ISSN:2790-1661 DOI: 10.56028/aemr.4.1.92.2023

Research on Carbon Peak Prediction in Electric Power Industry Based on DeBruyn and System Dynamics Model

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Abstract. As a critical field of carbon emission, the clean and low-carbon transformation of power industry is extremely critical to the smooth realization of country' s "dual carbon" goal. From the perspective of the whole power industry chain, the DeBruyn decomposition method was firstly used to determine critical influence factors of carbon emission in the power industry. Next, the response relationship between the influence factors and carbon emission was established. Finally, the peak value and its occurrence time under various scenarios were identified through designing four typical scenarios. The obtained results demonstrated that, under the context of interactive influence among positive driving factors (population size, thermal power generation, industrial structure, GDP), negative driving factors (forest area, energy structure, science and technology investment) and other factors, the carbon-emission amounts of the power industry under baseline scenario were increased continuously; conversely, the peak value of carbon emission under two single carbon reduction policy scenarios (i.e. carbon trading policy and renewable energy quota policy) and their composition scenario would become decrease, being 5.46×109 tons, 5.61×109 tons and 5.16×109 tons, respectively. Correspondingly, the occurrence time of peak value under three scenarios was in 2029, 2029 and 2028, respectively.

Keywords: carbon peak prediction; carbon emission reduction; DeBruyn; system dynamics; scenario analysis method; power industry.

1. Introduction

In recent years, under the dual pressure of global warming and fossil energy shortage, it is urgent for China to significantly reduce the carbon emission and achieve the "dual carbon" goal as soon as possible. According to the statistics of China Energy Administration, as a critical field of the energy conservation and carbon reduction, the annual carbon emission amounts of power industry reached more than 40% of national total carbon emission[1]. In addition, as a pillar industry in the energy field, the carbon emission of power industry was affected by many factors with the complex interaction, and even the national policy regulation. Therefore, it is important to quantitatively identify the variation trend of carbon emission in the power industry under different economic, social and policy factors, and accurately estimate the occurrence time of peak value, which is beneficial to provide the guidance for the clean development and low-carbon transformation of the power industry, and the reference to decision making of government.

Currently, there are many theoretical and practical studies about the identification of factors affecting carbon emission and prediction of carbon peak. According to different modeling principles, the carbon emission prediction model can be divided into four major categories, namely indicator decomposition method[2], optimization method[3], input-output model method[4] and scenario analysis method[5], respectively. For example, Meng[6] used the improved logistic model to estimate the carbon emission amount of fossil fuel. However, these traditional prediction methods are limited by the selection of influence factors, leading to the difficulties in evaluating the impact of all relevant factors on carbon emission and generating accurate predicted results. On the basis of quantitative assessment of social, economic and policy factors, the scenario analysis method is capable of accurately identifying the carbon emission trend under different scenarios through combining with the system dynamics model, which has the advantages of clarity and

ISSN:2790-1661 DOI: 10.56028/aemr.4.1.92.2023

simplicity. In recent years, a large amount of research has been conducted on the development of the integration of above two methods. For example, Zhan[7] predicted the carbon emission amounts of the industrial park from 2019 to 2030 by aid of this integration method, and concluded that the science and technology are the driving force for the coordinated development of pollution reduction and carbon reduction.

The above-mentioned studies realized the effective combination of the mathematical methods and system dynamics theory, which estimated the peak value of carbon emission and its occurrence time. In fact, the prediction accuracy depends not only on the selection of model and scenario, but also on the rationality and comprehensiveness of the influence factor determination. How to select suitable influence factors obtains more attentions. Steenhof[8] used the Laspeyres decomposition method to identify the main influence factors of carbon emission in Canada's power industry, and concluded that during 1990-2008, the carbon emission in the power industry were mainly affected by power consumption demand, power supply structure and weather condition..

The aforementioned studies identified the influence factors (carbon emission coefficient, power production structure and energy consumption structure) based on the power generation process and evaluated their direct impact on carbon emission through the mechanism analysis. In fact, in addition to direct factors, some indirect factors, including GDP, industrial structure, population and carbon sink, also have the large influence on carbon emission in the power industry. Therefore, from the macroscopic perspective of whole industrial chain of the power industry, the DeBruyn decomposition method was firstly used to identify seven major influence factors of carbon emission of the power industry. Secondly, the regression relationship among carbon emission amounts and influence factors was established by aid of software EViews. Secondly, four types of scenarios, including benchmark scenario, carbon n trading policy scenario, renewable energy policy scenario and multiple policy scenario, are designed through scenario analysis method. Next, the system dynamics model for the carbon emission prediction of the power industry under the influence of multiple factors was formulated, which calculated the carbon emission amounts of the power industry from 2021-2030 under different scenarios. Finally, the peak value of carbon emission and its occurrence time were predicated, which provides the scientific guidance for the realization of the carbon peak goal of the power industry.

2. Methodology

Figure 1 shows the overall technical roadmap for this article. Considering there are many influence factors of carbon emission in the power industry, the DeBruyn decomposition method was firstly utilized to accurately identify the influence factors of carbon emission, including population size, energy structure, thermal power generation, forest area, industrial structure, GDP and scientific and technological input. Secondly, the main system modules of the flow diagram were determined through establishing the relationship among various factors. Next, the system dynamics model of carbon emission in the power industry was formulated. Finally, four development scenarios of the power industry are designed based on the characteristics of relevant policies, leading to the predicted carbon emission amounts of the power industry from 2021-2030 under different scenarios. Correspondingly, the peak time is preliminarily determined, which provides an important reference for the low-carbon development of power industry and the formulation of relevant policies.

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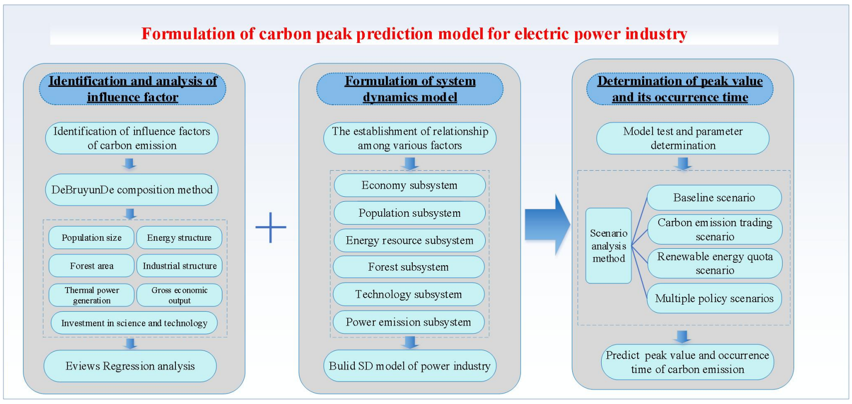

Figure 1. The overall technological roadmap

2.1 Identification of influencing factor of carbon emission in power industry based on DeBruyn decomposition method

As an usual method to evaluate the impact of influence factors on carbon emission[9], the DeBruyn decomposition method is capable of decomposing the influence factors into the following three forms, which are: (1) the scale effect caused by the expansion of economic scale; (2) the structural effect caused by industrial structure adjustment; (3) the technological effect caused by the change of carbon emission intensity. The specific formulation is written as follows:

$$CO_{2t} = Y_t \sum_t S_{it} I_{it} \tag{1}$$

where CO_{2t} is carbon dioxide emission amount, ×104 tons; Y_t is the total output value of the industry, ×104 Yuan; S_{it} is the proportion of the output value of industry i in total output value representing the structural effect; t is the time period, year; I is carbon emission intensity, Yuan/ton.

Referring to the extended DeBruyn model formulated by Xiang[10], the factors affecting carbon emission in the power industry were decomposed firstly. Considering the actual carbon emission amount of the power industry is greatly different from its generation magnitude along with national carbon reduction efforts, therefore, I_{it} is further subdivided into generation rate and actual emission rate of carbon dioxide through recognizing the difference between them. The specific formulation is formulated as follows:

$$I_{it} = I'_{it} Z_{it} = \frac{\overline{E_{it}}}{Y_{it}} \times \frac{E_{it}}{\overline{E_{it}}} \tag{2}$$

where I'_{it} is the generation rate of carbon dioxide, which represents the technical effect; Z_{it} is the actual emission rate of carbon dioxide, which reflects the governance effect of carbon emission; $\overline{E_{it}}$ is generated carbon dioxide amounts of subsystem i of the power industry, tons; Y_{it} is the output value of different industrial structure, ×104 yuan. The ratio of above two factors is the generation rate of carbon dioxide of the power industry. E_{it} is the actual carbon dioxide emission of the power industry, where the ratio with E_{it} and produced amount of carbon dioxide $\overline{E_{it}}$ is the actual emission rate of carbon dioxide of the power industry Z_{it}. Finally, the extended DeBruyn decomposition model is established through combining Eqs. (1) and (2), which is written as follows:

$$CO_{2t} = Y_t \sum_t S_{it} \overline{I_{it}} Z_n \tag{3}$$

Above equation indicates that the carbon emission of power industry is affected by the scale effect Y, the structure effect S, the technology effect I and the governance effect Z. After identifying the four influence factors representing the power link, on the basis of whole industrial chain of the power industry, the whole decomposition model of the influence factor of carbon emission in the power industry is constructed through adding the influence factors reflecting the terminal consumption link, which is written as follows:

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$$T_{CO_2}=c_1+\beta_1 I+\beta_2 ES+\beta_3 FT+\beta_4 TC+\beta_5 GG+\beta_6 P+\beta_7 RDP+\varepsilon_{it} \quad (4)$$

where the term I, ES, FT, TC, GG, P and RPD represent population size, energy structure, thermal power generation, forest area, industrial structure, GDP and R&D expenditure, respectively. TCO2 is the total carbon dioxide emission; c1 is a constant term; β i is the coefficient; ε i is the error term. Table 1 describes various influence factors in model (4).

Table 1 The main influence factors of carbon emission in the power industry

Term	Factor (Unit)
CO2	CO2 emission of the power industry (million tons)
I	Population Size (million)
ES	Energy structure
FT	Thermal power generation (108 KWH)
TC	Forest area (104 sq km)
GG	Industrial structure
P	Total output value of China's GDP (1012 yuan)
RDP	Investment in science and technology (1012 yuan)

2.2 The formulation of regression model between influence factors and carbon emission in the power industry

The accurate calculation of carbon emission in the power industry depend not only on the decomposition and identification of influence factors, but also on the construction of regression analysis model[11]. In this research, the software Eviews is used to finish the regression analysis of the influencing factors of carbon emission. The econometric software Eviews[12] is mainly applied to the statistics, analysis and processing of data, which is advantageous to deal with the error structure of complex data, such as heteroskedasticity, simultaneous correlation and serial correlation. Therefore, based on the influence factors of carbon emission in the power industry decomposed by DeBruyn method, the positive and negative effect-driven analysis was accomplished through regression analysis model with the F-test and Hausman test, which provide the useful reference and help for the construction of system dynamics model.

2.3 Formulation of carbon emission prediction model for power industry based on system dynamics method

System Dynamics, as an interdisciplinary discipline aimed at the information feedback systems, has the large advantage of solving nonlinear problem of complex system [13]. Therefore, considering the complex relationship among different subsystems and elements of the power industry, firstly, the internal structural framework of the system was described through causal loops and a stock-flow diagram indicating the logical relationships among system elements was plotted; secondly, the mathematical relationship among various elements is established through the equation. Finally, the VENSIM software was used to construct the system dynamics model of carbon emission in the power industry, where the simulation and analysis of carbon emission were accomplished.

ISSN:2790-1661 DOI: 10.56028/aemr.4.1.92.2023

3. Construction of system dynamic model of carbon emission in power industry

3.1 Causality analysis and causality map construction

According to the decomposed results of DeBruyn method, the carbon emission of power industry are divided into economic subsystem, population subsystem, energy subsystem, forest subsystem, technology subsystem and carbon emission subsystem. The interactive and causal feedback relationship exists among above six subsystems. For example, the economic subsystem affects the industrial structure of social economy; meanwhile, it can promote the investment in science and technology, and jointly determines the electricity consumption of whole society with the population subsystem. The energy subsystem influences the carbon emission through the variation in the energy consumption structure of power production. The proportion of thermal power in the carbon emission subsystem exerts the impact on the proportion of renewable energy generation, which directly affects the carbon emission. The increase in the science and technology investment and forest area is capable of improving the energy efficiency and carbon capture amounts, leading to the reduction of carbon emission. Table 2 lists six subsystems and main variables.

Table 2 Six subsystems and their main variables

Subsystem	The main variables
Economic subsystem	GDP, Growth Rate of GDP, Proportion of Primary Industry, Proportion of Secondary Industry, Proportion of Tertiary Industry, Output Value of Primary Industry, Output Value of Secondary Industry, Output Value of Tertiary Industry, Electricity Intensity of Primary Industry, Electricity Intensity of Secondary Industry, Electricity Intensity of Tertiary Industry, Electricity consumption
Population subsystem	Total Population, Growth Rate of Population, Residential Electricity Consumption, Electricity Consumption Per Capita
Energy subsystem	Natural gas consumption, Oil Consumption, Coal Consumption, Variation Rate of Natural Gas Consumption, Oil Consumption, Coal Consumption, Emission Factor of Thermal Power
Forest subsystem	Increase in Forest Area, Total Forest Area, Total Forest Area, Forest's Carbon Sequestration Factor, Forest's Carbon Sinks, Grassland Area, Grassland's Carbon Sequestration Factor, Grass's Carbon Sink, Carbon Sequestration in the Ocean, Carbon Sequestration
Science and technology subsystem	R&D Expense, Proportion of Investment in Science and Technology, R&D Personnel, Technology Innovation
Carbon emission subsystem	Electric Discharge System, Power Generation, The Internet Charge, Auxiliary Power Rate, Line Loss Suggestions, Renewable Energy Generation, Proportion of Electricity Generated by Renewable Energy Source, Proportion of Thermal Power Generation, Thermal Power Generation

A cause-and-effect diagram of carbon emission in the power industry was plotted through summarizing and refining the subsystems involved in the carbon emission of the power industry, which is shown in Figure 2.

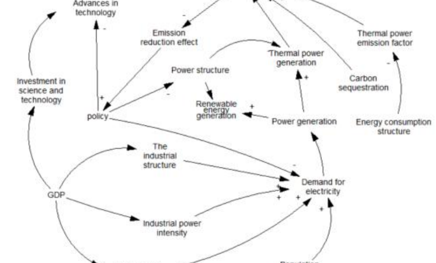

Figure 2 Casual loop diagram of carbon emission in power industry

ISSN:2790-1661 DOI: 10.56028/aemr.4.1.92.2023

Since the complex and diverse causal relationships exist among the subsystems, the main causal loops are selected and analyzed as follows:

Afforestation investment → Forest area → Carbon Sink → Carbon emissions → Afforestation investment

The rise of carbon sink price will encourage the enterprises to increase the investment of forestation fund. The increase in forest area will form carbon sink and reduce carbon emission, which in turn will affect the carbon sink price.

Investment in science and technology → Advance in technology → Carbon capture level of the power sector → Carbon emission from production process → Total carbon emission → Environmental quality → GDP → Investment in science and technology.

In the context of "double carbon", in order to effectively reduce the purchase cost of carbon emission quota, as a high-carbon industry, the power industry needs more investment in science and technology. On the one hand, the carbon emission is reduced through introducing carbon capture technology in the production process. On the other hand, the energy saving and consumption reduction was realized based on the improvement in production efficiency. Finally, the carbon emission in the production process was reduced, which improved the environmental quality and promoted the economic development. Correspondingly, the economic development drives electric power enterprises to increase the investment in science and technology.

GDP→ Electricity Demand → Power generation → Carbon emission → Carbon reduction policy → GDP

With the increase in the GDP of whole society, the industrial power intensity and residential power intensity will increase accordingly, which will lead to the increase in the power demand of whole society, and then affect total power generation and thermal power generation. The increase in power generation will lead to the large amount of carbon emission, which urges the government to release the relevant emission reduction policy for reducing the growth rate. It exerts the negative impact on GDP.

Energy consumption structure → Emission factor of thermal power → Carbon emission → Energy consumption structure

The decrease in proportion of coal in the energy consumption structure means that the emission factor of thermal power becomes smaller, leading to the reduction of carbon emission. The reduction of carbon emission will not only affect the policy making, but also further promote the continuous adjustment and upgrade of energy consumption structure.

3.2 The establishment of flow chart of carbon emission system

The 51 indicators affecting the carbon emission of the power industry are selected to formulate the system dynamics model. Figure 3 shows the flow chart of the cause-effect diagram by aid of VENSIM software.

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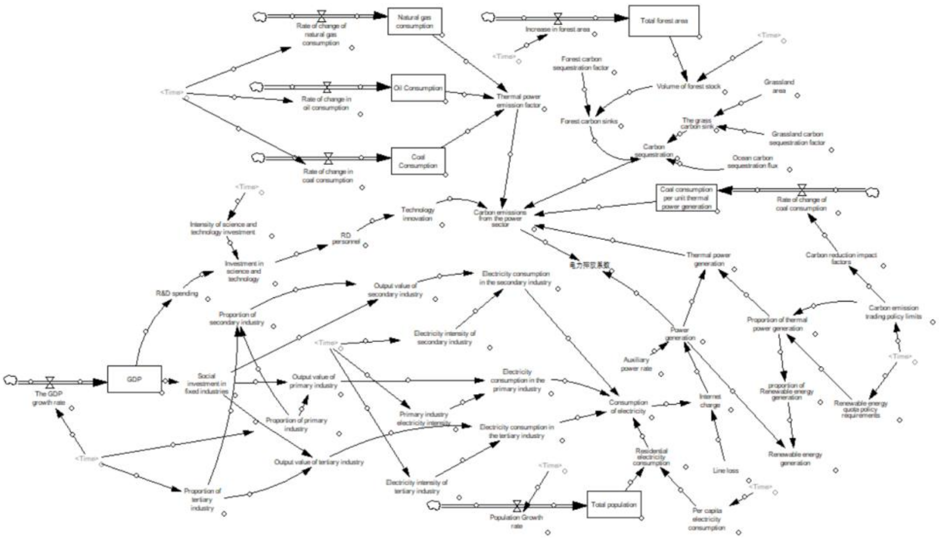

Figure 3 Flow chart of carbon emission based on system dynamics model

The functional relationship among different variables was established based on the energy, society and economy data from 2010 to 2019 sourced from China Statistical Yearbook, China Electric Power Yearbook, China Energy Statistical Yearbook and China Electric Power Industry Annual Development Report. Among them, the GDP growth rate, the increase rate of population, the variation rate of energy consumption, the investment intensity of science and technology, the electricity consumption per capita, the proportion of three industries, the industrial power intensity, the proportion of thermal power generation, the increase in forest area and the volume of forest stock were mainly affected by time factor. The trend can be fitted by historical data and determined as a table function.

4. Results analysis

4.1 The calculation of carbon emission of power industry

Considering the completeness of relevant statistical yearbooks, the energy, social and economic data from 2010 to 2019 provided by above mentioned yearbooks and reports was selected to identify the influence factors of carbon emission and predict the discharge magnitude. Currently, the carbon emission amounts are generally calculated based on carbon emission from energy combustion, where the IPCC carbon emission factor method is the most widely used method to measure the carbon emission, which has the advantages of simple operation and data availability. Therefore, the IPCC method is adopted to estimate the carbon emission amounts. The calculation formulation is written as follows:

$$CO_2 = \sum_{j=1}^{n} CO_2 = \sum_{j=1}^{n} \left(E_{ij} \times NCV_j \times CC_j \times COF_j \times \frac{44}{12} \right) \tag{5}$$

where j is the type of energy source, j = 1, ... ,15; CO2 represents the carbon dioxide emission, kilograms; Eij is the terminal consumption of j energy source in i industry, kilograms; NCVj is the average low calorific value of j energy source, kilojoules; CCj is the carbon content per unit calorific value of j energy source, as shown in Table 3, the parameter information is obtained from China Energy Statistical Yearbook and Guide to the Calculation Tool of Greenhouse Gas Emission Caused by Energy Consumption. COFj is the carbon oxidation rate of j energy source, which are sourced from the Guidelines for Compiling Provincial GHG Inventories of China. 44/12 is the ratio of the molecular weight of carbon dioxide to carbon, that is, the conversion coefficient of carbon to carbon dioxide.

ISSN:2790-1661 DOI: 10.56028/aemr.4.1.92.2023

Table 3 The description of net calorific value of energy source and IPCC coefficient

	The IPCC coefficient （kgCO2/TJ)	Net calorific value （kilojoules /kg）
Crude oil	7.33×104	4.18×104
Raw coal	9.83×104	2.09×104
Coke	1.07×105	2.84×104
Gasoline	7.41×104	4.3×104
Kerosene	7.19×104	4.3×104
Diesel	7.41×104	4.26×104
Fuel oil	7.74×104	4.18×104
Natural gas	5.61×104	3.89×104

Taking the national electric industry as the main research target, the energy consumption was determined by referring to China Statistical Yearbook, and the carbon emission magnitude of national electric industry were calculated based on the formulation 5. The computational results are shown in Table 4.

Table 4 Calculation results of carbon emission in the electric industry from 2010 to 2019

Year	Carbon emissions (× 109 tons)
2010	3.19
2011	3.63
2012	3.85
2013	4.06
2014	3.98
2015	3.84
2016	3.96
2017	4.21
2018	4.51
2019	4.64

4.2 The decomposition results of influence factors

On the basis of collected data of influence factors of carbon emission in the power industry from 2010 to 2019, the DeBruyn decomposition model established in Section 2.1 was used for impact analysis through incorporating relevant parameter values into the formulation 4. The F-test and Hausman-test were conducted on the empirical data by aid of Eviews7 software, respectively. Next, the selection between fixed effect model and random effect model is finished based on two test results in order to avoid spurious regression and large error. Finally, the feasibility and rationality of regression model are evaluated. Table 5 shows two test results.

Table 5 Results of F test and Hausman test

Name of inspection method	Statistic （Chi-Sq. Statistic）	d.f. (Chi-Sq.d.f.)	P-value
F	217.82	（36,451）	0.00
Hausman	56.25	7	0.00

From Table 5, it can be seen that the P-value of F-test is less than 0.05; similarly, the P-value of Hausman-test is also less than 0.05. It is means that the fixed-effect regression model is suitable to describe the relationship among influence factors and carbon emission . Eviews7 software was used to establish this model, where the regression analysis results are given in Table 6.

Table 6 Regression Analysis Results

Variables	Coefficient	Standard deviation	P-value
c1	14193.06	20.6	0.00
I	1.4537	0.08	0.00
ES	-3650.75	57.88	0.0047

ISSN:2790-1661 DOI: 10.56028/aemr.4.1.92.2023

FT	3.827	5.92	0.00
TC	-0.176	0.03	0.00
GG	11619.34	1874.17	0.0112
P	0.335	48.31	0.00
RDP	-2.963	414.92	0.298

As a result, the regression model is formulated according to the results in Table 6, which is written as follows:

$$CO_2 = 14193.06 + 1.4537I - 3650.75ES + 3.827FT - 0.176TC + 11619.34GG + 0.335P - 2.963RDP + \varepsilon_{it} \quad (6)$$

As shown in Table 6, the population size, thermal power generation, industrial structure and GDP have a positive driving effect, which is positively correlated with the carbon emission of the power industry. Moreover, P-values are all less than 0.05, indicating that their contribution to the increase in carbon emission cannot be underestimated. In addition, the forest area, energy structure and investment in science and technology have inhibitory effect on carbon emission in the power industry. Among them, the P-values of forest area and energy structure are less than 0.05, which significantly inhibit carbon emission in the power industry. It means that the clean transformation of energy structure in the power industry and the carbon sink effect of forest are capable of significantly reducing carbon emission. In addition, the P-value of the investment in science and technology is 0.298, greater than 0.05. Although the technology innovation plays the limited role in reducing the carbon emission, however, it should be paid more attentions by the government and enterprises in order to reach its greatest potential.

4.3 Model validation

In order to verify the effectiveness of the system dynamics model, based on the constructed flow chart and the correlation among various parameters, the statistical data from 2010 to 2019 were selected with a simulation step of 1 year, and the validity of the model was verified by aid of Vensim 9.1.1x64. Table 7 reflected the actual value, predicted value and error rate of carbon emission in the power industry.

Table 7 The validation of system dynamics model

Year	Actual value (× 109 tons)	Simulation value (× 109 tons)	Error rate
2010	3.19	3.47	8.06%
2011	3.63	3.95	7.97%
2012	3.85	4.19	8.09%
2013	4.06	4.40	7.78%
2014	3.98	4.35	8.54%
2015	3.84	4.18	8.18%
2016	3.96	4.29	7.75%
2017	4.21	4.58	8.04%
2018	4.51	4.90	7.89%
2019	4.64	5.07	8.39%

From Table 7, the prediction errors of carbon emission over the years are all less than 10%, which is within the allowable range of system dynamics error, indicating that the accuracy of carbon emission prediction model of the power industry is relatively high, and it has the ability to reflect the variation in carbon emission in the future.

4.4 Scenario design

The policy simulation aims to estimate the impact of the policy implementation on the carbon emission of the power industry through changing the parameter values highly related to the policy in the system dynamics model. It is not only the necessary function and advantage of system dynamics analysis, but also the main method to seek the peak value and its occurrence time of the carbon emission. The achievement of peak value of carbon emission means the reduction of thermal

ISSN:2790-1661 DOI: 10.56028/aemr.4.1.92.2023
power ratio and coal consumption, the increase in ecosystem carbon sink and the implementation of carbon reduction technology on the premise that the electric power consumption meets the demand of GDP growth. Therefore, on the basis of selecting typical emission reduction policies (carbon quota policy and renewable energy policy) in the power industry, combining with the variation trend of GDP, energy structure and other relevant factors[14], four kinds of simulation scenarios, including baseline scenario, carbon emission trading policy scenario, renewable energy quota policy scenario and multiple policy scenario, were established. Table 8 shows some parameter settings under four scenarios.

Scenario	Parameter design
All scenarios	The GDP growth rate is 5% in 2020-2024 and 4.5% in 2025-2030, respectively; Population growth rate will decrease from 0.34% to 0.26% by 2030; The growth rate of coal consumption will decrease from 0.9 percent to 0 percent by 2030; The tertiary industry will increase its share from 53.9 percent to 60 percent by 2030; The growth rate of forest area will rise from 0.09% to 0.2% by 2030
Baseline scenario	The share of thermal power decreased from 72.32% to 65.5%
Carbon emission trading policy scenario	The proportion of thermal power decreased from 72.32% to 57.8%; The variation rate of coal consumption is reduced by 6% per year
Renewable energy quota policy scenario	The share of renewable energy rose to 45.5% from 27.68%
Multiple policy scenarios	Share of thermal power =MIN(renewable energy quota policy, carbon quota policy)

Table 8 The parameter design corresponding to different scenarios

4.5 Result analysis

On the basis of model examination and validation using historical data from 2010-2019, Vensim software was used to simulate the carbon peak value and its occurrence time in the power sector under different scenarios from 2020 to 2030 with one year as the step. The predicted results are detailed in Figure 4.

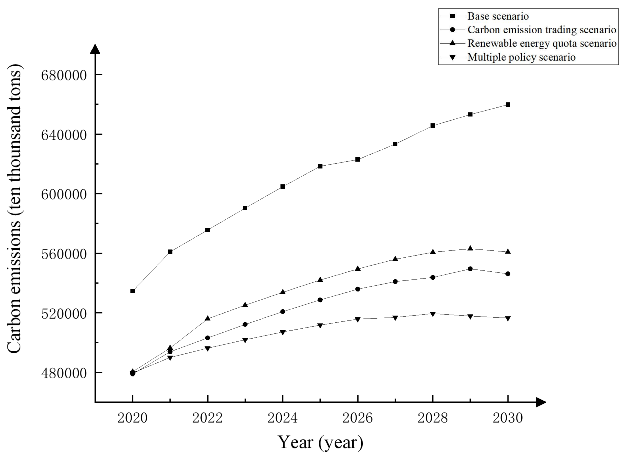

Figure 4 Total carbon emission of power industry under different scenarios

As shown in Figure 4, under the condition that GDP, energy structure, population growth, ecosystem carbon sink and scientific and technological investment and other factors maintain the normal change and no policies are implemented, the carbon emission of the power industry will increase continuously in the next decade and will reach 6.60×109 tons in 2030, making it difficult to achieve the strategic goal of carbon peaking in 2030. The main reason is that the rapid economic development leads to the increase in electricity demand, which in turn causes a rapid increase in

ISSN:2790-1661 DOI: 10.56028/aemr.4.1.92.2023
carbon emission. The carbon reduction effect of scientific and technological innovation and carbon sink in the ecosystem are incapable of offsetting the large carbon emission, leading to the difficulties in realizing the carbon peak as soon as possible. The overall trend of the three policy scenarios is generally consistent, but there are still some differences in the same variation trend. The carbon emissions in 2030 under the carbon emission trading policy scenario, renewable energy quota policy scenario and multiple policy scenario were 5.46×109 tons, 5.61×109 tons and 5.16×109 tons, respectively, which decreased by 17.2%, 14.9% and 21.7% compared with the benchmark scenario, respectively. The carbon peak will be achieved in 2029, 2029 and 2028, respectively. Among them, the carbon reduction effect of the single carbon emission trading policy is better than that of the renewable energy quota policy. This is because the carbon emission trading policy not only restricts the growth of thermal power generation and optimizes the power generation structure, but also stimulates thermal power enterprises to reduce the coal consumption through internalization of external environmental cost. As for the best carbon reduction effect of multiple policy scenarios, the reason is that the organic combination of carbon trading policy and renewable energy quota policy is beneficial to realize the maximum carbon reduction potential.

5. Conclusion

From the perspective of whole power industry chain, the DeBruyn decomposition method was firstly used to identify the critical factors affecting carbon emission of electric power industry; next, the relationship among influence factors and carbon emission was established by aid of Eviews software; finally, the carbon emission prediction under various scenarios was finished based on system dynamics model. The main conclusions are as follows: (1) Population size, thermal power generation, industrial structure and GDP have positive driving effects; Forest area, energy structure and investment in science and technology are the main negative driving factors. (2) Under the condition that the development status is maintained and no carbon reduction policy is implemented, the carbon emission of the power industry would increase continuously and reach 6.60×109 tons in 2030, which is difficult to achieve the carbon peak in 2030. On the contrary, the effective implementation of emission reduction policies is expected to reach the peak target by 2029. Among them, the carbon emission trading policy scenario, renewable energy quota policy scenario and multiple policy scenario reach the peak value of 5.50×109 tons, 5.63×109 tons and 5.19×109 tons respectively, and the peak time is 2029, 2029 and 2028, respectively. In the future, the introduction of other carbon emission reduction policies and the accurate estimation of interactive influence among multiple policies deserve in-depth research in order to further investigate the implementation effect of carbon reduction policies and improve the accuracy of carbon emission prediction model.

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