algorithm to simulate the evolution trend of carbon emission under different scenarios. We can find (1) economic output effect reached 3.817 billion tons from 2000 to 2018, which was the primary factor to increase the carbon emission. Population scale effect reached 251million tons, which had a weak promotion impact on carbon emission. (2) Conversion efficiency effect played a role in restraining carbon emissions, reaching 699 million tons from 2000 to 2018. (3) Emission factor effect and power intensity effect have obvious volatility. The power structure effect showed great volatility before 2013 and mainly played a role in restraining carbon emission after 2013. (4) Under the baseline scenario, the carbon emission of China's power industry shows a growth trend. Under green development scenario and enhanced carbon reduction scenario, the carbon emission shows a trend of first increasing and then decreasing.

Keywords Power industry · Carbon emission · LMDI · Monte Carlo algorithm

Introduction

As global warming has a profound impact on economic development, ecological environment, and human health, taking urgent action to deal with climate change and its impact has been listed as a sustainable development goal of the United Nations. According to the *Emissions Gap Report 2020* (UNEP 2020), despite the decline in global carbon dioxide emissions in 2020 due to the impact of COVID-19, the world is still heading for a 3.2°C temperature rise this century. Failure to achieve the Paris Agreement goal of limiting global warming to well below 2°C will have irreversible impacts on a wide range of areas, such as an increase in extreme weather, especially for developing countries with weak economic foundations. As the largest developing country in the world, China adheres to the concept of a community of common destiny for all mankind and actively responds to climate change. In 2020, President Xi Jinping promised that China would strive to achieve the peak of carbon dioxide emissions by 2030 and strive to achieve carbon neutrality by 2060, reflecting China's determination to strengthen green transformation and climate governance.

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Carbon emissions are closely related to energy production and consumption in the economic society, and the power industry plays an important role in the low-carbon transition. Electricity is a clean and efficient secondary energy, and electrification is the main mean of decarbonization in various industries in the future. At the same time, thermal power is still the main form of power generation in China, and the relevant carbon emissions reach more than 40% of China's total carbon emissions (Wang and Xie 2015). So the low-carbon development of the power industry is the key to the low-carbon development of the whole society. Moreover, compared with many sectors, the power sector can achieve decarbonization at a considerable speed (Staffell 2017). Therefore, it is necessary to identify the contribution of different driving factors to the change of carbon emissions in China's power industry, simulate the potential evolution trend of carbon emissions in the future, and choose feasible path for the power industry to reduce emissions and formulate operable policies.

Many scholars have carried out relevant research on the driving factors of carbon emission from China's power industry. Table 1 lists the relevant literature. The research models can be divided into three categories: econometric model, structural decomposition model, and index decomposition model. For research related to econometric models, Wang et al. (2019) investigated the impact of the share of nonfossil fuel power generation, GDP per capita, the capital stock of electricity sector, and other factors on carbon emissions of China's power industry with panel quantile regression model; Meng et al. (2017) used logarithmic linear equation and found that carbon emission of China's power industry is relatively sensitive to the total power generation and thermal power generation efficiency. For research related to structural decomposition model, Wei et al. (2020) divided the carbon emissions related to electricity in Shanghai into the carbon emissions caused by local power generation, carbon emissions embodied in the electricity consumed by a region after cross-regional electricity transmission, and the electricity-related carbon emissions induced by regional consumption and adopted the structural decomposition analysis for the latter two carbon emissions. Luo et al. (2020) investigated the effects of energy efficiency, production structure, consumption structure, and consumption volume on carbon emissions of China's power industry. Ma et al. (2019) decomposed the carbon emission change of China's power sector into energy structure, technical factor, final use structure, and final use level. Compared with the structural decomposition model, the index decomposition model has the characteristics of flexible use and low data requirements, among which the logarithmic mean Divisia index (LMDI) method is widely used. Zhang et al. (2022) decomposed the change of power carbon emission in Beijing into emission factor effect, energy structure effect,

conversion efficiency effect, power structure effect, power intensity effect, economic scale effect, and population scale effect. An et al. (2022) used DEA method to calculate the CRP (carbon reduction potential) of China's coal power and further decomposed CRP. The LMDI decomposition factors of carbon emission in China's power industry can be summarized into three aspects: scale (economic output, population, electricity consumption, power generation, etc.), structure (energy structure, power generation structure, industrial structure, etc.), and technology (carbon emission intensity, energy efficiency, power intensity, etc.). Scholars used LMDI method to analyze the driving factors of carbon emissions mainly from the perspective of power production (such as energy structure, power generation structure, power generation, etc.), economic activities, and population growth. In order to facilitate the carbon emission prediction of 3.4 Scenario analysis and prediction, we still select these conventional decomposition indicators, because the change trend of these indicators is easy to obtain from the policy documents. In general, this paper takes the carbon emission of China's power industry as the research object and constructs the LMDI model to analyze its driving factors from multiple perspectives of power production, power intensity, economic output, and population.

Another research hotspot is to simulate the carbon emission of the power industry, and the relevant literature is listed in Table 2. Scholars use energy-economy-environment system model, including top-down model (CGE model, etc.) and bottom-up model (LEAP model, TIMES model, etc.), STIRPAT model, IPSO-BP neural network model, gray prediction, and other methods and combine with scenario analysis to explore the evolution trend of carbon emissions under different policy scenarios. Existing studies often assume that the future change rate of carbon emission influencing factors is a fixed single value, which is not consistent with the reality. It should have uncertainty and show as a value range. Monte Carlo method, as an analysis method to deal with uncertainty, can take random values of benchmark variables according to a certain probability and calculate the target variables after combination. If scenario analysis is combined with Monte Carlo method, the future evolution trend of carbon emission in power industry and its probability can be calculated under different policy scenarios, and the scientific and feasible emission reduction path can be identified.

This paper takes the carbon emissions of China's power industry as the research object, constructs LMDI model to identify the influencing factors of the historical evolution, uses Monte Carlo method to simulate the future evolution trend of carbon emissions under multiple scenarios, and determines the feasible emission reduction path. The main contributions of this paper are as follows: (1) Provide policy suggestions for China's power industry to reach the peak of carbon emission before 2030. China is a country of high

Table 1 Literature on the driving factors of carbon emission from power industry

Authors	Time period	Country/region	Indicator	Methods	Driving factors
An et al. (2022)	2009–2016	China	(CRP) carbon reduction potential	LMDI (logarithmic mean Divisia index)	Coal-fired power generation efficiency, coal-fired power output rate, labor productivity, industry scale effect
Zhang et al. (2022)	2005–2019	Beijing, China	CO ₂	LMDI	Emission factor effect, energy structure effect, conversion efficiency effect, power structure effect, power intensity effect, economic scale effect, population scale effect
Wang et al. (2021)	1997–2017	China	CO ₂	Two-stage LMDI	Emission coefficient effect, TPGE effect, fossil fuel mix effect, nuclear effect, renewable effect, and total electricity generation effect
Luo et al. (2020)	2007–2015	China	CO ₂	IO-SDA (input output structural decomposition analysis) model	Energy efficiency, production structure, consumption structure, and consumption volume
Mai et al. (2020)	1998–2017	Northwest China	CO ₂	LMDI	Carbon intensity, energy mixes, generating efficiency, electrification, economy, and population
Wei et al. (2020)	2007–2012	Shanghai, China	CO ₂	LMDI SDA	Fuel structure, energy efficiency, power structure, and power generation volume (LMDI); electricity consumption volume, electricity transmission structure, electricity transmission scale (SDA); carbon emissions intensity of electricity, electricity efficiency, production technology, consumption structure, consumption volume, carbon intensity of electricity, per capita electricity consumption and the population of Shanghai (SDA)
Wang et al. (2019)	1991–2015	30 provinces, China	CO ₂	Panel quantile regression model	The share of nonfossil fuel power generation, GDP per capita, the capital stock of electricity sector, the average utilization hours of power generation equipment, the ratio of regional import electricity to total electricity consumption, auxiliary power consumption rate, the logarithm of substation capacity of extra high voltage, the ratio of electricity consumption of high energy-consuming industries to social electricity consumption
Ma et al. (2019)	2007–2015	China	CO ₂	SDA	Energy structure, technical factor, final use structure, and final use level
Liao et al. (2019)	2005–2015	30 provinces, China	CO ₂	LMDI	Energy structure effect, energy efficiency effect, electricity structure effect, electricity trade effect, electricity consumption scale effect
Peng and Tao (2018)	1980–2014	China	CO ₂ intensity	LMDI	Technological innovation, structural adjustment
Liu et al. (2017)	2000–2014	China	Aggregate carbon intensity	LMDI	Thermal efficiency effect, clean power penetration effect, the fossil fuel mix effect, and the regional shift effect
Wang et al. (2017)	1995–2012	Shandong, China	CO ₂	LMDI	Electricity power production, power production structure, energy conversion efficiency, energy mix, emission factor

Table 1 (continued)

Authors	Time period	Country/region	Indicator	Methods	Driving factors
Zhang et al. (2017)	1995–2014	Beijing-Tianjin-Hebei region, China	CO ₂	Hierarchical LMDI	Fuel mix, the coal consumption rate, power generation structure, the ratio of power generation to consumption, transmission, and distribution losses, production sectors' electricity intensity, industrial structure, household electricity intensity, economic scale, and population size
Meng et al. (2017)	2001–2013	China	CO ₂	Logarithmic linear equation	Total electricity consumption, nonfossil energy share of electricity generation, thermal power generation efficiency

carbon emission. Alleviating China's carbon emissions is an important part of alleviating global warming and can also provide reference for other countries and regions. (2) Combine scenario analysis with Monte Carlo methods, examine the uncertainty of the influencing factors, and analyze the evolution of carbon emission of China's power industry in multiple scenarios.

Method, variable, and data

Carbon emission measurement of electric power industry

As thermal power generation is the main source of carbon emissions in the power industry, this paper does not consider the carbon emissions of hydropower, wind power, nuclear power, and other forms of power generation. According to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories compiled by the Intergovernmental Panel on Climate Change, the carbon emission calculation model of power industry is constructed, as shown in Eq. (1)

$$C = \sum_{i=1}^{20} E_i \times H_i \times C_i \times O_i \times \frac{44}{12} \quad (1)$$

where C is the carbon emission of the power industry, the subscript i is the type of energy (raw coal, washing coal, other washing coal, coal gangue, coke, coke oven gas, blast furnace gas, converter gas, other gas, other coking products, crude oil, gasoline, diesel oil, fuel oil, petroleum coke, liquefied petroleum gas, refinery dry gas, other petroleum products, natural gas, liquefied natural gas), E_i is the consumption of the i th energy, H_i is the average low calorific value of the i th energy, C_i is the carbon content per calorific value of the i th energy, and O_i is the carbon oxidation factor of the i th energy. Due to the differences in fuel classification and carbon oxidation rate of oil gas combustion equipment, the carbon emission correlation coefficient provided by the Intergovernmental Panel on Climate Change (IPCC) is not completely consistent with China's reality. Therefore, the relevant calculations coefficient in this paper refers to the research results of Fu and Qi (2014).

LMDI model construction

$$C = \frac{C}{FC} \times \frac{FC}{TP} \times \frac{TP}{T} \times \frac{T}{G} \times \frac{G}{P} \times P \quad (2)$$

where C is the carbon emission of the power industry, FC refers to the sum of various fuel consumption (the unit of consumption is 100 million tons of standard coal), TP refers to the thermal power generation, T refers to the

Table 2 Literature on forecast of carbon emissions from power industry

Authors	Country/region	Time period	Methods	Scenarios
Yu et al. (2020)	China	2020–2050	TIMES (The Integrated MARKAL-EFOM System) model	The reference (REF) scenario, the structural emission reduction (SER) scenario, the technical emission reduction (TER) scenario, and the co-control (COC) scenario
Lin and Jia (2020)	China	2020–2030	Dynamic recursive CGE (Computable General Equilibrium) model	Two benchmark scenarios and six counter-measured scenarios
Tang et al. (2018)	China	2015–2050	National Energy Technology-Power model	Business as usual scenario, advanced technology scenario, Renewable energy development scenario, the combined scenario
Zhou et al. (2017)	Beijing-Tianjin-Hebei region, China	2015–2020	IPSO-BP (improved particle swarm optimization back propagation)	Low-speed scenario, policy scenario, high-speed scenario
Ma et al. (2017)	China	2014–2020	A novel hybrid model, combining the grey model, weakening buffer operator, and firefly algorithm, called FGM (1,1,4)	No
Huang et al. (2017)	China	2010–2050	China TIMES model	A reference scenario, two CO ₂ mitigation scenarios, two water cost scenarios and four combinations of carbon and water scenarios
Tang et al. (2017)	China	2016–2030	Optimal production planning model	Business as usual scenario, high-speed scenario, and medium-speed scenario
Cheng et al. (2016)	Guangdong, China	2010–2020	Two-region dynamic CGE model	Seven scenarios
Khanna et al. (2016)	China	2015–2050	China energy end-use model	No CCS scenario, base CCS policy scenario, accelerated CCS policy scenario, baseline coal-fired efficiency scenario, accelerated coal-fired efficiency scenario
Sun et al. (2016)	China	2016–2020	STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model	15 scenarios
Xu and Ma (2015)	China	2015–2030	Grey-Markov model	No
Wang et al. (2014)	China	2010–2030	Bottom-up optimization model for China's electricity sector	NC scenario, LC scenario, OC scenario, AC scenario, SQ scenario, AD scenario
Zhang et al. (2012)	China	2010–2050	A multi-period modeling and optimization framework	Base scenario and peak scenario
Zhang et al. (2007)	China	2000–2030	LEAP (Long-range Energy Alternatives Planning) China	Baseline scenario, recent policy scenario, new policy scenario

total power generation, G refers to GDP, and P refers to the population. Rewrite it as:

$$C = EF \times ES \times S \times EI \times E \times P \quad (3)$$

where $EF = \frac{C}{FC}$ represents the ratio of carbon emission to fuel consumption, which is mainly related to the internal composition of fuel in the process of power production. $ES = \frac{FC}{TP}$ represents the ratio of fuel consumption to thermal power generation, which is mainly related to the thermal power conversion efficiency. $S = \frac{TP}{T}$ represents the ratio of thermal power generation to total power generation. $EI = \frac{T}{G}$ represents the ratio of total power generation to GDP. $E = \frac{G}{P}$ represents the ratio of GDP to population.

When we assume the year goes from the base period to the t period, the carbon emission change of the power industry ΔC can be expressed as:

$$\Delta C = \Delta C_{EF} + \Delta C_{ES} + \Delta C_S + \Delta C_{EI} + \Delta C_E + \Delta C_P \quad (4)$$

$$\Delta C_{EF} = \frac{C^t - C^0}{\ln C^t - \ln C^0} \ln \left(\frac{EF^t}{EF^0} \right) \quad (5)$$

$$\Delta C_{ES} = \frac{C^t - C^0}{\ln C^t - \ln C^0} \ln \left(\frac{ES^t}{ES^0} \right) \quad (6)$$

$$\Delta C_S = \frac{C^t - C^0}{\ln C^t - \ln C^0} \ln \left(\frac{S^t}{S^0} \right) \quad (7)$$

$$\Delta C_{EI} = \frac{C^t - C^0}{\ln C^t - \ln C^0} \ln \left(\frac{EI^t}{EI^0} \right) \quad (8)$$

$$\Delta C_E = \frac{C^t - C^0}{\ln C^t - \ln C^0} \ln \left(\frac{E^t}{E^0} \right) \quad (9)$$

$$\Delta C_P = \frac{C^t - C^0}{\ln C^t - \ln C^0} \ln \left(\frac{P^t}{P^0} \right) \quad (10)$$

where ΔC_{EF} , ΔC_{ES} , ΔC_S , ΔC_{EI} , ΔC_E , ΔC_P represent the contribution of emission factor effect, conversion efficiency effect, power structure effect, power intensity effect, economic output effect, and population scale effect to the change of carbon emissions, respectively.

Carbon emission prediction model

Based on the factor decomposition model, the growth of carbon emissions is decomposed into six factors: emission factor, conversion efficiency, power structure, power intensity, economic output, and population scale. If the

change rates of EF , ES , S , EI , E , and P are α , β , γ , δ , ϵ , and ρ respectively, the carbon emission in the $t+1$ period can be expressed as:

$$\begin{aligned} C_{t+1} &= EF_{t+1} \times ES_{t+1} \times S_{t+1} \times EI_{t+1} \times E_{t+1} \times P_{t+1} \\ &= [EF_t(1+\alpha)] \times [ES_t(1+\beta)] \times [S_t(1+\gamma)] \times [EI_t(1+\delta)] \times [E_t(1+\epsilon)] \times [P_t(1+\rho)] \\ &= (1+\alpha) \times (1+\beta) \times (1+\gamma) \times (1+\delta) \times (1+\epsilon) \times (1+\rho) \times EF_t \times ES_t \times S_t \times EI_t \times E_t \times P_t \\ &= (1+\alpha) \times (1+\beta) \times (1+\gamma) \times (1+\delta) \times (1+\epsilon) \times (1+\rho) \times C_t \end{aligned} \quad (11)$$

The change rate of carbon emission is shown in Eq. (11)

$$c = (1+\alpha) \times (1+\beta) \times (1+\gamma) \times (1+\delta) \times (1+\epsilon) \times (1+\rho) - 1 \quad (12)$$

Data

This study focuses on the time span during 2000–2018. The energy consumption measuring carbon emissions in the power industry comes from the *China Energy Statistics Yearbook*, and the average low calorific value, carbon content per calorific value, and carbon oxidation factor refer to (Fu and Qi 2014) research results. The data about population, GDP, thermal power generation, and total power generation are from the website of National Bureau of statistics. To eliminate the influence of the price factor, the GDP is adjusted according to the constant price in 2000.

Results

Descriptive statistics

The maximum of carbon emission is 4.222 billion tons, and the minimum is 1.086 billion tons. The maximum of fuel consumption is 421 million tons of standard coal, and the minimum is 442 million tons of standard coal. The maximum of thermal power generation is 5096.318 billion kWh, and the minimum is 1114.1 billion kWh. The maximum of total power generation is 7166.133 billion kWh, and the minimum is 1355.6 billion kWh.

Historical trend of carbon emission

The historical trend of carbon emissions in China's power industry from 2000 to 2018 is shown in Fig. 1. In general, the carbon emission of the power industry was on the rise, from 1.086 billion tons in 2000 to 4.222 billion tons in 2018, with an average annual growth rate of 7.84%. From 2002 to 2006, the annual growth rate of carbon emissions was more than 12%. Notably, there was a downward trend in carbon emissions from 2013 to 2015, which might be related to the power sector's efforts to eliminate backward production capacity and accelerate the application of clean energy after

Fig. 1 Historical trend of carbon emission in China’s power industry (2000–2018)

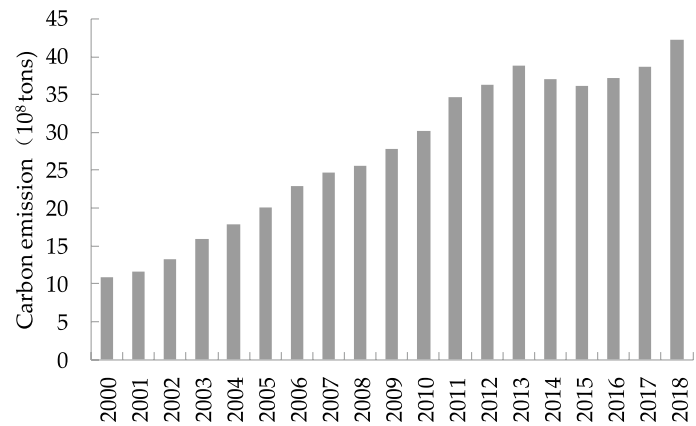


Table 3 Descriptive statistics

	Maximum	Minimum	Mean	Median	Standard deviation
Carbon emission	42.22	10.86	27.46	27.76	10.31
Population	139538.00	126743.00	133367.68	133450.00	3930.88
GDP	487365.13	100280.10	263602.11	246914.80	125548.97
Fuel consumption	14.77	4.21	9.76	9.75	3.46
Thermal power generation	50963.18	11141.90	30580.00	29827.76	13092.14
Total power generation	71661.33	13556.00	39623.95	37146.51	18600.22

the State Council issued the *Action Plan for Air Pollution Prevention and Control* in 2013.

Driving effect decomposition of carbon emission

In different “Five-Year Plan” periods in China, policies on carbon emission control could be different. In this paper, the time interval was divided into 2000–2005, 2005–2010, 2010–2015, and 2015–2018, and the trend of different effects was investigated on this basis.

According to Table 3, emission factor effect played a promoting role in carbon emissions except for 2010–2015. It indicated that the proportion of high emission fuels such as coal increased in most of the time. Conversion efficiency effect and power structure effect always inhibited carbon emissions. Power intensity effect promoted carbon emission in 2000–2005 and 2015–2018 and inhibited carbon emission in 2005–2015. It indicated that the power utilization efficiency in 2000–2005 and 2015–2018 was not ideal, and the power demand per unit GDP was on the rise, which led to the increase of carbon emissions. In contrast, the improvement of power efficiency from 2005 to 2015 was conducive to reducing carbon emissions of the power industry.

Because the four periods contain inconsistent lengths of years, we use the average to reflect the trend of the six factors. The average contribution value of emission factor effect to carbon emission change in different periods was 20 million tons, 19 million tons, -8 million tons, and 15 million tons, respectively. The negative value may be

related to the *12th Five-Year Plan for Energy Development*. The average contribution value of conversion efficiency effect to carbon emission reduction in different periods was 17 million tons, 60 million tons, 39 million tons, and 40 million tons, respectively. It showed that China actively improved energy efficiency, and the effect was the most obvious in 2005–2010. The inhibiting effect of power structure on carbon emission was first enhanced and then weakened, reaching the peak in 2010–2015, with an average reduction of carbon emissions of 48 million tons. It was closely related to the vigorous adjustment of electric power structure during the 12th Five-Year Plan period. The average contribution value of power intensity effect to carbon emission change in different periods was 44 million tons, -8 million tons, -39 million tons, and 15 million tons, respectively, with certain volatility. Economic output effect was the primary factor to promote carbon emissions in different periods, showing a trend of first strengthening and then weakening. Compared with the level in 2005–2010, the promoting effect of economic output was weakened after 2010. The population scale effect was weak in promoting carbon emissions, but it showed a trend of continuous growth. In 2015–2018, it resulted in an average increase in carbon emission of 20 million tons, which could be due to the continuous liberalization of China’s two-child policy to stimulate population growth.

For further analysis, the change trend of each effect year by year is calculated, and the results are shown in Fig. 2.

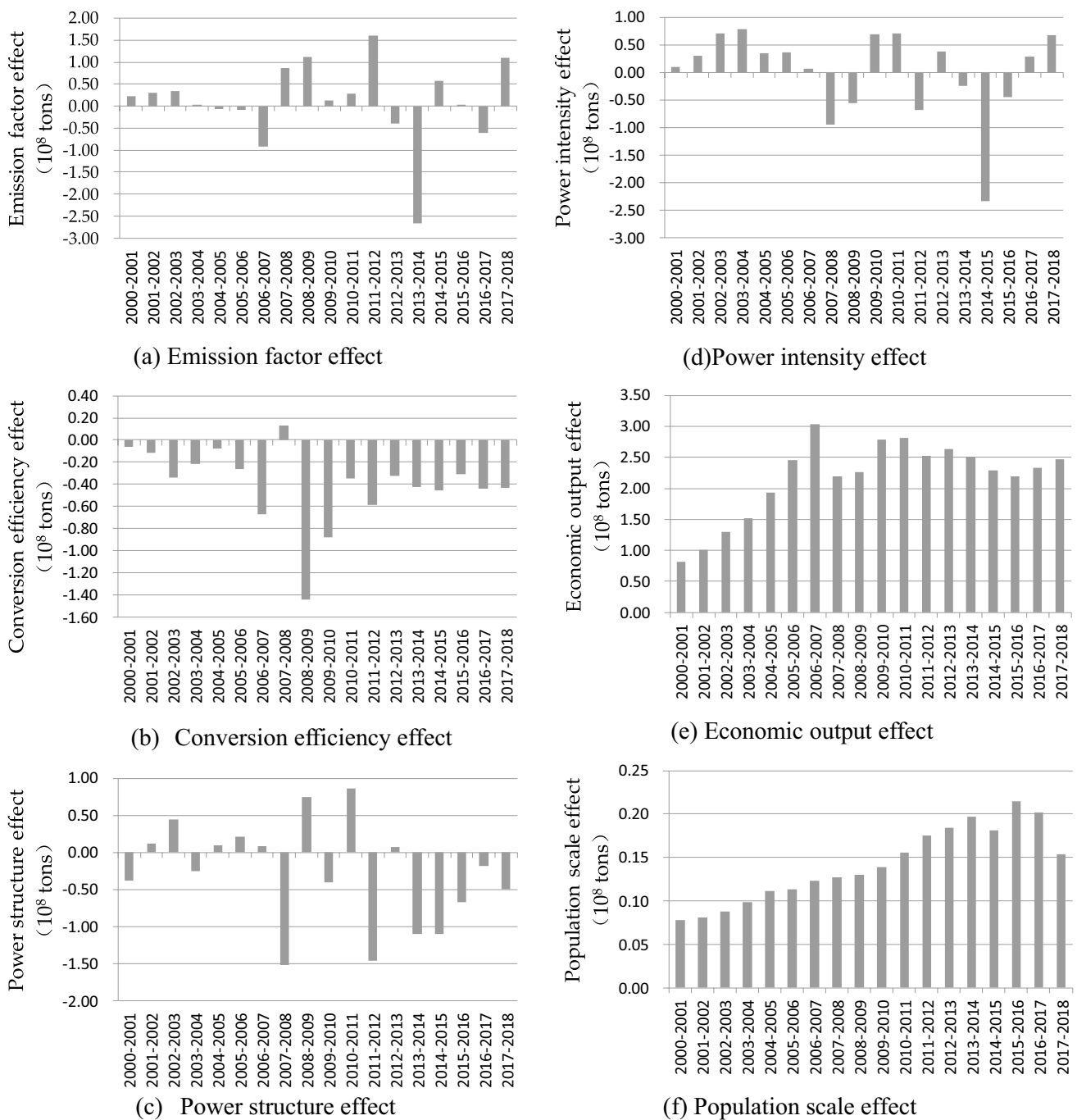


Fig. 2 Year-by-year trends of carbon emission effects in China's power industry from 2000 to 2018

- (1) Emission factor effect. Emission factor effect showed great volatility. The inhibition effect of emission factor reached the maximum in 2013–2014, which was 267 million tons. This was due to the significant reduction of raw coal consumption for thermal power generation from 1.925 billion tons to 1.819 billion tons. The proportion of natural gas and other fuels increased, and thermal power production became relatively clean.
- (2) Conversion efficiency effect. Except for 2007–2008, conversion efficiency effect had a restraining effect on carbon emissions. In 2008–2009 and 2009–2010, the restraining effect was more obvious, reaching 145 million tons and 88 million tons, respectively. This might aim to offset the promoting effect in 2007–2008, so as to meet the energy saving requirements of the 11th Five-Year Plan.

- (3) Power structure effect. Power structure effect showed great fluctuation before 2013, and the direction of the effect changed frequently, indicating that there are some difficulties in the reform of power structure. After 2013, power structure effect mainly curbed carbon emissions, which showed that China had achieved certain results in power structure adjustment.
- (4) Power intensity effect. Power intensity effect played a role in promoting carbon emissions from 2000 to 2007. After 2007, its direction changed frequently. The restraining effect of power intensity effect reached its peak in 2014–2015, reducing carbon emissions by 235 million tons, which was related to China's efforts to build an energy-saving country and reduce energy consumption per unit of GDP at the end of the 12th Five Year Plan.
- (5) Economic output effect. Economic output effect was always the primary factor to promote carbon emissions, and the change trend was roughly in the shape of “up-down-up-down-up.” The maximum value of promoting effect appeared in 2006–2007, reaching 304 million tons. After the outbreak of the financial crisis in 2008, economic output effect first weakened and then recovered. After 2010, with the decline in economic growth, China paid more attention to seeking high-quality development, and economic output effect showed a downward trend. From 2015 to 2018, economic output effect showed a slow growth momentum.
- (6) Population scale effect. Population scale effect always played a role in promoting carbon emissions, but the effect was relatively small. On the whole, the promoting effect increased first and then decreased. In 2015–2016 and 2016–2017, population scale effect was relatively significant, which might be related to the introduction of China's “two-child” policy. However, in 2017–2018, the effect decreases.

Scenario analysis and prediction

Based on the historical trends of various factors, existing policies or forecast data, three scenarios are set to simulate the future evolution trend of carbon emissions in China's power industry, namely the baseline scenario, the green development scenario, and the enhanced carbon reduction scenario. The future change rate of driving factors should be uncertain; that is, the change rate of factors should be a value range, rather than a specific single value. As an uncertainty analysis method, Monte Carlo simulation is widely used in the research of uncertain events. This method uses random numbers to solve the calculation problem. It can take random values of benchmark variables according to a certain probability and calculate the target variables after combination. When the value interval of the variable and the most likely

value result are determined, but the shape of the probability distribution is not timed, the triangular distribution is suitable for random selection of variables (Ramírez et al. 2008). The most likely potential change rate of each factor is its intermediate value, and the relationship between the maximum, intermediate; and minimum values is constructed based on the triangular distribution. This paper uses Matlab software to simulate the trend of carbon emissions.

The baseline scenario

The baseline scenario is based on the past development characteristics of the power industry and extrapolated according to the inertia trend of economic society. It assumes that the economic and technological conditions of the past will be continued and no new carbon reduction measures will be taken. Based on the research results of Shao et al. (2017), considering the cyclical characteristics of China's 5-year development plan, this paper designs the annual change rate of driving factors as follows. The annual change rate of each factor in 2019–2030 is determined by reference to the annual change rate in 2000–2018, 2005–2018, 2010–2018, and 2015–2018. The maximum and minimum values of the change rate of each factor are selected in the above four periods. For the two annual change rates in the middle, the annual change rate in the recent period is selected as the intermediate value.

The minimum, intermediate, and maximum annual change rates of emission factor, conversion efficiency, power structure, power intensity, economic output, and population scale under the baseline scenario are shown in Table 4.

Figure 3 shows the evolution trend of carbon emission under the baseline scenario. It can be seen that the carbon emission of the power industry shows an increasing trend. The range of carbon emissions in 2019 is 4.371–4.560 billion tons, and the most probable carbon emission is 4.459 billion tons. In 2030, the range of carbon emissions will be 6.396–9.854 billion tons, and the most probable carbon emissions will be 8.116 billion tons. It means that if the fuel structure, conversion efficiency, power structure, power intensity, economic growth, and population continue the past trend, the carbon emissions of China's power industry will continue to grow. Therefore, policies must be adjusted to reduce carbon emissions.

The green development scenario

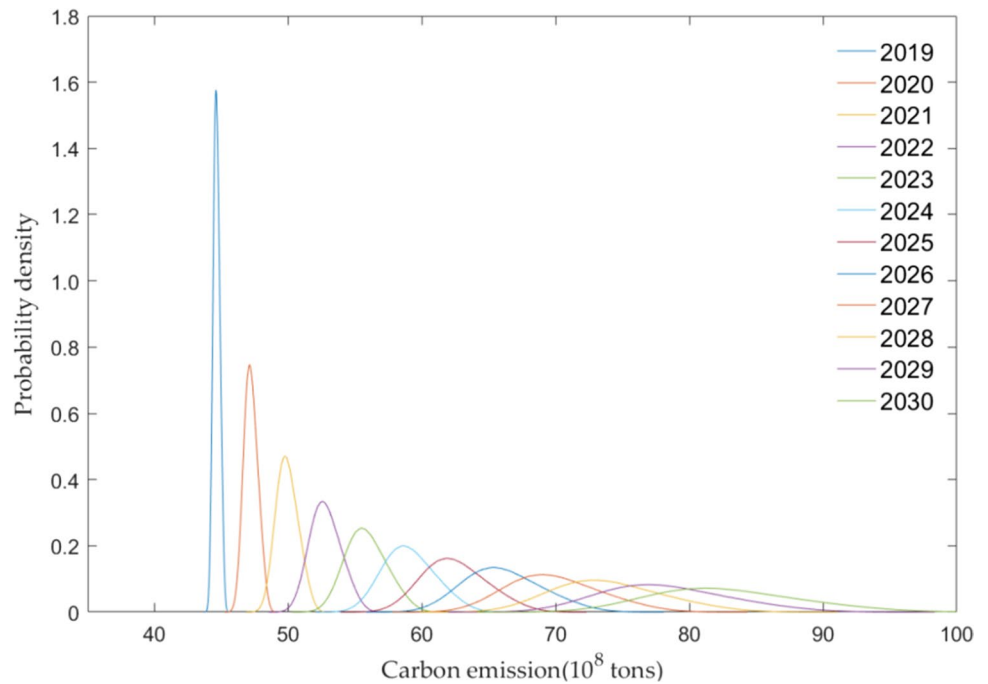
Guidance of the State Council on Accelerating the Establishment and Improvement of the Green and Low-Carbon Development Economic System points out that the promotion of the comprehensive green transformation of economic social is the basic measure to solve China's environmental problems. The green development scenario assumes accelerating

Table 4 Decomposition results of driving factors of carbon emission in power industry in different periods (10⁸ tons)

	ΔC_{EF}	ΔC_{ES}	ΔC_S	ΔC_{EI}	ΔC_E	ΔC_P	ΔC
2000–2005	0.98 (0.20)	-0.84 (-0.17)	-0.06 (-0.01)	2.19 (0.44)	6.54 (1.31)	0.47 (0.09)	9.28 (1.86)
2005–2010	0.95 (0.19)	-2.98 (-0.60)	-0.83 (-0.17)	-0.38 (-0.08)	12.68 (2.54)	0.63 (0.13)	10.07 (2.01)
2010–2015	-0.40 (-0.08)	-1.97 (-0.39)	-2.39 (-0.48)	-1.93 (-0.39)	11.82 (2.36)	0.82 (0.16)	5.95 (1.19)
2015–2018	0.45 (0.15)	-1.20 (-0.40)	-1.39 (-0.46)	0.46 (0.15)	7.13 (2.38)	0.59 (0.20)	6.04 (2.01)

The values in parentheses indicate the average

Fig. 3 Evolution trend of carbon emission distribution of China’s power industry from 2019 to 2030 under the baseline scenario



the green transformation of the power industry, deepening the carbon reduction policy, further controlling the scale of coal-fired power and increasing the proportion of natural gas use, strengthening the energy-saving transformation of thermal power facilities, bringing the proportion of nonfossil energy power generation closer to the world average or even closer to the world advanced level, and maintaining the medium speed of economic development. Each factor changes according to the planning requirements or forecast indicators. The change rate of each factor is constructed as follows (Table 5):

(1) Emission factor

It is assumed that the change rate of emission factor in 2019–2020 will continue the trend of 2015–2018; that is, 0.39% is taken as the average annual change rate. In addition,

Table 5 Potential annual change rate of each factor under baseline scenario (%)

	2019–2030		
	Minimum value	Intermediate value	Maximum value
<i>EF</i>	-0.01	0.39	0.57
<i>ES</i>	-1.61	-1.11	-1.01
<i>S</i>	-1.34	-1.17	-0.80
<i>EI</i>	-0.58	0.39	0.47
<i>E</i>	6.27	6.98	8.60
<i>P</i>	0.49	0.50	0.54

it is assumed that the proportion of natural gas use will gradually increase in 2021–2025 and 2026–2030, and the change rate of emission factors will decrease by 0.2 and 0.4 percentage points, respectively, on the basis of the previous

period; that is., 0.19% and –0.01% are taken as the average annual change rate. The above average annual change rates are taken as the intermediate value of potential change rate. The minimum and maximum of the potential change rate are obtained by adjusting 0.5 percentage points downward and upward on the basis of the intermediate value, respectively.

(2) Conversion efficiency

It is assumed that the change rate of conversion efficiency in 2019–2020 will continue the trend of 2015–2018; that is, –1.01% is taken as the average annual change rate. In addition, it's assumed that energy-saving transformation will be promoted in 2021–2025 and 2026–2030, and the change rate of conversion efficiency will decrease by 0.2 and 0.4 percentage points respectively on the basis of the previous period; that is, 1.21% and –1.41% are taken as the average annual change rate. The above average annual change rates are taken as the intermediate value of potential change rate. The minimum and maximum of the potential change rate are obtained by adjusting 0.5 percentage points downward and upward on the basis of the intermediate value, respectively.

(3) Power structure

According to the *13th Five-Year Plan for Electric Power Development*, the proportion of power generation from non-fossil energy will increase to 31% in 2020,; that is, the proportion of fossil energy generation will reach 69%. Since the fossil energy generation accounted for 71.12% in 2018, it can be calculated that the average annual change rate of power structure from 2019 to 2020 is –1.50%. China's power production is still dominated by coal, and the share of thermal power is higher than the world average, but the government has increased its support for clean energy. Based on the data of *Statistical Review of World Energy 2020* (BP 2020), we assume that in 2025, China's share of thermal power can drop to 64.20%, which is the world average in 2018. And we further assume that in 2030, China's share of thermal power can drop to 55.76%, which is the average level of OECD member countries in 2018. It can be calculated that the average annual change rate of power structure in 2021–2025 and 2026–2030 is –1.43% and –2.78%, which are regarded as the intermediate value of potential change rate. The minimum and maximum of the potential change rate are obtained by adjusting 0.5 percentage points downward and upward on the basis of the intermediate value, respectively.

(4) Power intensity

It is assumed that electricity production and consumption are basically balanced. According to the *13th Five-Year Plan for Electric Power Development*, the average annual growth

rate of electricity consumption is expected to be 3.6–4.8% during the 13th Five-Year Plan period. We take the median value of 4.2% as the average annual change rate of power generation from 2019 to 2020. According to the *Research on the 14th Five-Year Plan for China's Power Development* (GEIDCO, 2020), we predict that China's electricity consumption will reach 9200 billion kwh in 2025. According to the estimated power generation, it can be calculated that the average annual change rate of power generation from 2021 to 2025 is 3.41%. We assume the power generation in 2026–2030 will continue the trend of 2021–2025. As the average annual change rates of GDP in 2019–2020 and 2021–2030 are predicted to be 4.13% and 5.32%¹, the average annual change rates of power intensity in 2019–2020, 2021–2025, and 2026–2030 are supposed to be 0.07%, –1.81%, and –1.81% respectively, which are regarded as the intermediate value of potential change rates. The minimum and maximum of the potential change rate are obtained by adjusting 0.5 percentage points downward and upward on the basis of the intermediate value, respectively.

(5) Economic output

According to the data of National Bureau of Statistics, China's GDP grew by 6.0% and 2.3% in 2019 and 2020, respectively. So the average annual change rate of GDP from 2019 to 2020 is 4.13%. As the average annual change rate of population in the same period is predicted to be 0.88%², the average annual change rate of per capita GDP from 2019 to 2020 is supposed to be 3.22%, which is regarded as the intermediate value. Referring to the research on the feasible growth path of China's GDP (Sheng and Zheng 2017) and considering the negative impact of COVID-19 on economic development, we choose the low economic growth rate of 5.32% as the average annual growth rate of China's GDP from 2021 to 2030. As the average annual change rate of population in 2021–2030 is predicted to be 0.21%³, the average annual change rate of per capita GDP in the same period is supposed to be 5.10%, which is regarded as the intermediate value. The minimum and maximum of the potential change rate are obtained by adjusting 1 percentage points downward and upward on the basis of the intermediate value, respectively.

(6) Population scale

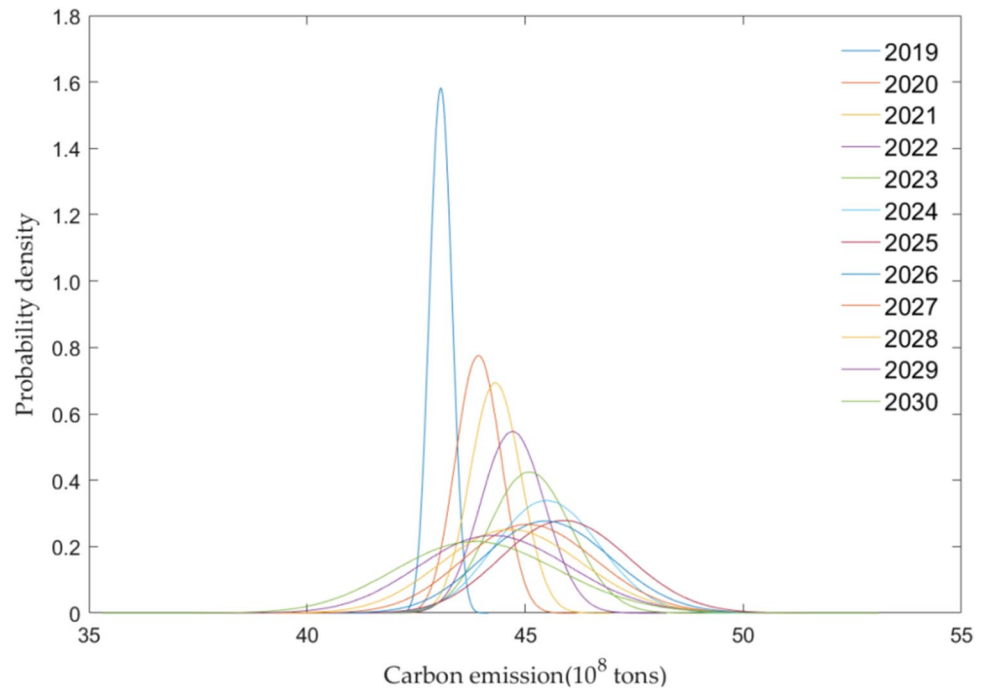
According to the *Notice of the State Council on Printing and Distributing the National Population Development Plan*

¹ The specific explanation is in (5) Economic output

² The specific explanation is in (6) Population scale

³ The specific explanation is in (6) Population scale

Fig. 4 Evolution trend of carbon emission distribution of China's power industry from 2019 to 2030 under the green development scenario



2016–2030, the population of China in 2020 and 2030 is expected to be 1.42 billion and 1.45 billion, respectively. As the population of China in 2018 was 1.3954 billion, it can be calculated that the average annual change rates of population in 2019–2020 and 2021–2030 are 0.88% and 0.21%, respectively. We take them as intermediate values. The minimum and maximum of the potential change rate are obtained by adjusting 0.1 percentage points downward and upward on the basis of the intermediate value, respectively.

Under the green development scenario (Fig. 4), the carbon emission of China's power industry shows a trend of first increasing and then decreasing. In 2019, the carbon emission ranges from 4.201 billion tons to 4.411 billion tons, and the carbon emission with the highest probability is 4.307 billion tons. In 2025, carbon emissions range from 3.982 billion tons to 5.292 billion tons. The carbon emission with the highest probability is 4.591 billion tons, and it reaches its peak. The carbon emission in 2030 range from 3.565 billion tons to 5.331 billion tons, and the carbon emission with the highest probability is 4.369 billion tons. The average annual change rates of carbon emissions with the highest probability in 2019–2025 and 2026–2030 are 1.07% and -0.99% , respectively. It indicates that if the carbon reduction policy is implemented according to the planning requirements or forecast indicators and the green transformation of economic society is strengthened, China's power industry can achieve the peak of carbon emissions before 2030.

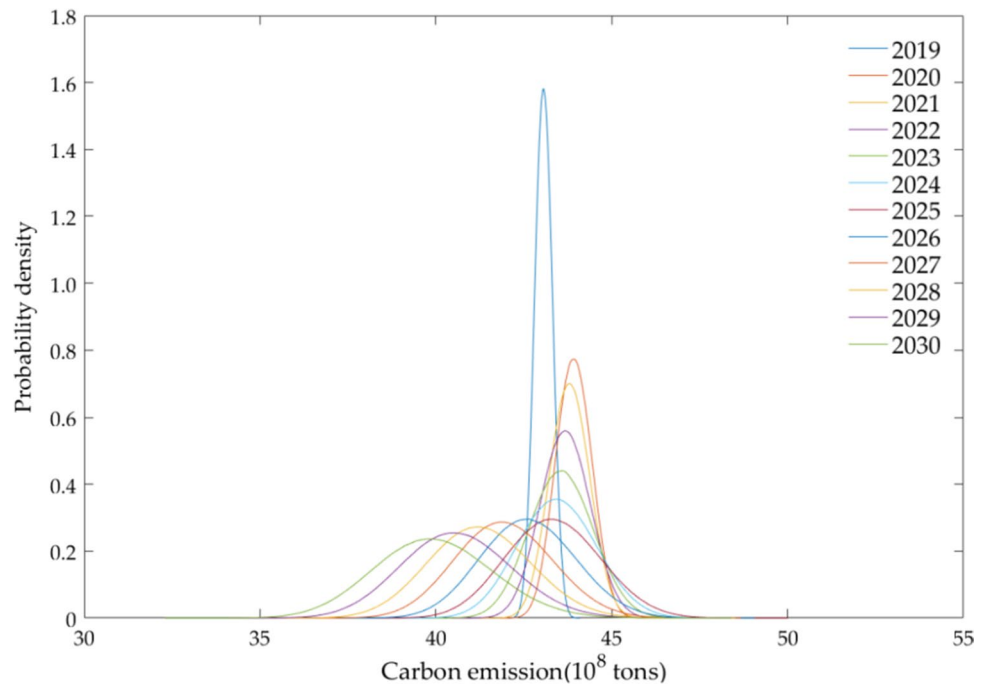
The enhanced carbon reduction scenario

Energy efficiency and development of new energy are the technical factors that have a profound impact on carbon emissions. The enhanced carbon reduction scenario emphasizes that the breakthrough of energy technology makes energy structure and energy efficiency more ideal. We assume that change trends of economic output and population scale remain the same as those in the green development scenario. For other factors, we assume that the change rates from 2019 to 2020 remain the same as those in the green development scenario and the change rates from 2021 to 2030 are further strengthened. For emission factor, compared with the average annual change rate of 2019–2020, it is assumed that the average annual change rate of 2021–2025 and 2026–2030 will decrease by 0.3 and 0.6 percentage points, respectively, namely 0.09% and -0.21% . For conversion efficiency, compared with the average annual change rate in 2019–2020, it is assumed that the average annual rate of change in 2021–2025 and 2026–2030 will decrease by 0.3 and 0.6 percentage points, respectively, namely -1.31% and -1.61% . For power structure, compared with the average annual change rate from 2019 to 2020, it is assumed that the average annual change rate of 2021–2025 and 2026–2030 will decrease by 0.75% and 1.5%, respectively, namely -2.25% and -3.00% . For power intensity, compared with the average annual change rate from 2019 to 2020, it is assumed that the average annual change rate from 2021 to

Table 6 Potential annual change rate of each factor under green development scenario (%)

	2019–2020			2021–2025			2026–2030		
	Minimum value	Inter-mediate value	Maximum value	Minimum value	Inter-mediate value	Maximum value	Minimum value	Inter-mediate value	Maximum value
<i>EF</i>	-0.11	0.39	0.89	-0.31	0.19	0.69	-0.51	-0.01	0.49
<i>ES</i>	-1.51	-1.01	-0.51	-1.71	-1.21	-0.71	-1.91	-1.41	-0.91
<i>S</i>	-2.00	-1.50	-1.00	-1.93	-1.43	-0.93	-3.28	-2.78	-2.28
<i>EI</i>	-0.43	0.07	0.57	-2.31	-1.81	-1.31	-2.31	-1.81	-1.31
<i>E</i>	2.22	3.22	4.22	4.10	5.10	6.10	4.10	5.10	6.10
<i>P</i>	0.78	0.88	0.98	0.11	0.21	0.31	0.11	0.21	0.31

Fig. 5 Evolution trend of carbon emission distribution of China’s power industry from 2019 to 2030 under the enhanced carbon reduction scenario



2030 will decrease by 2 percentage points, namely -1.93%. The setting of the maximum value, intermediate value, and minimum value of potential change rate is the same as that in the green development scenario. The change rate of each factor is as follows (Table 6).

Under the enhanced carbon reduction scenario (Fig. 5), the carbon emission of China’s power industry shows a trend of first increasing and then decreasing, and the decreasing trend is more obvious than the green development scenario. In 2019, the carbon emission of power industry ranges from 4.201 to 4.411 billion tons, and the carbon emission with the highest probability is 4.307 billion tons. In 2020, the carbon emission ranges from 4.178 to 4.608 billion tons, and the carbon emission with the highest probability is 4.391 billion tons, reaching its peak. The range of carbon emissions in 2030 is 3.221–4.847 billion tons, and the most probable carbon emission is 3.977 billion tons, which is less than

that in 2018. The average annual change rates of carbon emissions with the highest probability in 2019–2020 and 2020–2030 are 1.95% and -0.99%, respectively. This shows that if we can achieve a breakthrough in energy technology and overfulfill the planning of energy structure adjustment and energy efficiency improvement, China’s power industry will have full potential for emission reduction in the future (Table 7)

Scenario comparison

The green development scenario assumes that all factors change according to the planning requirements or forecast indicators, and carbon emission is expected to reach its peak before 2030. The enhanced carbon reduction scenario assumes that the change trend of energy technical factors is more ideal. It is assumed that various technical indicators continue to make

Table 7 Potential annual change rate of each factor under enhanced carbon reduction scenario (%)

	2019–2020			2021–2025			2026–2030		
	Minimum value	Inter-mediate value	Maximum value	Minimum value	Inter-mediate value	Maximum value	Minimum value	Inter-mediate value	Maximum value
<i>EF</i>	-0.11	0.39	0.89	-0.41	0.09	0.59	-0.71	-0.21	0.29
<i>ES</i>	-1.51	-1.01	-0.51	-1.81	-1.31	-0.81	-2.11	-1.61	-1.11
<i>S</i>	-2.00	-1.50	-1.00	-2.75	-2.25	-1.75	-3.50	-3.00	-2.50
<i>EI</i>	-0.43	0.07	0.57	-2.43	-1.93	-1.43	-2.43	-1.93	-1.43
<i>E</i>	2.22	3.22	4.22	4.10	5.10	6.10	4.10	5.10	6.10
<i>P</i>	0.78	0.88	0.98	0.11	0.21	0.31	0.11	0.21	0.31

phased breakthroughs. However, it requires a lot of capital and technology investment and may bring heavy financial burden. In addition, with the increase of the proportion of clean energy, the technical difficulty and marginal cost will rise (Shao et al. 2017). Therefore, there may be a big bottleneck in the process of realizing the enhanced carbon reduction scenario. Compared with the enhanced carbon reduction scenario, the green development scenario, largely based on existing policy documents, can better balance the requirements of economic efficiency and environmental protection. China's planning documents always give binding goals and expected goals. The former must be completed, while the latter is an expectation without compulsion. The green development scenario can be used as the basic implementation path to determine the binding goals of carbon reduction work. As an ideal scenario, the enhanced carbon reduction scenario can be used to determine the expected goals of carbon reduction work. In this case, the work of emission reduction can take into account bottom-line consciousness and dynamic adjustment awareness.

Conclusions and policy implications

This paper applies LMDI method to decompose the driving factors of carbon emission in China's power industry from 2000 to 2018, and further use Monte Carlo method to study the evolution trend of carbon emission from 2019 to 2030. We find that (1) economic output effect is the primary factor to promote the increase of carbon emission and population scale effect has a weak promotion impact on carbon emission. (2) Except for 2007–2008, conversion efficiency effect played a role in restraining carbon emissions. (3) Emission factor effect and power intensity effect have obvious volatility. The power structure effect showed great volatility before 2013 and mainly played a role in restraining carbon emission after 2013. (4) Under the baseline scenario, the carbon emission of China's power industry shows a continuous growth trend. Under the green development scenario and enhanced carbon reduction scenario, the carbon emission

shows a trend of first increasing and then decreasing. The peak values appear in 2025 and 2020, respectively, with the maximum probability emissions of 4.591 billion tons and 4.391 billion tons. The enhanced carbon reduction scenario is relatively ideal, while the green development scenario can better balance the requirements of economic efficiency and environmental protection.

Based on the above research, the paper puts forward the following policy suggestions:

- (1) As economic output effect is the primary factor to promote the growth of carbon emissions in the power industry, high-quality development should be encouraged, and the economic layout and industrial structure should be determined according to the requirements of energy conservation and emission reduction. The government should promote the transformation of energy production and utilization and abandon the extensive development mode.
- (2) In general, conversion efficiency effect plays a role in restraining carbon emissions. Therefore, the government should continue to strengthen the energy-saving transformation of thermal power facilities; encourage the construction of large capacity, high parameter, and environment-friendly thermal power facilities; and eliminate small-scale coal-fired power plants.
- (3) Within thermal power, carbon emissions from coal-fired power generation are greater than those from natural gas power generation. Due to the scarcity of gas sources and low profit margin restricting the development of natural gas power generation, the reform of the fuel structure is not smooth, and emission factor effect shows strong volatility. To solve the gas source problem of natural gas power generation, the government should encourage domestic natural gas exploitation and promote the implementation of long-term agreements on imported liquefied natural gas. To improve the economic efficiency of natural gas power generation, the government should give full play to its advantage of

flexibility compared with other forms of power generation and grasp the peak-valley price difference of electricity to make natural gas power generation projects more profitable. In addition, the scale of coal power should be controlled, and research on CCS (carbon capture and storage) technology should be enhanced to reduce carbon emissions.

- (4) In order for the power supply structure effect to continue to play a role in limiting carbon emissions, we should accelerate the transformation of energy structure. For example, island areas can rely on their rich renewable energy, including solar, wind, and biomass energy, to meet their own power demand and reduce their dependence on fossil energy. In addition, energy storage technology should be optimized and the economic efficiency of new energy generation should be improved in parallel with the large-scale development of renewable energy.
- (5) Rational coordination of power production and economic development. It is necessary to avoid both insufficient power supplies to the extent that it cannot meet the needs of electrification, and overproduction leading to increased resource consumption and pollution emissions.

Author contribution All authors contributed to the study conception and design. Material preparation, data collection and processing, and results analysis were performed by Changxin Xu, Chenjun Zhang, Teli Ma, and Jingru Xu. The first draft of the manuscript was written by Xiaoyuan Wu and Teli Ma, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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