Environmental Science and Pollution Research (2023) 30:46711–46726
https://doi.org/10.1007/s11356-023-25544-1

RESEARCH ARTICLE

Simulation analysis of carbon peak path in China from a multi-scenario perspective: evidence from random forest and back propagation neural network models

Yang Li[1] · Shiyu Huang[1] · Lu Miao[2] · Zheng Wu[2]

Received: 27 May 2022 / Accepted: 20 January 2023 / Published online: 1 February 2023

Abstract
China faces tough challenges in the process of low-carbon transformation. To determine whether China can achieve its new 2030 carbon peaking and carbon intensity reduction commitments, accurate prediction of China's CO_2 emissions is vital. In this paper, the random forest (RF) model was used to screen 26 carbon emission influencing factors, and seven indicators were selected as key variables for prediction. Subsequently, a three-layer back propagation (BP) neural network was constructed to forecast China's CO_2 emissions and intensity from 2020 to 2040 under the 13th Five-Year Plan, 14th Five-Year Plan, energy optimization, technology breakthrough, and dual control scenarios. The results showed that energy structure factors have the most significant impact on China's CO_2 emissions, followed by technology level, and economic development factors are no longer the main drivers. Under the 14th Five-Year Plan scenario, China can achieve its carbon peaking on time, reaching 10,434.082 Mt CO_2 emissions in 2030. Although the new commitment to intensity reduction (over 65%) under this scenario cannot be achieved, the 14th Five-Year Plan can bring about 73.359 and 539.710 Mt of CO_2 reduction in 2030 and 2040 respectively, compared to the 13th Five-Year Plan. Under the technology breakthrough and dual control scenarios, China will meet its new commitments ahead of schedule, with the dual control scenario being the optimal pathway for CO_2 emissions to peak at 9860.08 Mt in 2025. It is necessary for Chinese policy makers to adjust their current strategic planning, such as accelerating the transformation of energy structure and increasing investment in R&D to achieve breakthroughs in green technologies.

Keywords CO_2 emissions · Random forest · Back propagation neural network · Carbon peaking · The 14th Five-Year Plan · Scenario analysis

Introduction

With the rapid development of the global economy and human society, total energy consumption, especially of fossil fuels, is increasing, leading to the continuous radiation of the greenhouse effect on a global scale (Dai et al. 2018). The ensuing climate warming issues have become more and more serious. As the main gas that causes the greenhouse effect, CO_2 poses a great threat to the survival of human beings and the sustainable development of society (Liu et al. 2022). According to information published by the IEA (2020), China's CO_2 emissions reached 9876.5 Mt in 2019, accounting for 29.4% of the world's total emissions. Furthermore, as shown in Fig. 1, China's CO_2 emissions have been on an increasing trend, with an especially faster rate between 2000 and 2010, increasing nearly 2.5 times. Since 2007, China has overtaken the USA as the world's largest emitter of carbon dioxide. As the world's second-largest economy after the USA and the largest energy consumer and importer, China is under unprecedented pressure to mitigate climate warming and reduce CO_2 emissions, but its excess carbon emissions are often underpinned by significant mitigation potential from a global governance perspective.

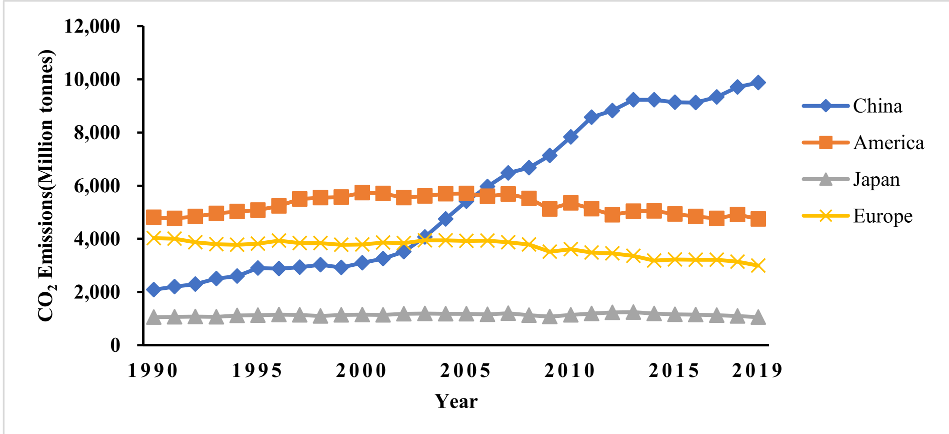
Responsible Editor: Eyup Dogan

Miao Lu
miaol@szu.edu.cn

[1] School of Business Administration, Zhongnan University of Economics and Law, 430073 Wuhan, People's Republic of China

[2] China Center for Special Economic Zone Research, Shenzhen University, Shenzhen, Guangdong 518060, People's Republic of China

Fig. 1 CO_2 emissions of China, Japan, America, and the Europe (1990 to 2019) (Source: OECD database)



Faced with such a severe emission situation, in recent years China has actively implemented various policies to reduce CO_2 emissions and to contribute to a slowdown in global climate warming (Ding et al. 2020). At the United Nations General Assembly, the Chinese government proposed the Intended Nationally Determined Contributions (INDCs) of peaking CO_2 emissions by 2030 and achieving carbon neutrality by 2060 (Central People's Government of the People's Republic of China 2020a). According to IPCC calculations, the world must reach net zero CO_2 emissions by 2050 if human society is to achieve the temperature control targets of the Paris Agreement (IPCC 2017). Currently, more than 120 countries and regions around the world have proposed carbon neutrality targets, covering 75% of the global GDP, 53% of the population, and 63% of carbon emissions (Lv and Hu 2021). The announcement of China's dual carbon targets has undoubtedly energized the global carbon neutrality process and propelled global climate governance into a new era of INDCs to tackle climate change. Alongside the targets, the Chinese government has tightened its voluntary reduction commitment to reduce CO_2 emission per unit of GDP by more than 65% by 2030 compared to 2005, which was 60–65% (Central People's Government of the People's Republic of China 2020b). The upward revision of this percentage in the commitment puts China under greater pressure to reduce emissions, which has a direct and significant impact on global trends of CO_2 emissions. Hence, accurate prediction of China's CO_2 emissions is vital to achieving the 2030 emission commitments(Sun and Ren 2021), which can provide a reference for policy makers to designate medium to long-term development strategies and adjust current plans.

This paper attempts to answer two research questions: Q1. Can China's new commitment to independent contributions under the 14th Five-Year Plan be realized? Q2. How to achieve it? To answer these questions, this paper uses the random forest (RF) model to screen China's CO_2 emission predictors and then uses the back propagation (BP) neural network to construct a forecast model. Based on this model, this study sets up five scenarios to predict the trend of China's future total CO_2 emissions and determine the optimal path to achieve the dual carbon goals.

The main contributions of this study are presented as follows. Firstly, this paper examines the topic of carbon peaking and carbon neutrality from a fresh perspective of policy adjustments under the 14th Five-Year Plan. By constructing the 13th Five-Year Plan scenario as a reference scenario, this paper measures the specific emission reduction potential that the 14th Five-Year Plan will bring in the future. Secondly, this paper uses RF to filter predictors, which allows for considering as many influencing factors of carbon emissions as possible, thus avoiding the limitations of exist literature that selects only a few influencing factors and omits other important factors. Finally, from the research findings, this paper reveals the influence degree of various factors on CO_2 emissions, predicts the time and total amount of carbon peak under the 14th Five-Year Plan, and seeks the optimal development path for carbon neutrality goals. The findings can not only help China achieve its new commitments in tackling climate change, and maximize its emission reduction potential, but also provide references for other developing countries similar to China's development model and make greater contributions to global climate governance.

Literature review

Current research on carbon emissions focuses on two main areas: analysis of the factors influencing carbon emissions and prediction of carbon emissions.

Research on the factors influencing CO_2 emissions

This section compares the study on the identification and quantification methods of carbon emission influencing factors.

Identification of CO_2 emission influencing factors

The identification of CO_2 emission influencing factors has traditionally been the focus of research (Lin et al. 2018). Although there is considerable research on the cause of huge CO_2 emissions, the factors that influence carbon emissions at various stages of development in different countries and regions are heterogeneous. Brizga et al. (2013), for instance, analyzed the specific impact of the industrial percentage on carbon emissions in the former Soviet Union. Hanif and Gago-de-Santos (2017) studied 86 developing countries to add empirical evidence to the positive impact of urbanization on CO_2 emissions. Analyzing five EU countries, Balsalobre-Lorente et al. (2018) found a tight relationship between economic growth and carbon emissions. Lu (2018) discovered that energy consumption has a significant positive effect on carbon emissions in twelve Asian countries. Ma et al. (2019b) investigated the impact of trade between China, Japan, and South Korea on carbon emissions. Anser et al. (2020) conducted research on the South Asian Association for Regional Cooperation countries, taking into account the impact of population size and urbanization on carbon emissions. Xie et al. (2021) analyzed the impact of technological progress on carbon emission efficiency in 59 countries and found that technological progress will significantly improve carbon emission efficiency. Jiang et al. (2022) analyzed the impact of global industrial structure adjustment on carbon emissions. The above factors also have an impact on China's carbon emissions. In China, researchers have also examined the impact of economic development (Zhu et al. 2020), demographic factors (Zhu and Peng 2012), urbanization, etc. on China's carbon emissions. Accurately identifying the primary influencing factors has an important guiding effect on regional carbon emissions reduction.

Method for quantifying CO_2 emission affecting factors

Numerous research have measured the factors influencing carbon emissions in order to better propose policies for carbon emission reduction. Currently, the majority of quantitative methods are centered on composition analysis, such as structural composition analysis (SDA), index composition analysis (IDA), logarithmic mean division index (LMDI), IPAT (Human Impact Population Affluence Technology) model, and STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model. José et al. (2016), for instance, used SDA to decompose the influencing factors of carbon emissions in Spain. Yao et al. (2015) used IDA to analyze the main driving forces of G20 countries' carbon emissions. Raza and Lin (2020) used LMDI to decompose the carbon emissions generated by Pakistan's transport sector. Shuai et al. (2017) analyzed the impact of different income levels on carbon emissions in 125 countries using the combination of IPAT and STIRPAT models. Ma et al. (2019a) quantified the drivers of carbon emissions from energy consumption in China using a combination of Kaya identity and LMDI. Ding et al. (2022) used the STIRPAT model to analyze the specific impact of urban form compactness on China's carbon emissions.

Various machine learning methods, such as random forest (RF), can fully consider various influencing factors and well fit the variable relationship (Ye et al. 2019; Luo et al. 2020). Performance-wise, RF is completely distinct from other linear regression methods. It can accommodate the intricate nonlinear relationship between influential factors (Ye et al. 2019). Using the RF model, Fang et al. (2021) forecasted the carbon emissions created by China's construction industry in the Pearl River Delta region. Sun et al. (2018) used the RF model to forecast the carbon dioxide influencing factors in China's Hebei Province. Sun et al. (2018) believed that the RF model was more accurate than other models when estimating the factors influencing carbon emissions in China's Hebei Province. Numerous academics employ RF models due to their capacity to quantify the importance of variables (Wei et al. 2018). Consequently, this article utilized RF to identify the primary determinants of CO_2 emissions in China.

Research on CO_2 emissions

This section will sort out the research status of CO_2 emission and compare relevant measurement and prediction methods. This is the basis for finding a CO_2 emission prediction method suitable for this study.

Research status of CO_2 emission

Currently, the measurement and forecasting of carbon emissions are the focus of a great deal of study, including that conducted by nations and businesses. For example, Zhu and Du (2019) estimated the carbon emissions of the transportation industry in the six Asia Pacific countries from 1990 to 2016. Wang et al. (2022a) analyzed the carbon emissions of the railway transportation industry in the Brazil, Russia, India, and China from 1997 to 2017. Gao et al. (2021) analyzed the carbon emission efficiency of 28 industry sectors in China by measuring the differences between direct carbon emissions and embedded carbon emissions between 2005 and 2017. At the provincial level, Zhao et al. (2022) pointed out that the developed coastal areas in the east will be able to achieve the expected carbon emission reduction by 2030, but most provinces will hinder economic development due to carbon emission transfer. In addition, the behavior of countries in formulating carbon-peaking strategies has also led to an increase in relevant research. Jiang et al. (2019) believed that the carbon emissions of developing countries would greatly affect global carbon emissions, and predicted the possible carbon peak time in the future with China and India as examples. Duan et al. (2022) analyzed the impact mechanism between the social economic system and the energy economic system based on the experience of 10 typical developed countries in carbon peaking. Moreover, the experience of carbon peaking in developed countries can provide a good reference for developing countries (Dong et al. 2019). Li and Qin (2019) simulated the challenges that China may face in achieving the carbon peak path in 2030. Wang et al. (2022b) also put forward corresponding suggestions for China to achieve carbon peak. The time scope of the above literature research on carbon peaking is relatively short. However, with the introduction of various policies, the medium and long-term forecast is more important to optimize the path for carbon peak. Therefore, in order to better analyze the effectiveness of policies, this paper expands the time scope to the medium and long-term.

Research on CO_2 emission measurement and prediction methods

For CO_2 emissions, the commonly used forecasting models mainly consist of the input–output method, grey forecast model, system dynamics, and machine learning methods. For instance, Li et al. (2015) calculated the direct and indirect carbon emissions of Chinese households based on the input–output method. The grey forecast model was constructed by Li et al. (2018) to predict China's CO_2 emissions from 2016 to 2030 to explore the conditions for achieving the carbon peak target in 2030. At present, scholars have also frequently applied machine learning methods to forecasting studies due to advances in artificial intelligence techniques and demand for forecasting accuracy (Nishan and Ashiq 2020). A new prediction model Gaussian process regression based on a modified Particle Swarm Optimization algorithm (PSO-GPR) was proposed by Fang et al. (2018) for predicting the total CO_2 emission of Japan, the USA, and China between 2013 and 2020. Sun and Liu (2016) employed least squares support vector machine (LSSVM) to predict the trend of carbon emissions in the three major industries and residential consumption sectors in China. Combining the Back Propagation neural network and scenario analysis, Guo et al. (2018) forecasted China's respective CO2 emissions and intensity in 2030 under business-as-usual (BAU), strategic planning (SP), and low-carbon (LC) scenarios. BP is currently the most widely used artificial neural network (Sun and Xu 2016; Wang et al. 2016). Because it can simulate various complex nonlinear relationships, it is often used in prediction research (Wen and Yuan 2020). In contrast to econometric models and other traditional models such as IPAT and STIRPAT, which require the form of the functional relationship between input data and output results to be determined at the early stage of model construction, BP neural network is not subject to such constraints, and due to its powerful non-linear mapping capabilities, as well as its high degree of adaptability and robustness (Lu et al. 2020). This paper used BP neural network to predict the future trend of China's CO_2 emissions.

Materials and methods

Identification model of key influencing factors of CO_2 emissions

Potential influencing factors

With reference to previous studies (Niu et al. 2020), this paper classified influencing factors of CO_2 emissions into nine categories: economic development, population size, age structure, urbanization, energy consumption, energy structure, industry structure, technological level, and trade exchange, and selected representative indicators in each category as the bases for identifying the key factors, as shown in Table 1.

Random Forest

An excessive number of predictors will increase the training time of the model and the difficulty of prediction. Therefore, it was necessary to identify the key factors of CO_2 emissions from the abovementioned 26 potential influencing indicators as predictors. This paper adopted RF to measure the importance of factors through the Gini index obtained by the algorithm, so as to analyze the impact of factors on China's CO_2 emissions and identify the key variables.

In RF, the Gini index can reflect the impurity of the internal attribute division of the node. The larger the Gini index, the higher the impurity of the node division. Assuming that there are C variables, namely, $X_1, X_2, X_3, \ldots, X_C$, the calculation formula of the Gini Index is as follows:

$$GI_m = \sum_{k=1}^{K} p_k(1 - p_k) = 1 - \sum_{k=1}^{K} p_k{}^2. \tag{1}$$

In the formula, GI_m represents the Gini index of node m, K indicates that there are K categories in node m, p_k is the sample weight of category k in node m.

The importance of the variable X_j in the node m, that is, the change of the Gini index before and after the split of the node m, is calculated as follows:

$$VIM_{jm}^{(Gini)} = GI_m - GI_r - GI_l. \tag{2}$$

where GI_r and GI_l, respectively, represent the Gini index of two new nodes r and l formed after node m is split.

Table 1 Categories and indicators of potential influencing factors of China's CO_2 emissions

Category	Factor indicator (unit)	Category	Factor indicator (unit)
Economic development	GDP (10^8 yuan)	Energy structure	Share of coal in total energy consumption (%)
	GDP per capita (yuan)		Share of oil in total energy consumption (%)
	GDP growth rate (%)		Share of natural gas in total energy consumption (%)
	Fixed asset investment (10^8 yuan)		Share of renewable energy in total energy supply (%)
Population size	Total population (10^4 people)		Proportion of thermal power generation (%)
	Urban population (10^4 people)	Industry structure	Share of primary industry in GDP (%)
Age structure	Ratio of population aged 0–14 (%)		Share of secondary industry in GDP (%)
	Ratio of population aged 15–64 (%)		Share of tertiary sector in GDP (%)
	Ratio of population aged over 65 (%)		Ratio of total industrial output to service output
Urbanization	Urbanization rate (%)	Energy consumption	Total energy consumption (10^4 tons of standard coal)
Technological level	Energy consumption per unit of GDP (tons of standard coal/10^4 yuan)		Energy consumption per capita (kg standard coal/people)
	Ratio of R&D expenditure to GDP (%)		Electricity consumption (10^8 kWh)
Trade exchange	Trade openness (%)		Total primary energy consumption (Million toe)

Impact factors of carbon emission are diverse. Referring to Niu et al. (2020), here are only the 26 indicators considered in this paper

If the node where the variable X_j appears in the decision tree i is in the set M, then the importance of X_j in the i-th decision tree is calculated by the formula:

$$VIM_{ij}^{(Gini)} = \sum_{m \in M} VIM_{jm}^{(Gini)}. \tag{3}$$

Assuming that RF constructs n trees, the importance of the variable X_j in the entire forest is:

$$VIM_{j}^{(Gini)} = \sum_{i=1}^{n} VIM_{ij}^{(Gini)}. \tag{4}$$

Finally, the abovementioned importance is normalized to obtain the importance score of variable X_j:

$$VIM_j = \frac{VIM_j^{(Gini)}}{\sum_{c=1}^{C} VIM_c^{(Gini)}}. \tag{5}$$

The algorithm evaluates the relative importance (VIM) of each influencing factor by calculating the average reduction degree of the Gini index before and after the node splitting (Wei et al. 2018). When VIM is very large, it indicates that the impact of this variable on CO_2 emissions is very significant.

Carbon peak forecast model: Back Propagation neural network

This paper used this model to predict the future trend of China's CO_2 emissions.

Assuming that the input layer has n neurons, the hidden layer has p neurons, and the output layer has q neurons, the input vector $X = (x_1, x_2, x_3, \ldots, x_n)$, $x_1 \sim x_n$ respectively represent the key influencing factors screened by RF. The training process of BP can be divided into the following parts: the first is the forward propagation of information, that is, the calculation of the input and output of each layer of neurons.

The output formula of hidden layer neurons is shown in (6):

$$hO_h(k) = f\left(\sum_{i=1}^{n} w_{hi} x_i(k) - b_h\right) \quad h = 1, 2, 3, \ldots, p. \tag{6}$$

In the formula, k represents the k-th sample data, $k = 1, 2, \ldots, m$; $hO_h(k)$ is the output of the hidden layer neuron h, w_{hi} is the weight of the influence degree of the input layer neuron i on the hidden layer neuron h,b_h represents the threshold of the hidden layer neuron h, $f(.)$ is the activation function of the hidden layer; this paper used the hyperbolic tangent activation function:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} = \frac{2}{1 + e^{-2x}} - 1, \; f(x) \in (-1, 1). \tag{7}$$

The output formula of neurons in the output layer is shown in (8):

$$yO_o(k) = g\left(\sum_{h=1}^{p} w_{oh} hO_h(k) - b_o\right) \quad o = 1, 2, 3, \ldots, q. \tag{8}$$

Similarly, $yO_o(k)$ is the actual output of the output layer neuron o, that is, the predicted value of the k-th sample; w_{oh} represents the weight of the hidden layer neuron h's influence on the output layer neuron o, b_o represents the threshold of the output layer neuron o, $g(.)$ is the activation function of the output layer; this paper used the identity activation function:

$$g(x) = x. \tag{9}$$

The second part of the process is error back propagation. The expected output and actual output of the network are used to calculate the error function, and the weights and thresholds are updated by back-propagating error layer by layer so that the actual output is as close to the expected output as possible.

The error function is defined as Formula (10):

$$e = \frac{1}{2}\sum\nolimits_{o=1}^{q}(d_o(k) - yO_o(k))^2. \tag{10}$$

Among them, $d_o(k)$ is the expected output of output layer neuron o, that is, the actual value of the k-th sample; $yO_o(k)$ is the actual output of output layer neuron o, that is, the predicted value of the k-th sample.

Finally, the global error is calculated as shown in Formula (11). When the error reaches the preset accuracy or the number of iterations exceeds the set maximum number of times, BP training is ended; otherwise, the above steps are returned until the output error meets the requirements.

$$E = \frac{1}{2m}\sum\nolimits_{k=1}^{m}\sum\nolimits_{o=1}^{q}(d_o(k) - yO_o(k))^2. \tag{11}$$

Based on the above principles, this paper selected the coefficient of determination R^2, mean absolute percentage error MAPE, mean absolute error MAE, mean square error MSE and root mean square error RMSE for evaluating the reliability of the model (Yan et al. 2018; Hu et al. 2020). The calculation methods of these five error indicators are presented as follows:

$$R^2 = 1 - \left(\frac{\sum_{k=1}^{m}(d(k) - yO(k))^2}{\sum_{k=1}^{m}d(k)^2}\right). \tag{12}$$

$$\text{MAPE} = \frac{1}{m}\sum\nolimits_{k=1}^{m}\left|\frac{yO(k) - d(k)}{d(k)}\right| \times 100\% \tag{13}$$

$$\text{MAE} = \frac{1}{m}\sum\nolimits_{k=1}^{m}|yO(k) - d(k)| \tag{14}$$

$$\text{MSE} = \frac{1}{m}\sum\nolimits_{k=1}^{m}(d(k) - yO(k))^2 \tag{15}$$

$$\text{RMSE} = \sqrt{\frac{1}{m}\sum\nolimits_{k=1}^{m}(d(k) - yO(k))^2} \tag{16}$$

In the above formula, $d(k)$ is the actual value of the CO_2 emission of the k-th observation sample; $yO(k)$ is the predicted value of the CO_2 emission obtained by BP of the k-th sample. The closer R^2 is to 1, the better the prediction effect of the BP. For MAPE, MAE, MSE, and RMSE, the lower the indicator value, the higher the forecasting accuracy.

Scenario analysis setting

To analyze the impact of different development paths and policy preferences on China's achievement of carbon peaking, five scenarios based on the adjustments to the 14th Five-Year Plan and potential space for abatement were constructed:

(i). The 13th Five-Year Plan scenario: this scenario continues the low-carbon development policies set out during China's 13th Five-Year Plan period, but no further energy savings or emission reduction policies will be considered.

(ii). The 14th Five-Year Plan scenario: this scenario follows the new emission reduction, energy, and technology measures deployed in China's 14th Five-Year Plan, and the values of the predictors are consistent with the target values of the 14th Five-Year Plan. This scenario differs from the 13th Five-Year Plan scenario in terms of economic growth, population size, energy structure, and innovation-drive intensity. It can be used as a reference for comparison with the energy optimization, technology breakthrough, and dual control scenarios.

(iii). Energy optimization scenario: under the 14th Five-Year Plan, the greatest potential of energy structure optimization will be realized. In this scenario, the Chinese government will encourage the use of renewable and clean energy to replace traditional fossil fuels through energy technology changes, pricing policies, clean energy subsidies, and mandatory energy structure reforms, in order to maximize the decarbonization and cleanliness of the energy system. Under this scenario, the rate of change of the variables related to energy structure is set optimally compared to other scenarios, and the value of investment in R&D will be strengthened based on the 14th Five-Year Plan.

(iv). Technology breakthrough scenario: under this scenario, the government will increase R&D intensity of green technology based on the 14th Five-Year Plan and strive to achieve technological breakthroughs in plastic waste recycling, carbon capture and storage, and battery energy storage, in order to promote the efficient recycling and reuse of resources. With the development of technology, the popularization of clean energy will also break through the existing technological bottleneck and lead to a significant increase in energy efficiency. Therefore, based on the 14th Five-Year Plan scenario, this paper strengthened the expected rate of change parameters for energy consumption intensity, share of renewable energy, and natural gas. The growth rate in the ratio of R&D expenditure to GDP is higher than in the other scenarios.

(v). Dual control scenario: this paper obtained an optimal scenario, called the dual control scenario, by combining the energy optimization and technology breakthrough scenarios. Under the dual control scenario, China is expected to adopt a two-pronged approach from both green technology innovation and energy structure transformation.

Data source

This paper selected China's CO_2 emissions data from 1990 to 2019 for research, which was collected from the OECD database. The data on influencing factors came from the *China Statistical Yearbook* (National Bureau of Statistics of China 2020), *China Energy Statistical Yearbook* (National Bureau of Statistics of China 2020), *China Electricity Statistical Yearbook* (China Electricity Council 2020), the official website of National Bureau of Statistics, and OECD. Two of the potential influencing factors, share of renewable energy in total primary energy supply and total primary energy consumption, were obtained from the OECD database. The data collection of variables was based on the latest materials, and this paper used extrapolation to fill in data that were not updated. GDP and GDP per capita were deflated to 1990 prices to eliminate the effects of inflation.

Results

Results of the identification of key influencing factors

The importance scores (VIMs) of each indicator obtained by constructing the RF model using Stata 16.1 are shown in Table 2.

The results showed that the impact of the energy structure indicator on emissions was the most significant, indicating that China's energy restructuring measures have made substantial progress in emission reduction in recent years. In the future, it will be possible to achieve emission reduction targets through the development of renewable energy and clean energy. However, the impact of total energy consumption also remained significant, reflecting to a large extent that the current energy mix is dominated by fossil energy and will remain so for some time to come.

The importance score of the ratio of R&D expenditure to GDP was as high as 0.7887, indicating that the role of technology effects cannot be ignored, and as the Chinese government increases the intensity of R&D in low-carbon technologies, the returns to emission reductions from high investment are gradually coming to the fore. In addition, China is undergoing a period of disappearing demographic dividend opportunities, and the impact of the share of the working population on carbon emissions is becoming increasingly important.

The importance of GDP and fixed asset investment variables was relatively low, suggesting that economic factors are no longer the main drivers of CO_2 emissions and that as China's economy enters a new normal, the concept of economic development has changed from the pursuit of total economic expansion to the concept of sustainable development that balances economic development and environmental protection.

Based on the results of RF and the way the predictors were selected in previous literature, e.g., Wen and Yuan (2020), Niu et al. (2020) selected the top seven indicators in terms of VIM value, seven indicators with VIM $\geq$ 0.65 (share of renewable energy in the total primary energy supply, ratio of R&D expenditure to GDP, share of primary industry in GDP, share of natural gas in total energy consumption, total

Table 2 Importance (VIM) of factors influencing CO_2 emissions

Factors	VIM	Factors	VIM
Share of renewable energy in total primary energy supply	1.0000	Ratio of population aged 0–14	0.5703
Ratio of R&D expenditure to GDP	0.7887	GDP per capita	0.5651
Share of primary industry in GDP	0.7685	Urban population	0.5441
Share of natural gas in total energy consumption	0.7169	Total population at the end of the year	0.5387
Total energy consumption	0.6914	Fixed asset investment	0.5165
Energy consumption per unit of GDP	0.6636	Urbanization rate	0.5065
Ratio of population aged 15–64	0.6548	Proportion of thermal power generation	0.4732
Total primary energy consumption	0.6213	GDP	0.4695
Electricity consumption	0.6077	GDP growth rate	0.1934
Ratio of total industrial output to service output	0.6073	Share of coal in total energy consumption	0.1607
Energy consumption per capita	0.5994	Share of secondary industry in GDP	0.1119
Share of tertiary sector in GDP	0.5800	Trade openness	0.1029
Ratio of population aged over 65	0.5751	Share of oil in total energy consumption	0.0281

energy consumption, energy consumption per unit of GDP, ratio of population aged 15–64) were selected as predictors, excluding other factors with relatively weak effects.

Back Propagation neural network for forecasting CO_2 emissions

In this paper, the above seven key influencing factors of CO_2 emissions were used as the input layer of the BP, and China's CO_2 emissions from 1990 to 2019 were used as the output layer. In order to ensure the generalization ability of the neural network, 70%, 15%, and 15% of the full sample size were randomly selected as the training set, validation set, and test set respectively in this paper. The results of the full sample fit of the model are shown in Fig. 2.

It can be seen that the actual and predicted values of CO_2 emissions were in very good agreement ($R^2 = 0.998$). To further evaluate the predictive ability of the completed BP neural network, the fitted values obtained from the ordinary least square regression (OLS) were compared with BP, as shown in Table 3. For MAPE, MAE, MSE, and RMSE, the lower the indicator value, the higher the forecasting accuracy. The MAPE of the BP neural network was 1.89%, while the error of OLS was 1.96%. By comparing multiple error indicators, it is confirmed that the forecasting errors of the BPNN model are smaller than those of OLS. In general, the BP neural network was stronger than OLS in terms of prediction.

Results of scenario analysis

Parameter of variables

Based on the development scenarios constructed above, each carbon emission predictor was set with reference to past development trends and relevant policy objectives.Specific parameter values are shown in Table 5 of the Appendix.

GDP As China's economic development enters a new normal, GDP growth will gradually slow down after a long period of high growth (Xu et al. 2019). Studies have predicted that China's economy will grow at a moderate rate between 2010 and 2030, and at a low rate of high-quality growth after 2030 (Wang et al. 2018). Combining the above findings with the target of 6.5% set in the 13th Five-Year Plan (NDRC 2016), the average annual GDP growth rates under the 13th Five-Year Plan scenario for 2021–2025, 2026–2030, 2031–2035, and 2036–2040 were set at 6.5, 5.5, 4.5, and 3.5%, respectively, which is used to project GDP for each year. The 14th Five-Year Plan does not specify an economic development target, but over the past few 5-year plans, China has gradually reduced its GDP growth target by 0.5 percentage points, for example to 7% during the 12th Five-Year Plan and 6.5% during the 13th Five-Year Plan. Considering the ongoing impact of COVID-19 on the global economy, and referring to the parameters of Niu et al. (2020), the annual GDP growth rates for the other four scenarios are set at 5.5, 4.5, 3.5, and 2.5%.

Share of primary industry in GDP The share of primary industry in GDP fell from 8.4 to 7.1% between 2015 and 2019, while the share of the secondary industry fell slightly and the share of tertiary industry rose significantly, reflecting the trend of China's industrial restructuring, and the share of the primary industry will continue to maintain this momentum of gradual decline in the future. According to the World and China Energy Outlook 2050 (CNPC 2020), the structure of China's three industries is expected to evolve to 6:31:63 in 2035, with the share of primary industry decreasing to 4% in 2050. The average annual growth rates of the share of primary industry in GDP from 2021 to 2035 and 2036 to 2040 under the 13th Five-Year Plan scenario was calculated from this, which were −1.65% and −2.67% respectively. In the 14th Five-Year Plan scenario, this paper referred to "China's Energy and Electricity Development

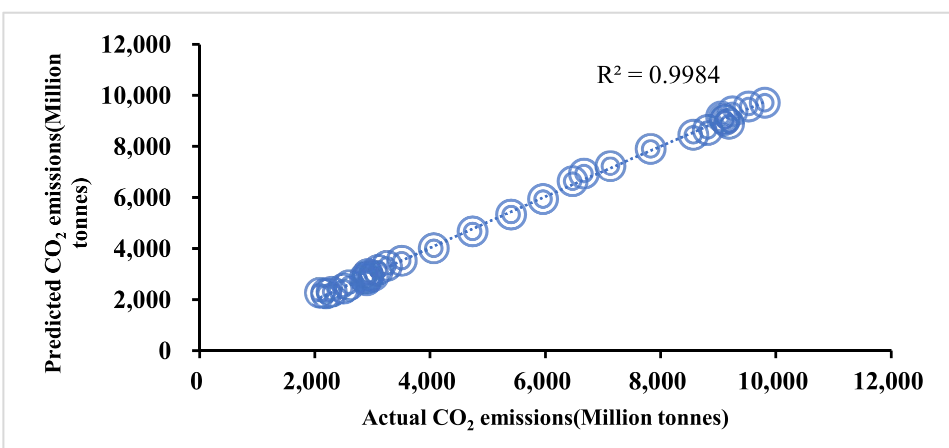


Fig. 2 Back propagation neural network fitting results (1990–2019)

Table 3 Comparison of actual and predicted values of CO_2 emissions in China

Year	Actual value of CO_2 emissions in China (million tons)	BP neural network		OLS	
		Predicted value	Relative error (%)	Predicted value	Relative error (%)
1990	2088.854	2266.574	8.51	2216.484	6.11
1991	2200.885	2244.943	2.00	2250.705	2.26
1992	2295.775	2310.92	0.66	2240.567	2.40
1993	2500.73	2427.965	2.91	2351.068	5.98
1994	2599.503	2568.828	1.18	2533.655	2.53
1995	2900.265	2751.662	5.12	2833.114	2.32
1996	2871.981	2862.086	0.34	2916.22	1.54
1997	2925.749	2885.301	1.38	2932.003	0.21
1998	3020.717	2934.798	2.84	2933.306	2.89
1999	2920.897	2996.74	2.60	2888.392	1.11
2000	3099.685	3155.233	1.79	3231.622	4.26
2001	3255.951	3320.678	1.99	3335.584	2.45
2002	3511.728	3518.075	0.18	3515.335	0.10
2003	4068.095	4014.692	1.31	3925.766	3.50
2004	4741.831	4673.658	1.44	4731.485	0.22
2005	5407.518	5334.347	1.35	5518.728	2.06
2006	5961.808	5935.961	0.43	6050.772	1.49
2007	6473.211	6634.821	2.50	6621.774	2.30
2008	6669.112	6932.983	3.96	6804.283	2.03
2009	7131.512	7236.915	1.48	7105.661	0.36
2010	7830.969	7904.091	0.93	7844.707	0.18
2011	8569.653	8452.455	1.37	8346.275	2.61
2012	8818.413	8650.408	1.91	8658.672	1.81
2013	9188.381	8886.471	3.29	8905.344	3.08
2014	9116.341	9031.354	0.93	9110.081	0.07
2015	9093.304	9102.761	0.10	9186.184	1.02
2016	9054.476	9175.979	1.34	9269.595	2.38
2017	9245.582	9371.353	1.36	9353.227	1.16
2018	9528.214	9568.146	0.42	9525.992	0.02
2019	9809.198	9717.827	0.93	9763.737	0.46
MAPE (%)			1.89		1.96
MAE			90.41		90.43
MSE			13,030.95		13,116.35
RMSE			114.15		114.53

Planning Study 2030 and Outlook 2060" published in 2021 (GEIDCO 2021), which estimated that the share of the primary industry will reach 6.4, 5.9, and 4.2% in 2025, 2030, and 2050, respectively. This resulted in an average annual growth rate of − 3.63, − 1.61, and − 1.68% for this variable for 2021–2025, 2026–2030, and 2031–2040, respectively.

Ratio of population aged 15–64 With the release of the "two-child policy" dividend, the total fertility rate fell rapidly to 1.5 in 2018 and again to around 1.45 in 2019 (Yang 2021). In accordance with the declining trend of the total fertility rate during the 13th Five-Year Plan period, it will likely continue to fall below 1.4 after 2020, and the variable is expected to reach 67.64% in 2030. Subsequently, the total working-age population will fall by around 10 million every year and is expected to drop to below 900 million in 2036 (Zhang et al. 2020). In the 14th Five-Year Plan period, the relevant population plan stated that in order to actively respond to the trend of population aging, it will implement the policy of allowing one couple to have three children along with supporting measures (Central People's Government of China 2021). With the introduction of the three-child policy, this paper suggested that the lower fertility rate in 2020 owing to COVID-19 will soon return to 1.6, and it drew on the results of Yang (2021) to set age structure parameters for the 14th Five-Year Plan scenario.

Share of renewable energy in total primary energy supply The average annual growth rate of this variable from 2015 to 2019 was about 2.5%, and the 13th Five-Year Plan scenario will follow the historical trend, with annual growth rates set at 2.5, 3.5, 3, and 3%, respectively, for each phase. The 14th Five-Year Plan proposes to further expand the scale of wind power and photovoltaic power generation on the basis of the 13th Five-Year Plan and to achieve the goal of renewable energy becoming the mainstay of energy and electricity supply and consumption by 2025 (CCTV News 2021). Considering the overlapping effects of the various energy deployments in the 14th Five-Year Plan, the share of renewable energy in the 14th Five-Year scenario should grow faster than in the 13th Five-Year scenario (CCTV News 2021). This paper used the maximum annual growth rate of 5.4% in the past 5 years as the basis for the energy optimization scenario, in order to maximize the potential of energy structure transformation.

Share of natural gas in total energy consumption According to the development target of the 13th Five-Year Plan for Energy Development, the proportion of natural gas consumption is expected to increase by 4.1 percentage points during the 13th Five-Year Plan period, with the proportion of natural gas consumption aiming to reach 15% in 2030 (National Energy Administration 2016). Wang and Wang (2019) predicted that the share of natural gas will be 21.8% in 2040, driven by the national 13th Five-Year Energy Policy. This paper set the parameters for the share of natural gas in the 13th Five-Year Plan scenario based on the above studies. The 14th Five-Year Plan stated that the process of optimizing energy structure should be accelerated, so the share of natural gas consumption in the 14th Five-Year Plan scenario should be significantly higher than in the 13th Five-Year Plan scenario, with a maximum annual growth rate of 13.1% in the last 5 years as the energy optimization scenario.

Ratio of R&D expenditure to GDP With reference to the 13th Five-Year Plan, which proposed that the intensity of investment in R&D is expected to increase by 0.4 percentage points over 5 years, the average annual growth rate of this variable in the 13th Five-Year Plan scenario from 2021 to 2025 was calculated as 3.1%. According to the 14th Five-Year Plan, the average annual growth rate of whole social investment in R&D was more than 7%, and the investment intensity was higher than that of the 13th Five-Year period. According to this target, the average growth rate for the 14th Five-Year Plan scenario from 2021 to 2025 was set as 3.4%. The historical data for 2015–2019 were calculated and the maximum growth rate of 4.2% for this variable was taken as the technology breakthrough scenario.

Energy consumption intensity factor In the 13th Five-Year Plan, the target was to reduce energy consumption per unit of GDP by a cumulative 15% over 5 years. Considering that China exceeded the binding target in both the 12th and 13th Five-Year Plan periods, this paper set a cumulative reduction in energy consumption per unit of GDP of 16% for the period 2021–2025 under the 13th Five-Year Plan scenario. According to the 13th Five-Year Plan for Energy Development, the growth rate of energy consumption is expected to fall from an annual average of 9% since the 10th Five-Year Plan to around 2.5%, with an average annual growth rate of less than 3% set as the development target (National Energy Administration 2016). The Energy Production and Consumption Revolution Strategy (2016–2030) stated that total energy consumption is to be controlled at 6 billion tons of standard coal in the period 2021–2030 (NDRC and National Energy Administration 2016). In the medium to long term, the growth rate of energy consumption in China will slow down, reaching a peak in 2040. After combing the various materials, the average annual growth rates of energy consumption per unit of GDP for each phase under the 13th Five-Year Plan scenario were predicted to be –3.4, –4.4, –2.4, and –2.9%, respectively.

The 14th Five-Year Plan set the target of "reducing energy consumption per unit of GDP by a cumulative 13.5%," and this paper assumed a cumulative reduction of 14.5% from 2021 to 2025 under the 14th Five-Year scenario. Referring to the forecast in "China's Energy and Electricity Development Planning Study 2030 and Outlook 2060", which predicted negative growth in energy consumption after 2035, the average annual growth rates of –3.1, –3.1, –3, and –2.8% were predicted for phases of the 14th Five-Year Plan scenario. The maximum annual average rate of reduction in energy consumption per unit of GDP from 2015 to 2019 is –5.3% as the double control scenario. The forecast value of total energy consumption was calculated by multiplying the energy consumption per unit of GDP by GDP for each scenario.

Scenario predictions for carbon peaking

The predicted trends of China's CO_2 emissions under the five scenarios are presented in Fig. 3. Under the 13th Five-Year Plan scenario, China's CO_2 emissions were predicted to reach 10,507.441 and 10,683.734 Mt in 2030 and 2040, respectively. Under the 14th Five-Year Plan scenario, CO_2 emissions would reach 10,434.082 Mt in 2030 and were predicted to be 10,144.024 Mt in 2040. The new development targets and policies in the 14th Five-Year Plan resulted in carbon emission reductions of 73.359 and 539.71 Mt in 2030 and 2040, respectively. The 13th Five-Year Plan scenario reached its peak in 2035, while the 14th Five-Year Plan scenario corresponded to 2030, suggesting that China can achieve the 2030 carbon peak target on schedule by following the constraints of relevant strategic plans and environmental policies during the 14th Five-Year Plan period. However, by continuing the 13th Five-Year Plan, China will not be able to meet even the basic 2030 emission peak target, which was consistent with the studies by Hong et al. (2021) and Niu et al. (2020). Compared to previous literature, this paper measured the potential for emission reductions arising from the 14th Five-Year Plan.

Under the energy optimization and technology breakthrough scenarios, China will enter the peak carbon plateau in 2030 and 2028, respectively, with corresponding emission peaks of 10,137.986 and 10,142.486 Mt. The trends of CO_2 emissions in the two scenarios largely coincided between 2020 and 2030, and once the long-term intensive R&D investment has achieved substantial green technology breakthroughs, the emission reduction effect of technological innovation will immediately become apparent, and China's total carbon emissions will fall rapidly after 2030 under the technology breakthrough scenario. Under the dual control scenario, China's carbon peak will be further advanced, peaking in 2025, with the lowest emissions peak of the five scenarios, at 9860.08 Mt, followed by an accelerated decline in CO_2 emissions to below 8500 Mt by 2040. If this trend continues, China is expected to reach its long-term goal of carbon neutrality by 2060.

Thus, with the basic peak target completed, will China be able to meet its new commitment to reduce CO_2 emissions per unit of GDP by more than 65% in 2030 compared to 2005? The predictions of China's carbon emissions intensity in 2030 and the achievement of INDCs are shown in Table 4. Under the 14th Five-Year Plan scenario, it would be difficult to achieve China's carbon intensity reduction target, while under the energy optimization, technology breakthrough, and dual control scenarios, CO_2 emission intensity values in 2030 were estimated to be 0.02319, 0.02320, and 0.02192 Mt/10^8 Yuan, respectively, a reduction of 65.21, 65.20, and 67.12% compared to 2005.

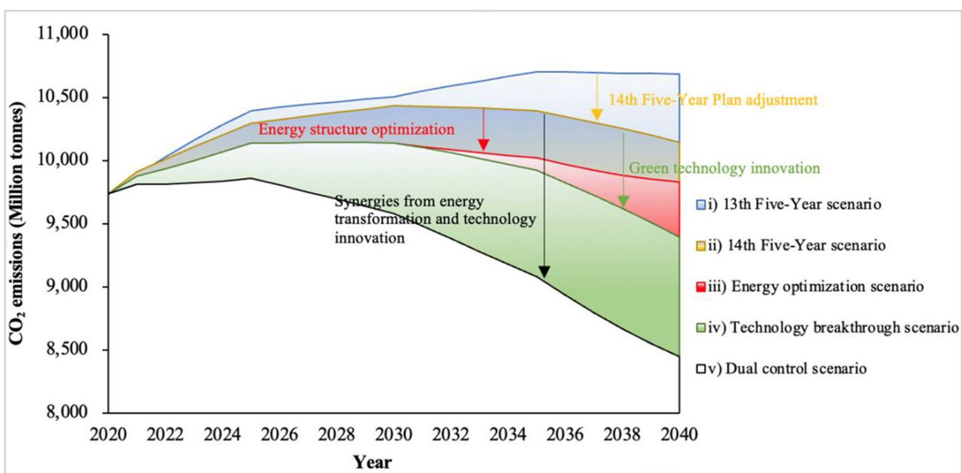


Fig. 3 China's CO_2 emission trends under different scenarios (2020–2040)

Table 4 Forecasting results of carbon intensity in 2030 under different scenarios

Scenario	CO_2 emissions (Million tonnes)	Carbon emission intensity (Mt/10^8 Yuan)	Carbon peak time	Over 65% reduction in carbon intensity
i)	10,507.441	0.02186	2035	Yes (67.21%)
ii)	10,434.082	0.02387	2030	No (64.20%)
iii)	10,137.986	0.02319	2030	Yes (65.21%)
iv)	10,140.825	0.02320	2028	Yes (65.20%)
v)	9582.016	0.02192	2025	Yes (67.12%)

Therefore, in order to ensure the achievement of INDCs, China should actively carry out measures related to energy optimization and technological breakthroughs during the 14th Five-Year Plan period.

Discussion and suggestions

By combining the results of different scenarios, it was clear that the 14th Five-Year Plan would help China achieve its emission peak target on time, but it would still be difficult to meet the new commitment of intensity reduction. The transformation of energy structure would, to a certain extent, reduce the CO_2 emissions peak. However, the emission reduction effect of energy optimization was not as strong as the effect of technological breakthroughs at a later stage. In order to advance to the carbon peaking plateau and achieve the ultimate goal of carbon neutrality, we propose the following policy suggestions to move society quickly from the 14th Five-Year Plan scenario to the three development scenarios of energy optimization, technological breakthrough, and dual control, as shown in Fig. 4:

(1) Measures towards Energy Optimization Development Scenario.

The energy intensity targets of the 13th Five-Year Plan are more effective, and reaching the inflection point for carbon growth in the next decade will require continued improvements in energy use efficiency and, crucially, long-term adherence to controls on total consumption. Firstly, a national plan for total primary energy consumption could be drawn up, which could then be implemented in accordance with the principle of equity and regional development strategies, taking into account the level of economic development and industrial structure of each province, and energy consumption targets could be allocated to the corresponding provinces according to demand and production. Secondly, China should strive to reduce energy losses in the processes of production, conversion, transportation, and consumption to further improve energy efficiency. On the other hand, it needs to vigorously develop green industries and assist in the transformation of overcapacity, high pollution, and energy-intensive industries toward low carbon and energy saving.

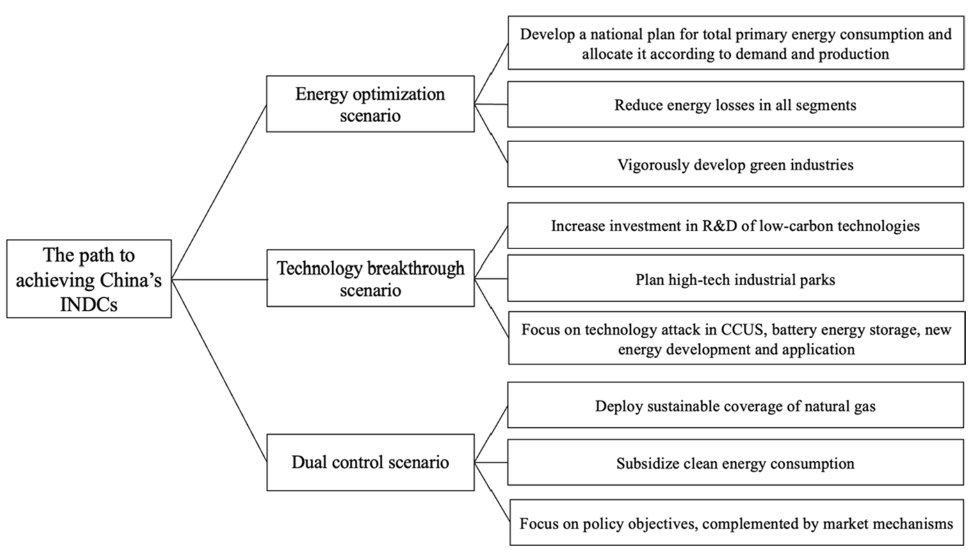
(2) Measures towards Technology Breakthrough Development Scenario.

Promoting technological advancement by increasing investment in the R&D of low-carbon technologies are vital for China to curb CO_2 emissions. The Chinese government should actively plan high-tech industrial parks to provide sophisticated support facilities for green technology innovation. It will be necessary to set up special groups to address technical challenges and promote the flow of talent, technology, and funding between regions to achieve breakthroughs in core technologies. In particular, a number of cutting-edge and disruptive successes in areas such as carbon capture, utilization, and storage (CCUS), battery energy storage, and new energy development and application are expected to be created and industrial coverage achieved.

(3) Measures Towards Dual-Control Development Scenario.

According to the parameters set, the share of natural gas under the double control scenario is expected

Fig. 4 Policy suggestions towards three peak scenarios



to be 23.374% in 2030, while the target for the share of natural gas under the 14th Five-Year Plan is about 15%. However, in either scenario, it is lower than the share in 2020 of the US (34%), which has already achieved peak carbon. In terms of the share of renewable energy, according to historical trends and the constraints of current policy targets, the value would only reach 13.615% under the 14th Five-Year Plan scenario, which is still some way from the 17.122% in the dual control scenario. The high proportion of coal and the crude energy structure dominated by fossil fuels have led to a huge pressure on China to transform its energy systems. If China is to move into a double-control development path and achieve optimal emission reduction potential, it should, on the one hand, control total coal consumption in key regions such as the Pearl River Delta, Yangtze River Delta, and Beijing-Tianjin-Hebei economic zone, gradually phase out or renovate coal-fired power stations, gradually guide the low-carbon transformation of traditional heavy industries that are dominated by coal consumption and strictly limit their expansions (Wang et al. 2018). The focus on the other hand is to deploy sustainable coverage of natural gas, and strengthen the development and use of renewable energy such as wind, water, and solar in the future, such as accelerate the construction of domestic natural gas pipelines and increase the supply of natural gas from both sea and land extraction; improve the supply and demand mechanism in the natural gas market by liberalizing price instruments to guide reasonable market competition; improve the implementation of laws and regulations related to renewable energy; and subsidize the consumption of clean energy.

Focus on policy objectives, supplemented by market mechanisms. The Chinese government needs to strengthen energy and technology-related targets based on the current strategic plan and urge local governments to put carbon reduction targets and policy plans in place. Along with policy constraints, the advantage of market mechanisms in carbon abatement should be emphasized to push China's CO_2 emissions onto the peak plateau earlier. For example, the implementation of carbon pricing needs to be accelerated, a unified carbon trading market needs to be established and a carbon tax needs to be levied. Ultimately, by playing a complementary role of the market mechanism, the efficiency of resource allocation will be improved and the purpose of carbon offsetting will be achieved.

There are three limitations to this study. First, due to the limitations of the existing database, more potential factors influencing China's CO_2 emissions, such as policy, energy, and environmental factors, are yet to be explored. Second, with the development of society and the change of policies, the importance of factors influencing CO_2 emissions will also change. When selecting carbon emission predictors, this paper only selected the indicators with greater relative impact in the current stage based on the results of random forest and previous literature. Third, only five scenarios were constructed for emission projections in this study to ensure that the paper is reasonably concise, but the reality is much more than that, so more scenarios are worth exploring in the future.

Conclusions

From carbon emission peaking to carbon neutrality, the developed world will have a transition period of 50–70 years, but China will have only 30 years. Therefore, this paper discusses the realization of carbon neutrality before 2060 from the new perspective of policy adjustment in China. In this paper, the RF model was used to identify key influencing factors of CO_2 emission to improve the efficiency of forecasting. To determine whether China can achieve its new 2030 carbon peaking and carbon intensity reduction commitments, a BP neural network was employed to forecast China's CO_2 emissions and intensity in 2020–2040 under the 13th Five-Year Plan, 14th Five-Year Plan, energy optimization, technology breakthrough, and dual control scenarios. The conclusions are as follows:

Firstly, energy structure factors have the most significant impact on China's CO_2 emissions, with economic development factors no longer being the dominant driver. Secondly, China's CO_2 emissions in 2030 are predicted to range from 9582.016 to 10,507.441 Mt. Thirdly, the 14th Five-Year Plan will help China achieve the carbon peak target on schedule, delivering 73.359 and 539.71 Mt CO_2 reductions in 2030 and 2040 respectively and under the dual control and technology breakthrough scenarios, the times are advanced to 2025 and 2028, respectively. Finally, China cannot meet its new commitment to reducing carbon intensity under the 14th Five-Year Plan scenario, so energy optimization, technological breakthroughs, and dual control should be actively pursued, with dual control having the best emission reduction effect and the ability to achieve a 67.12% reduction in CO_2 emissions intensity in 2030, compared to 2005.

Developing countries face more challenges than developed countries to meeting their carbon–neutral target. This study will not only help China to achieve its new commitments in tackling climate change and maximize its emission reduction potential but also be a reference for other developing countries considering scenarios similar to China's development model and make greater contributions to global climate governance.

Appendix

Table 5 Parameter setting for each variable under different scenarios

Predictors (unit)	Scenario	Baseline	Annual growth rate (%)			
		2020	2021–2025	2026–2030	2031–2035	2036–2040
GDP (10^8 yuan)	i	268,389.36	6.5	5.5	4.5	3.5
	ii/iii/iv/v		5.5	4.5	3.5	2.5
Share of primary industry in GDP (%)	i	7.7	− 1.65	− 1.65	− 1.65	− 2.67
	ii/iii/iv/v		− 3.63	− 1.61	− 1.68	− 1.68
Share of renewable energy in total primary energy supply (%)	i	9.65	2.5	3.5	3	3
	ii		3	4	3.5	3.5
	iii		5.4	6.4	5.9	5.9
	iv		4.2	5.2	4.7	4.7
	v		5.4	6.4	5.9	5.9
Share of natural gas in total energy consumption (%)	i	8.4	8.3	3.7	3.8	3.8
	ii		8.5	3.9	4	4
	iii		13.1	8.5	8.6	8.6
	iv		10.8	6.2	6.3	6.3
	v		13.1	8.5	8.6	8.6
Ratio of R&D expenditure to GDP (%)	i	2.4	3.1	3.3	3.5	3.7
	ii		3.4	3.6	3.8	4
	iii		3.8	4	4.2	4.4
	iv		4.2	4.4	4.6	4.8
	v		4.2	4.4	4.6	4.8
Energy consumption per unit of GDP (tons of standard coal/10^4 yuan)	i	1.86	− 3.4	-4.4	− 2.4	− 2.9
	ii		− 3.1	− 3.1	− 3	− 2.8
	iii		− 4.2	− 4.2	− 4.1	− 3.9
	iv		− 3.9	− 3.9	− 3.8	− 3.6
	v		− 5.3	− 5.3	− 5.2	− 5
			Parameter values			
		2020	2025	2030	2035	2040
Ratio of population aged 15–64 (%)	i	68.55	68.09	67.64	64.54	61.58
	ii/iii/iv/v		69.46	68.22	66.06	63.24
Total energy consumption (10^4 tons of standard coal)	i	498,000	573,134.65	599,713.52	661,872.56	678,535.04
	ii		556,490.50	592,458.72	604,252.58	593,156.32
	iii		525,193.31	528,114.61	508,771.73	471,801.41
	iv		533,468.25	544,887.66	533,192.56	502,213.72
	v		495,725.82	470,514.36	427,874.42	374,587.84

Author contribution The contributions of each author are as follows: conceptualization, Yang Li and Lu Miao; methodology, Shiyu Huang; software, Shiyu Huang; resources, Shiyu Huang; data curation, Zheng Wu; writing—original draft preparation, Yang Li; writing—review and editing, Yang Li and Lu Miao; visualization, Shiyu Huang; supervision, Yang Li and Lu Miao; project administration, Yang Li and Lu Miao; funding acquisition, Yang Li and Miao Lu.

Funding This research received funding from the National Natural Science Foundation of China (No.71804195); Humanities and Social Sciences Youth Foundation, Ministry of Education of the People's Republic of China (No.22YJC790068).

Data availability Not applicable.

Declarations

Ethical approval The manuscript was reviewed and ethical approved for publication by all authors.

Consent to participate The manuscript was reviewed and consents to participate by all authors.

Consent for publication The manuscript was reviewed and consents to publish by all authors.

Competing interests The authors declare no competing interests.

References

Anser MK, Alharthi M, Aziz B, Wasim S (2020) Impact of urbanization, economic growth, and population size on residential carbon emissions in the SAARC countries. Clean Techn Environ Policy 22:923–936. https://doi.org/10.1007/s10098-020-01833-y

Balsalobre-Lorente D, Shahbaz M, Roubaud D, Farhani S (2018) How economic growth, renewable electricity and natural resources contribute to CO2 emissions? Energ Policy 113:356–367. https://doi.org/10.1016/j.enpol.2017.10.050

Brizga J, Feng K, Hubacek K (2013) Drivers of CO2 emissions in the former soviet union: a country level IPAT analysis from 1990 to 2010. Energy 59:743–753. https://doi.org/10.1016/j.energy.2013.07.045

CCTV News (2021) National energy administration: "14th Five-Year Plan" renewable energy development will enter a new phase. https://baijiahao.baidu.com/s?id=1695659936354680498&wfr=spider&for=pc. Accessed 8 Dec 2021

Central People's Government of the People's Republic of China (2020a) Address by Xi Jinping to the general debate of the 75th session of the United Nations General Assembly. http://www.gov.cn/xinwen/2020a-09/22/content_5546169.htm. Accessed 7 Dec 2021

Central People's Government of the People's Republic of China (2020b) Xi Jinping delivers keynote speech at climate ambition summit. http://www.gov.cn/xinwen/2020b-12/13/content_5569136.htm. Accessed 7 Dec 2021

Central People's Government of the People's Republic of China (2021) Decision of the Central Committee of the Communist Party of China State Council on Optimising Fertility Policy for Long-term Balanced Population Development. http://www.gov.cn/zhengce/2021-07/20/content_5626190.htm. Accessed 8 Dec 2021

China Electricity Council (2020) China Electricity Statistical Yearbook. China Statistics Press, Beijing, China

CNPC (2020) World and China Energy Outlook 2050. http://www.360doc.com/content/20/1225/22/33506793_953479378.shtml. Accessed 7 Dec 2021

Dai S, Niu D, Han Y (2018) Forecasting of energy-related CO2 emissions in China based on GM(1,1) and least squares support vector machine optimized by modified shuffled frog leaping algorithm for sustainability. Sustainability 10:958. https://doi.org/10.3390/su10040958

Ding S, Xu N, Ye J et al (2020) Estimating Chinese energy-related CO2 emissions by employing a novel discrete grey prediction model. J Clean Prod 259:120793. https://doi.org/10.1016/j.jclepro.2020.120793

Ding GQ, Guo J, Pueppke SG, Yi JL, Ou MH, Ou WX, Tao Y (2022) The influence of urban form compactness on CO2 emissions and its threshold effect: evidence from cities in China. J Environ Manage 322:116032. https://doi.org/10.1016/j.jenvman.2022.116032

Dong F, Wang Y, Su B, Hua Y, Zhang Y (2019) The process of peak CO2 emissions in developed economies: a perspective of industrialization and urbanization. Resour Conserv Recy 141:61–75. https://doi.org/10.1016/j.resconrec.2018.10.010

Duan HY, Sun XH, Song JN, Xing JH, Yang W (2022) Peaking carbon emissions under a coupled socioeconomic-energy system: evidence from typical developed countries. Resour Conserv Recy 187:106641. https://doi.org/10.1016/j.resconrec.2022.106641

Fang D, Zhang X, Yu Q et al (2018) A novel method for carbon dioxide emission forecasting based on improved Gaussian processes regression. J Clean Prod 173:143–150. https://doi.org/10.1016/j.jclepro.2017.05.102

Fang Y, Lu X, Li H (2021) A random forest-based model for the prediction of construction-stage carbon emissions at the early design stage. J Clean Prod 328:129657. https://doi.org/10.1016/j.jclepr

Gao P, Yue S, Chen H (2021) Carbon emission efficiency of China's industry sectors: from the perspective of embodied carbon emissions. J. Clean. Prod 283:124655. https://doi.org/10.1016/j.jclepro.20

GEIDCO (2021) China's energy and electricity development planning study 2030 and outlook 2060. https://news.bjx.com.cn/html/20210319/1142777.shtml. Accessed 7 Dec 2021

Guo D, Chen H, Long R (2018) Can China fulfill its commitment to reducing carbon dioxide emissions in the Paris Agreement? Analysis based on a back-propagation neural network. Environ Sci Pollut Res 25:27451–27462. https://doi.org/10.1007/s11356-018-2762-z

Hanif I, Gago-de-Santos P (2017) The importance of population control and macroeconomic stability to reducing environmental degradation: an empirical test of the environmental Kuznets curve for developing countries. Environ Dev 23:1–9. https://doi.org/10.1016/j.envdev.2016.12.003

Hong J, Li Y, Cai W (2021) Simulating China's carbon emission peak path under different scenarios based on RICE-LEAP model. Resour Sci 43:639–651 (in Chinese)

Hu Z, Gong X, Liu H (2020) Prediction of household consumption carbon emission in western cities Based on BP model: case of Xi'an city. J Arid Land Resour Environ 34:82–89 (in Chinese)

IEA (2020) International Energy Agency. https://www.iea.org. Accessed 7 Dec 2021

IPCC (2017) Intergovernmental panel on climate change. https://www.ipcc.ch/. Accessed 7 Dec 2021

Jiang J, Ye B, Liu J (2019) Research on the peak of CO2 emissions in the developing world: current progress and future prospect. Appl Energy 235:186–203. https://doi.org/10.1016/j.apenergy.2018.10.089

Jiang M, An H, Gao X (2022) Adjusting the global industrial structure for minimizing global carbon emissions: a network-based multi-objective optimization approach. Sci Total Environ 829:154653. https://doi.org/10.1016/j.scitotenv.2022.154653

José M, Cansino R, Manuel O (2016) Main drivers of changes in CO2 emissions in the Spanish economy: a structural decomposition analysis. Energ Policy 89:150–159. https://doi.org/10.1016/j.enpol.2015.11.020

Li H, Qin Q (2019) Challenges for China's carbon emissions peaking in 2030: a decomposition and decoupling analysis. J Clean Prod 207:857–865. https://doi.org/10.1016/j.jclepro.2018.10.043

Li YM, Zhao R, Liu TS, Zhao JF (2015) Does urbanization lead to more direct and indirect household carbon dioxide emissions? Evidence from China during 1996–2012. J Clean Prod 102:103–114. https://doi.org/10.1016/j.jclepro.2015.04.037

Li F, Xu Z, Ma H (2018) Can China achieve its CO2 emissions peak by 2030? Ecol Indic 84:337–344. https://doi.org/10.1016/j.ecolind.2017.08.048

Lin C-C, He R-X, Liu W-Y (2018) Considering multiple factors to forecast CO2 emissions: a hybrid multivariable grey forecasting and genetic programming approach. Energies 11:3432. https://doi.org/10.3390/en11123432

Liu Z, Jiang P, Wang J, Zhang L (2022) Ensemble system for short term carbon dioxide emissions forecasting based on multi-objective tangent search algorithm. J Environ Manag 302:113951. https://doi.org/10.1016/j.jenvman.2021.113951

Lu WC (2018) The impacts of information and communication technology, energy consumption, financial development, and economic growth on carbon dioxide emissions in 12 Asian countries. Mitig Adapt Strateg Glob Change 23:1351–1365. https://doi.org/10.1007/s11027-018-9787-y

Lu C, Li W, Gao S (2020) Driving determinants and prospective prediction simulations on carbon emissions peak for China's heavy chemical industry. J Clean Prod 251:119642. https://doi.org/10.1016/j.jclepro.2019.119642

Luo Y, Peng J, Ma J (2020) When causal inference meets deep learning. Nat Mach Intell 2:426–427. https://doi.org/10.1038/s42256-020-0218-x

Lv Z, Hu A (2021) China's construction of a modern economic system with green and low - carbon circular development: realization path and practical significance. J Beijing Univ Technol 21:35–43 (in Chinese)

Ma X, Wang C, Dong B et al (2019a) Carbon emissions from energy consumption in China: its measurement and driving factors. Sci Total Environ 648:1411–1420. https://doi.org/10.1016/j.scitotenv.2018.08.183

Ma Z, Cai S, Ye W, Gu A (2019b) Linking emissions trading schemes: economic valuation of a joint China–Japan–Korea carbon market. Sustainability 11:5303. https://doi.org/10.3390/su1119

National Bureau of statistics of the People's Republic of China (2020) China Energy Statistical Yearbook. China Statistics Press, Beijing, China

National Bureau of Statistics of the People's Republic of China (2020) China Statistical Yearbook. China Statistics Press, Beijing, China

National Energy Administration (2016) The 13th Five-Year Plan For Energy Development. http://www.nea.gov.cn/135989417_14846217874961n.pdf. Accessed 8 Dec 2021

NDRC (2016) Outline of the Thirteenth Five-Year Plan for National Economic and Social Development of the People's Republic of China. https://www.ndrc.gov.cn/fggz/fzzlgh/gjfzgh/201605/P020191029595713709470.pdf. Accessed 7 Dec 2021

NDRC, National Energy Administration (2016) The energy production and consumption revolution strategy (2016–2030). http://www.gov.cn/xinwen/2017-04/25/5230568/files/286514af354e41578c57ca38d5c4935b.pdf. Accessed 7 Dec 2021

Nishan AMK, Ashiq M (2020) Role of energy use in the prediction of CO2 emissions and economic growth in India: evidence from artificial neural networks (ANN). Environ Sci Pollut Res 27:23631–23642. https://doi.org/10.1007/s11356-020-08675-7

Niu D, Wang K, Wu J et al (2020) Can China achieve its 2030 carbon emissions commitment? Scenario analysis based on an improved general regression neural network. J Clean Prod 243:118558. https://doi.org/10.1016/j.jclepro.2019.118558

Raza MY, Lin B (2020) Decoupling and mitigation potential analysis of CO2 emissions from Pakistan's transport sector. Sci Total Environ 730:139000. https://doi.org/10.1016/j.scitotenv.2020.139000

Shuai C, Shen L, Jiao L, Wu Y, Tan Y (2017) Identifying key impact factors on carbon emission: evidences from panel and time-series data of 125 countries from 1990 to 2011. Appl Energy 187:310–325. https://doi.org/10.1016/j.apenergy.2016.11.029

Sun W, Liu M (2016) Prediction and analysis of the three major industries and residential consumption CO2 emissions based on least squares support vector machine in China. J Clean Prod 122:144–153. https://doi.org/10.1016/j.jclepro.2016.02.053

Sun W, Ren C (2021) Short-term prediction of carbon emissions based on the EEMD-PSOBP model. Environ Sci Pollut Res 28:56580–56594. https://doi.org/10.1007/s11356-021-14591-1

Sun W, Xu Y (2016) Using a back propagation neural network based on improved particle swarm optimization to study the influential factors of carbon dioxide emissions in Hebei Province, China. J Clean Prod 112:1282–1291. https://doi.org/10.1016/j.jclepro.2015.04.097

Sun W, Wang Y, Zhang C (2018) Forecasting CO2 emissions in Hebei, China, through moth-flame optimization based on the random forest and extreme learning machine. Environ Sci Pollut Res 25:28985–28997. https://doi.org/10.1007/s11356-018-2738-z

Wang Y, Wang Y (2019) Feasibility and optimal pathway of China's double targets for carbon reduction——The perspective of energy structure optimization. China Environ Sci 39:4444–4455 (in Chinese)

Wang S, Zhang N, Wu L, Wang Y (2016) Wind speed forecasting based on the hybrid ensemble empirical mode decomposition and GA-BP neural network method. Renew Energy 94:629–636. https://doi.org/10.1016/j.renene.2016.03.103

Wang Y, Shang P, He L et al (2018) Can China achieve the 2020 and 2030 carbon intensity targets through energy structure adjustment? Energies 11:2721. https://doi.org/10.3390/en11102721

Wang M, Zhu CZ, Cheng Y, Du WB, Dong S (2022a) The influencing factors of carbon emissions in the railway transportation industry based on extended LMDI decomposition method: evidence from the BRIC countries. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-022-23167-6

Wang W, Kao X, Lin Z, Zhang Y (2022b) Has China's coal consumption really peaked?—Prediction and scenario analysis of China's coal consumption peak under the double-carbon target. Front Environ Sci 10:974763. https://doi.org/10.3389/fenvs.2022.974763

Wei S, Yuwei W, Chongchong Z (2018) Forecasting CO2 emissions in Hebei, China, through moth-flame optimization based on the random forest and extreme learning machine. Environ Sci Pollut Res 25:28985–28997. https://doi.org/10.1007/s11356-018-2738-z

Wen L, Yuan X (2020) Forecasting CO2 emissions in Chinas commercial department, through BP neural network based on random forest and PSO. Sci Total Environ 718:137194. https://doi.org/10.1016/j.scitotenv.2020.137194

Xie Z, Wu R, Wang S (2021) How technological progress affects the carbon emission efficiency? Evidence from national panel quantile regression. J Clean Prod 307:127133. https://doi.org/10.1016/j.jclepro.2021.127133

Xu G, Schwarz P, Yang H (2019) Determining China's CO2 emissions peak with a dynamic nonlinear artificial neural network approach and scenario analysis. Energy Policy 128:752–762. https://doi.org/10.1016/j.enpol.2019.01.058

Yan Z, Li W, Yan T, Wang J (2018) Application and validity of BP neural networks on prediction of carbon emissions from corn production in Hexi Oasis. Chin J Eco-Agric 26:1100–1106 (in Chinese)

Yang G (2021) China's population changes and major transition during the 14th Five-Year Plan Period. J Beijing Univ Technol Soc Sci Ed 21:17–29 (in Chinese)

Yao C, Feng K, Hubacek K (2015) Driving forces of CO2 emissions in the G20 countries: an index decomposition analysis from 1971 to 2010. Ecol Inf 26:93–100. https://doi.org/10.1016/j.ecoinf.2014.02.003

Ye T, Zhao N, Yang X et al (2019) Improved population mapping for China using remotely sensed and points-of-interest data within a random forests model. Sci Total Environ 658:936–946. https://doi.org/10.1016/j.scitotenv.2018.12.276

Zhang X, Zhai Z, Tao T (2020) Trends and patterns of negative population growth in China. Popul Res 44:3–20 (in Chinese)

Zhao B, Sun L, Qin L (2022) Optimization of China's provincial carbon emission transfer structure under the dual constraints of economic development and emission reduction goals. Environ Sci Pollut Res 29:50335–50351. https://doi.org/10.1007/s11356-022-19288-7

Zhu C, Du W (2019) A research on driving factors of carbon emissions of road transportation industry in Six Asia-Pacific Countries based on the LMDI decomposition method. Energies 12:4152. https://doi.org/10.3390/en12214152

Zhu Q, Peng X (2012) The impacts of population change on carbon emissions in China during 1978–2008. Environ Impact Assess Rev 36:1–8. https://doi.org/10.1016/j.eiar.2012.03.003

Zhu H, Zheng J, Zhao Q, Kou D (2020) Economic growth, energy structure transformation and carbon dioxide emission —empirical analysis based on panel data. Res Econ Manag 41:19–34 (in Chinese)