Heliyon 10 (2024) e38883

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Research on the prediction and realization path of urban carbon peak along the Yellow River Basin

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ARTICLE INFO

Keywords:
Cities along the Yellow River basin
Carbon peak
Carbon emission prediction
Machine learning fusion model

ABSTRACT

China and the international community attach great importance to sustainable development goals such as peaking carbon emissions. As an important energy base in China, the Yellow River Basin has significant capacity for reducing carbon emissions and increasing carbon sinks. To accelerate the achievement of carbon peak targets, social and natural development data as well as carbon emission data of 56 cities along the Yellow River Basin from 2000 to 2021 were analyzed. Based on the evaluation indicators of the model, the PSO-XGBoost-RF model was selected from the comparative models to predict the carbon peak of cities in the Yellow River Basin under different paths. Under the current economic and social development, cities along the Yellow River Basin in China are facing huge pressure to reduce emissions. It is expected to achieve a carbon peak in 2033, with a peak of 2,051,320,000 tons, so the target of reaching the peak of carbon emissions before 2030 will not be accomplished. But through comprehensive optimization of the industrial structure and reduction of energy consumption, cities along the Yellow River Basin as a whole may achieve carbon peak by 2026, with a peak of 1,917,132,000 tons.

1. Introduction

With the increasingly severe global climate change, low-carbon development has become a major issue of concern to the international community. In recent years, China has been committed to promoting the construction of a cooperative, win-win, fair and reasonable global climate governance system, making tangible contributions to advocating global green development and maintaining ecological security. Regional low-carbon transformation is not only related to the quality of its own development, but also a key link in achieving global climate governance goals. In the process of regional low-carbon development, China also attaches great importance to the development and management of cross basin areas, and has proposed a national strategy for ecological protection and high-quality development in the Yellow River Basin. The Outline of the Plan for Ecological Protection and High-Quality Development of the Yellow River Basin points out that the realization of the "dual carbon"(Carbon Peak and Carbon Neutrality)goal in the Yellow River Basin has a strong impetus and significance for China to achieve the goals of carbon peak by 2030 and carbon neutrality by 2060. Promoting the realization of the "dual carbon" goal in the region is an effective path to guide high-quality economic development, and it is also a landmark achievement to highlight cross-regional coordinated development. Therefore, predicting the carbon peak in the Yellow River Basin is of particular importance. Under the new situation, strengthening the ecological environmental protection of the Yellow River Basin and boosting the high-quality development of the Yellow River Basin are both emphasized. At the same time, we can provide a

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https://doi.org/10.1016/j.heliyon.2024.e38883
Received 27 March 2024; Received in revised form 13 September 2024; Accepted 1 October 2024
Available online 3 October 2024
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scientific reference and basis for the proposal of low-carbon emission reduction policies to stimulate the endogenous power of energy conservation, consumption reduction and emission reduction through the comparison of carbon peak time under different path settings. As a result, promote the realization of the national carbon peak and carbon neutrality goal with the important link of carbon peak in the Yellow River Basin.

When studying carbon emissions, it is crucial to investigate the influential factors that contribute to carbon emissions. This research provides a practical foundation and viable approach for controlling and reducing carbon dioxide emissions. By combing the literature, the relevant factors that impact carbon emissions are identified and listed.

Economic growth is a key factor affecting carbon dioxide emissions. Narayan et al. [1] investigated the dynamic relationship between economic growth and carbon dioxide in 181 countries around the world, and concluded that nearly 10 % of the relationship between national income and carbon emissions meets the environmental Kuznets curve (EKC) assumption based on a new method of cross-correlation estimation. Under the background of high-quality, sustainable economic development requirements and the "dual carbon" goal, green finance and green investment have emerged, and green investment, an indicator to measure economic development, can stimulate economic growth and promote the occurrence of carbon emission reduction effects. Lyeonov et al. [2] used the panel unit root test, panel cointegration test, completely modified least squares method and dynamic least squares method to study the relationship among per capita domestic GDP, green investment and carbon emissions in EU countries. The results show that green investment can boost economic growth which is represented by GDP per capita, while reducing greenhouse gas emissions.

Industrial structure upgrading and energy consumption structures also have a significant impact on carbon emissions. China's industrial layout needs to be adjusted and transformed urgently, and the economy needs to be transformed and upgraded. The industrial structure and energy consumption structure can also serve as indicators of economic development. Yang et al. [3] conducted an empirical study using China's data from 2000 to 2017 to examine the logical relationship among industrial structure upgrading, improvement in green total factor productivity, and reduction in carbon emissions.The rationalization of industrial structure constrains carbon emissions. Liu et al. [4] used the SBM model to analyze China's provincial CO_2 emission efficiency and energy consumption structure, and used K-means cluster analysis to divide China into five groups according to energy consumption structure.The results showed that environmental pollution can be improved by guiding the consumption structure.

Zhou et al. [5] has studied and analyzed the 30-year data of RCEP countries from the perspective of economic globalization and classified energy, which further highlights the close relationship among economic globalization growth, renewable energy use and carbon emissions. Luo et al. [6] used a composite prediction model as a bridge and validated the necessity of energy structure adjustment, promotion of clean and renewable energy, carbon emission control, and industrial structure optimization with a focus on developing the tertiary industry using DEA methods.

The analysis of the influencing factors of carbon dioxide emissions has certain practical guiding significance for the selection of path indicators for carbon peak prediction and for China's future low-carbon emission reduction and sustainable development. Many experts and scholars are committed to carbon emission calculations and the creation of prediction models, including the Kaya model [7], the computable general equilibriummodel(CGE) [8], the production function theory [9], the logarithmicmean square index method (LMDI) [10], and other carbon emission calculation and prediction models [11].In addition to different studies using different models, there are also studies using a combination of algorithms and models to improve the prediction accuracy. Different scholars use different theoretical methods and assumptions to predict carbon emissions, and the differences of results are within the range of reasonable estimates. The most commonly used model methods for carbon peak prediction include the STIRPAT model (expandable random environmental impact assessment model) and its combination with scenario analysis [12–17], the LEAP model (long-term energy substitution planning model) and its combination with scenario analysis [18–20], multi-objective optimization model [21], machine learning methods [22] and so on.

Among them, machine learning is a form of predictive analysis, which is forward-looking, autonomous decision-making. Mardani et al. [23] used an auto-organizing mapping clustering algorithm to cluster data, and then used an adaptive neural fuzzy inference system and artificial neural network to construct a prediction model in clustering, and developed a multi-stage method to predict carbon emissions. Zhao et al. [24] proposed a new machine learning prediction model. Namely the long short-term memory network optimized by a sparrow search algorithm is applied to the carbon emission prediction in the Yellow River Basin. Compared with the single long short-term memory network model, its average absolute percentage error is reduced by nearly 50 %.Compared with traditional prediction models, composite machine learning models have better approximation performance, faster calculation speed, no need to establish mathematical models, high accuracy, solid theoretical basis, rigorous derivation process, and strong non-linear fitting ability [25].From the above articles related to machine learning and carbon peak prediction, we can see the advantages of machine learning fusion models in predicting carbon emissions. However, nowadays, machine learning fusion models are rarely used for carbon emission prediction. This article innovates feasible carbon emission prediction methods and provides relevant policy recommendations for achieving carbon peak in the Yellow River Basin. Translated from the articles related to machine learning and carbon peak prediction mentioned above, we can see the advantages of machine learning fusion models in predicting carbon emissions. However, nowadays, machine learning fusion models are rarely used for carbon emission prediction. This article innovates feasible carbon emission prediction methods and further provides relevant policy recommendations for the Yellow River Basin to achieve carbon peak.

Based on the above analysis, this paper constructs a composite ensemble model in the Yellow River Basin, namely PSO (Particle Swarm Algorithm)-XgBoost (Extreme Gradient Boosting Tree)-RF (Random Forest) model to predict carbon emissions through the city-level data of the Yellow River Basin.The city data of the Yellow River Basin is selected as the carrier for prediction model training to predictthe carbon peak of the Yellow River Basin. The parameters in the XGBoost model and the RF model are optimized separately using the particle swarm optimization algorithm, which improves the prediction effect of the two base models. In addition, the stacking ensemble method is used to combine the two base models of the RF model running in parallel and the XGBoost model running serially, and the results of the two base models are retrained through a meta-model to further improve the final prediction effect. And it improves the accuracy of prediction by accurately extracting features and combining model algorithms. In addition to the advantages of the model, the content innovation has the following one points. We use city-level data in the Yellow River Basin to construct the model and test to find out the optimization in the process of using machine learning algorithms. Most of the existing articles use national or provincial-level data for model construction and prediction analysis, and rarely use city-level datasets.

In summary, this study further validates the impact of factors such as population, industrial structure, and energy on carbon emissions using an innovative machine learning fusion model; At the same time, combined with path prediction, it provides more theoretical and practical prediction data, feasible emission recommendations, and low-carbon development directions for cities along the Yellow River Basin than traditional prediction methods. This study creates more innovative methods for predicting carbon peak and carbon neutrality, and helps China achieve its "dual carbon" goals, and alleviates and solves environmental pressures and problems for the world.

2. Study areas and data sources

2.1. Research areas

According to the official standard data of the State Administration of Cultural Heritage, and the Yellow River Basin and Administrative Plan in 2023, the Yellow River Basin flows through nine provincial-level administrative units (provinces and autonomous regions) and 69 prefecture-level administrative units (prefecture-level cities, regions, autonomous prefectures, and leagues). However, due to the availability of data and the excessive number of missing values in individual regions, 14 cities are excluded in this paper. The statistical data of social and economic environmental indicators of the remaining 56 cities flowing through the Yellow River Basin from 2001 to 2021 are selected as the research objects to predict the carbon peak time and carbon emission peak in the region, which provides a path option for China and the Yellow River Basin to achieve carbon peak as soon as possible.

2.2. Data sources

The dataset contains a total of 1233 pieces of data, which is composed of 22 years of data from 2000 to 2021 for 56 cities, and the data are from the China City Statistical Yearbook, China Energy Statistical Yearbook, China Carbon Accounting Database, and Provincial Statistical Bulletins. According to the comprehensive description in the literature review and the combing of multiple documents [26], the data of each city are selected from 12 influencing factors such as energy consumption and registered population, and so on. For the initialization of the dataset, it is necessary to interpolate the missing values that cannot be obtained through the statistical yearbook and statistical bulletin in the data set, and eliminate the outliers.Due to the different magnitude units and large differences among each factor index, the training process will be greatly affected in the process of model training and prediction, which makes the final prediction results deviate.So this paper needs to standardize the dataset before model training to eliminate the influence of magnitude units and to improve the prediction efficiency of the model.

3. Research methodology

3.1. Particle swarm (PSO) algorithm

In particle swarm optimization, the problem is represented as finding an optimal solution in the solution space, just like a flock of birds trying to find the most suitable location for their survival.

Specifically, the steps of the particle swarm algorithm are as follows: First, initialize the particles: randomly generate a group of particles, and each particle has its initial position and velocity. Second, assess fitness: calculate the fitness of each particle, which is the value of the objective function of the problem. Third, update the individual optimal solution and update the global optimal solution simultaneously: compare the fitness of each particle's current position with the fitness of its individual best solution. If the current position is better, the individual optimal solution will be updated. Compare the individual optimal solutions of all particles to select the solution with the best global fitness as the global optimal solution. Fourth, update particle velocity and position: update the velocity and position of particles based on individual and global optimal solutions. This involves two important parameters, namely the learning factor and the inertia weight. Finally, repeat steps 2 through 4 until the stopping conditions are met, such as reaching a predetermined number of iterations or finding a satisfactory solution within a specified range.

Overall, the key point of particle swarm optimization is to guide the movement of particles through information about individual and global optimal solutions, so that they are more likely to arrive at the optimal solution.

3.2. XGBoost algorithm

XGBoost is extensively utilized for tackling classification and regression problems.It is an enhancement on the Gradient Boosting Decision Tree (GBDT) algorithm within the Boosting framework.This means that XGBoost can build a strong learner by combining multiple weak learners. At the same time, in each iteration, the new learner is fitted by calculating the negative gradient of the loss function. That is to say, by iteratively adding the tree model,in each iteration, the model introduces a new weak learner for fitting according to the training residuals of the current model to find a better fit and finally adds to obtain the final predicted value, so that it can perform well when approaching the complex relationship and improve the performance of the model. The sum of the final predicted values reflects that XGBoost is a parallelization algorithm, especially when the dataset is large, it can effectively parallel processing and accelerate the training process, which makes XGBoost a powerful tool for processing large-scale datasets.

The expression of the prediction function of the XGBoost model for the i-th sample is shown in equation (1):

$$\widehat{y}_i^{(t)} = \sum_{j=1}^{t} w_{ij} \tag{1}$$

$\widehat{y}_i^{(t)}$ represents the prediction result of sample i after the t-th iteration, w_{ij} is the weight of the decision tree leaf node, and t is the number of iterations of the decision tree.

The training process is implemented by optimizing the objective function which includes a loss function and a regularization term. The following is the expression formula for the objective function:

$$OBJ^{(t)} = \sum_{i=1}^{n} l\left(y_i, \widehat{y}_i^{(t)}\right) + \sum_{j=1}^{t} \Omega(f_i) \tag{2}$$

In the formula, $\sum_{i=1}^{n} l\left(y_i, \widehat{y}_i^{(t)}\right)$ represents the loss function which is generally the mean square deviation function. $\sum_{j=1}^{t} \Omega(f_i)$ is the sum of the complexity of t trees.

If the objective function is quadratically expanded according to Taylor's formula, the objective function can be rewritten as follows:

$$OBJ^{(t)} = \sum_{i=1}^{n} \left[l\left(y_i, \widehat{y}_i^{(t-1)}\right) + g_i f_i(x_i) + \frac{1}{2} h_i f_i^2(x_i) \right] + \sum_{j=1}^{t} \Omega(f_i) \tag{3}$$

$\widehat{y}_i^{(t-1)}$ is the predicted value of the i-th sample in the previous t-1 trees, and $f_i(x_i)$ is the score of the i-th sample in the t-th tree. g_i、 h_i is the first and second derivative of the loss function to the model.

The sum of the complexity of all the decision trees is the regularization term, which is as follows:

$$\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \sum_{K}^{T} w_k^2 \tag{4}$$

Where T is the number of leaf nodes, γ is the penalty term of its number, w_k represents the weight of leaf nodes, and λ is the regular penalty term of L_2. Increasing the penalty for leaves with larger node scores by $\lambda \sum_{K}^{T} w_k^2$ maintains generalization ability, which is also one of the purposes of the XGBoost algorithm.

From the above equation, we can get the complexity function $\sum_{j=1}^{t} \Omega\left(f_j\right)$:

$$\sum_{j=1}^{t} \Omega\left(f_j\right) = \Omega(f_t) + con = \gamma T + \frac{1}{2} \lambda \sum_{K}^{T} w_k^2 + con \tag{5}$$

Where con is a constant.

When considering the optimization function, the loss function is a fixed value. Since neither it nor the constant con has any effect on the optimization process, the objective function can be written after t iterations as follows:

$$OBJ^{(t)} = \sum_{i=1}^{n} \left[g_i f_i(x_i) + \frac{1}{2} h_i f_i^2(x_i) \right] + \gamma T + \frac{1}{2} \lambda \sum_{K}^{T} w_k^2 \tag{6}$$

In the XGBoost algorithm, we need to establish a decision system to predict the overall carbon emissions of cities along the Yellow River Basin to obtain the real carbon emission values called a. Firstly, a decision tree 1 is established based on the selected carbon emission influencing factors. At this point, the prediction is b, and a residual value is obtained, which is a-b. To improve accuracy, an additional tree can be added to the decision system, denoted as Tree 2. Tree 2 is designed to compensate for the residuals in the previous tree. Assuming its prediction result is c, the overall residual value is (a-b) – c. The goal of XGBoost is to find and optimize this objective function through f, so that the final result is small enough. And the actual output carbon emission prediction value of the model is the results of several tree predictions.

3.3. Random forest (RF) algorithm

Random forest, an ensemble learning algorithm, is characterized by a randomly selected training data set returned and Bagging idea. Its core idea is to improve the robustness and generalization performance of the model by constructing multiple weak classifiers—decision trees, and integrating them. For regression problems, the mean method is used to obtain the predicted value. For classification issues, the voting method is used to select the final classification category based on the highest number of votes.The specific formula is expressed as follows:

$$\text{Regression Issues}: \hat{y}_{ensemble} = average(\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_n) \tag{7}$$

$$\text{Classification Questions}: \hat{y}_{ensemble} = majorityVote(\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_n) \tag{8}$$

Among them, $\hat{y}_{ensemble}$ is the final prediction of the random forest, and $\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_n$ is the prediction of each individual decision tree. Where $\hat{y}_i = f(x_i), i = 1, 2\cdots n$, x_i is the input feature, and f is a function of the decision tree.

In the random forest algorithm, it belongs to the regression problem, where the predicted result is the carbon emissions of cities along the route, and the input features are the influencing factors related to carbon emissions that we select (see Table 1).

4. Results and discussion

4.1. Carbon emission prediction based on the PSO-XGBoost-RF model

4.1.1. Correlation of influencing factors of carbon emissions

Through literature review and referencing multiple articles by scholars such as Zhao et al. [27], we select the following twelve influencing factor indicators related to carbon emissions, and use Pearson correlation analysis to measure the correlation and direction trend between the two.With the help of Pearson correlation analysis tool, we rank the correlation coefficients of the carbon emission influencing factors with carbon emissions according to their absolute magnitude. The specific values are shown in Table 2.

Based on the absolute correlation values, the sorting order is as follows: registered population, energy consumption, average wage of employed individuals, GDP, proportion of workers in the primary industry, population density, total import and export value, built-up area, proportion of the service industry in GDP, proportion of the manufacturing industry in GDP, fixed asset investment, and urbanization rate. Among them, the proportion of employees in the primary industry and the proportion of the tertiary industry in the GDP are negatively correlated with carbon dioxide emissions.

4.1.2. Model parameter optimization

By verifying various tree structure models such as vector regression (SVR), K-nearest neighbor regression, decision tree regression (DT), neural network (BP) model,RF-XGBoost and gradient boosting decision tree (GBDT), the tree structure model RF and XGBoost with better prediction effect are finally selected as the basic model of the hybrid model in this paper. Since the tree structure model contains many parameters that have a significant impact on the prediction effect of the model, this paper optimizes the three important parameters by the particle swarm optimization algorithm with strong global optimization ability. The parameters are the number of decision trees, the maximum depth and the maximum number of nodes.Finally,the optimal parameters of the two basic models are obtained as shown in Table 3.

4.1.3. Segmentation of the datasets

In this paper, the data set is divided into training set and test set according to the general allocation ratio of traditional machine learning 8:2.In order to ensure the stability and effectiveness of the model, we select the data of 2005, 2010, 2015 and 2020 from the 22 years of data in each city and merged as the test set, and used the rest of the data as the training set for training the model.

4.1.4. Experimental results and analysis

In order to verify the superiority and stability of the hybrid model PSO-XGBoost-RF in carbon emission prediction and achieve accurate results in the prediction of carbon peaking in the following paper, a total of 7 different models, including PSO-RF-XGB, RF-XGB, RF, XGB, GBDT, DT, BP, etc., are selected in this part to compare and analyze the prediction effects, and the fitting effect of each model is shown in Fig. 1, and the evaluation index results are shown in Table 4.

Firstly, we verify the effect of adding the particle swarm algorithm by horizontal comparison, and compare and analyze the results of the PSO-RF-XGB model and the RF-XGB model.The comparison chart of the fitting effect is shown in 1.It can be seen from the

Table 1
Provincial cities in the study area.

Province	City
Gansu Province	Lanzhou City, Baiyin City, Tianshui City, Wuwei City, Pingliang City, Qingyang City, Dingxi City, Longnan City
Ningxia Hui Autonomous Region	Yinchuan City, Shizuishan City, Wuzhong City, Guyuan City, Zhongwei City
Inner Mongolia Autonomous Region	Hohhot City, Baotou City, Ulanqab City, Ordos City, Bayannur City, Wuhai City
Shaanxi Province	Xi'an City, Tongchuan City, Baoji City, Xianyang City, Weinan City, Yan'an City, Yulin City, Shangluo City
Shandong Province	Jinan City, Zibo City, Dongying City, Jining City, Tai'an City, Dezhou City, Liaocheng City, Binzhou City, Heze City
Shanxi Province	Taiyuan City, Datong City, Yangquan City, Changzhi City, Jincheng City, Shuozhou City, Jinzhong City, Yuncheng City, Xinzhou City, Linfen City, Luliang City
Henan Province	Zhengzhou City, Kaifeng City, Luoyang City, Anyang City, Xinxiang City, Jiaozuo City, Puyang City, Sanmenxia City
Qinghai Province	Xining City,

Table 2
Correlation coefficient of factors influencing carbon emissions.

Emission influencing factors	Correlation
Registered population (10,000 people)	0.377
Energy consumption (10,000 tons of standard coal)	0.367
The average salary of on-the-job workers (RMB)	0.362
GDP for the year (100 million yuan)	0.333
Population density (per square kilometer per person)	0.234
Total import and export value (10,000 yuan)	0.200
Built-up area (sq km)	0.177
The secondary sector accounted of GDP	0.126
Investment in fixed assets	0.096
The urbanization rate	0.022
The share of the tertiary sector in GDP	−0.149
Employees in the primary industry	−0.322

Table 3
Optimal parameter values of the basic model.

	The number of the decision tree	the maximum depth	the maximum number of features
RF	115	7	9
XGBoost	130	9	8

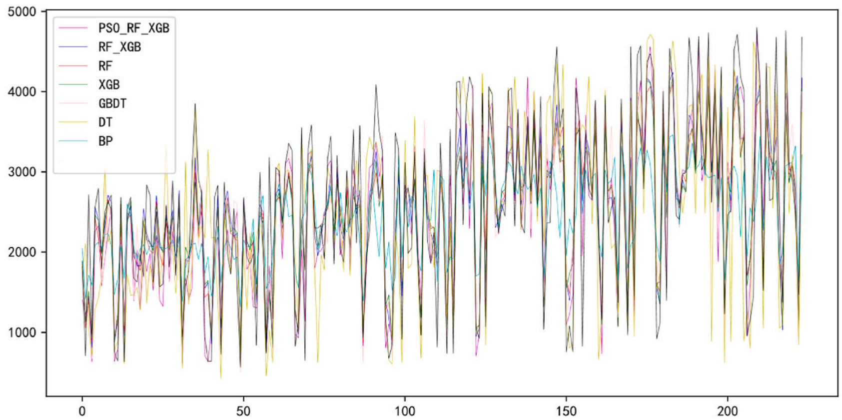

Fig. 1. Comparison of the prediction effect of each model.

Table 4
Results of evaluation indicators.

	R^2	MAE	RMSE
PSO-RF-XGB	0.872	311.5	419.8
RF-XGB	0.824	342.8	447.5
RF	0.786	369.9	465.8
XGB	0.795	360.3	460.2
GBDT	0.768	389.7	491.3
DT	0.567	509.9	761.1
BP	0.479	670.8	846.5

evaluation index results that the fitting degree R^2 of the PSO-RF-XGB model after the optimization parameters of the particle swarm optimization algorithm increased from 82.4 % to 87.2 %, an increase of nearly 5 %, the value of MAE (Mean Square Error) decreased from 342.8 to 311.5, a decrease of 9.13 %, and the RMSE (Root Mean Square Error) index decreased from 447.5 to 419.8, a decrease of 6.19 %, which verified the improvement effect of the particle swarm optimization algorithm on the hybrid model RF-XGB. Then, we perform the longitudinal comparison analysis between the models. It can be seen from the evaluation index results that the prediction effect of the BP neural network model is the worst among all models, with a fitting degree of only 47.9 %, which is 40 % lower than the PSO-XGBoost-RF model constructed in this paper. So BP neural network model is not suitable for carbon emission prediction. The DT model is a decision tree model, which is a sub-model of the basic model RF, XGB, GBDT and other models used in this paper.The performance of the DTM model is better than that of the neural network model in carbon emission prediction, with a fitting degree of 56.7 %.But because the single decision tree model is so susceptible to the influence of extreme values and outliers that it cannot well handle the data of multiple feature indicators, it cannot be well used in the prediction of carbon emission data compared with the tree structure model RF, XGB and GBDT composed of multiple decision trees. RF, XGB, GBDT and other models are composed of multiple single decision tree models, which are not easily affected by extreme values and outliers in the carbon emission data of multi-feature indicators, and the prediction results are better. XGBoost model and GBDT model are both serial structure models. Because XGBoost model adds coefficient penalty term on the basis of GBDT model, compared with GBDT model, the prediction performance is better. From the evaluation index results, it can also be seen that the XGBoost model in the degree of fitting compared with the GBDT model has an increase of 2.7 %, and MAE value and RMSE value also have 7 % and 6 % improvement. Therefore, this paper selects the RF model and the XGBoost model as the basic model to further improve the prediction effect of the model on carbon emission data through the stacking integration idea. After integrating the models, the prediction performance of the RF-XGB model has shown a significant enhancement. As can be seen from the fitting effect Fig. 2, the RF-XGB model has the highest fitting degree and the best following effect compared with other models.It can be seen from the evaluation index results, the MAE value and RMSE value of the error evaluation index of the RF-XGB model are the lowest among all models, and R^2 value reached 82.4 %, which is highest among all of models. This verifies the good prediction effect of the hybrid model RF-XGB constructed in this paper in predicting carbon emissions.Through a series of vertical and horizontal comparative analysis, it is proved that the hybrid model RF-XGB has good performance in predicting carbon emission data and the prediction effect of the hybrid model RF-XGB is further improved after adding the particle swarm PSO algorithm. Therefore, this paper uses the PSO-XGBoost-RF model as the final prediction model, which will be used in the next part to predict the carbon peak under different paths (see Fig. 3).

4.2. *Prediction of carbon peaking in cities along the Yellow River Basin based on different path settings*

4.2.1. *Influencing factor rate of change settings*

With the world's largest population, China has consistently maintained positive population growth. Nevertheless, according to the National Bureau of Statistics website, factors like a continual reduction in the population of women of childbearing age have led to a minor decrease in fertility rates, which causes a slowdown in China's population growth. From 2010 to 2020, China's average annual population growth rate was 0.53 %, which represents a decrease compared with the average annual population growth rate of 0.57 per cent from 2000 to 2010. *The National Population Development Plan* issued by the State Council predicts that the Chinese population will peak in 2030. At the same time, Wang et al. [28] and many other scholars believe that the Chinese population will enter negative growth around 2030.

According to the data of the seventh national population census (2020) in China, there are 1.412 billion people in China. Scholars such as Zhang [29] predict that the population growth will peak at 1.418 billion in 2027 and reach 1.333 billion by 2050 under the negative growth era of China 's population pattern. The total population growth will reach 1.426 billion in 2032 and 1.374 billion by 2050 under the high plan.

Based on this, the growth rate of the population size is set as shown in Table 5.

China's economic growth rate is among the highest in the world's economies and its economic scale continuously holds the second position in the world, playing a vital role in driving global economic growth (see Table 6). The country's economy is transitioning from high-speed expansion to high-quality development. China's GDP growth rate decreased year by year from 2010 to 2020.From a medium and long-term perspective, China's economic growth rate will show a wave-shaped slow decline, but the total volume of the economy will rise year by year. During the 13th Five-Year Plan period, China's economy basically maintained a steady and rapid growth trend.

Chen et al. [30] pointed out that China's economy has basically maintained a stable and rapid growth trend during the 13th Five-Year Plan period. It is anticipated that during the 2020s, China's economic growth rate will enter the "5 era," with an average

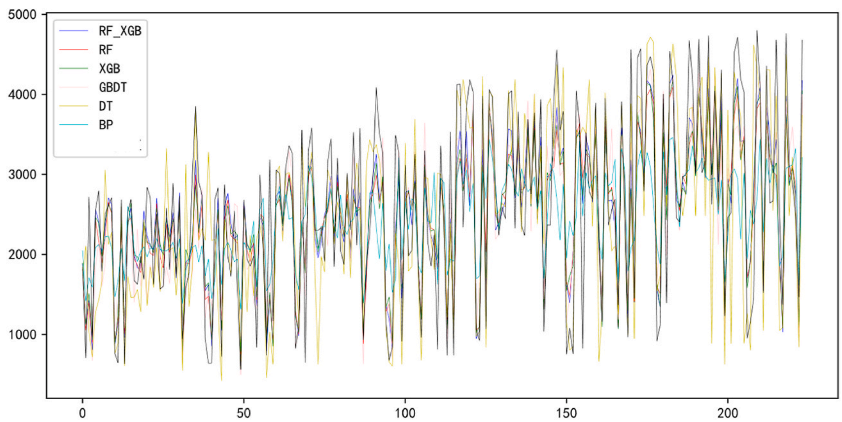

Fig. 2. Comparison of the prediction results of the RF-XGB model with other single models.

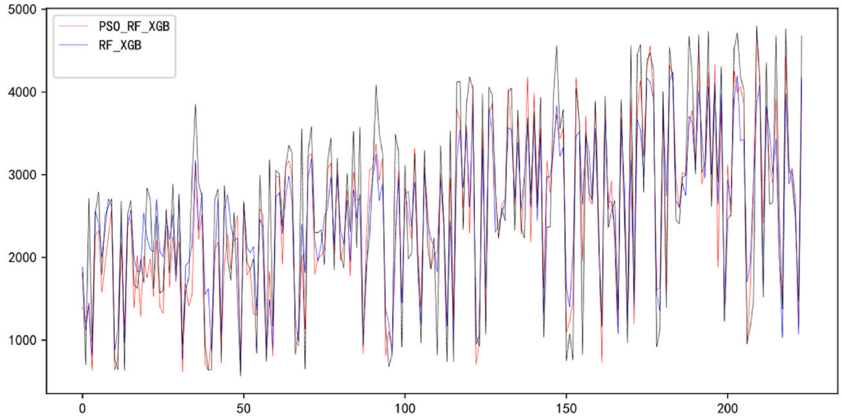

Fig. 3. Comparison of the prediction results of the PSO-RF-XGB model and the RF-XGB model.

Table 5
The limited value of population growth rate.

	Growth rate	2021–2025	2026–2030	2031–2035	2036–2040
Population size	quick	0.099 %	0.099 %	−0.18 %	−0.18 %
	medium	0.085 %	−0.24 %	−0.24 %	−0.24 %

Table 6
Setting values for economic growth rate.

	Growth rate	2021–2025	2026–2030	2031–2035	2036–2040
GDP	medium	5.7 %	5.1 %	4.4 %	4.2 %
	quick	6 %	5.5 %	4.9 %	4.7 %

annual growth rate of approximately 5.3 %.And in the 2030s, China's economic growth rate will enter the "4 era" - the average growth rate is likely to be about 4.4 %. This serves as a reference point for economic growth, upon which the economic growth rate is determined.

Reasonable control of total energy consumption is one of the important measures to achieve carbon peaking. And accelerating the reduction of total energy consumption helps to reduce carbon emissions and promote green development. According to *the Energy Economy Forecast and Prospect Research Report*, it is predicted that during the "14th Five-Year Plan" period, China's energy consumption will grow at an average annual rate of about 2 %, which will be regarded as the growth rate of energy consumption at a medium rate. As a result, the average annual increase will reachabout 100 million tons of standard coal, and the total energy consumption can be controlled at 5.5 billion tons of standard coal. And the scale of non-fossil energy will continue to increase significantly, and fossil energy consumption is expected to be close to the peak. Based on the above references, the energy consumption growth rate is set as Table 7.

Urbanization is not only the country's inevitable paths of modernization but also a significant driving force for China's economic development in the future. *The Green Paper on Population and Labor: Report on Chinese Population and Labor Issues No. 22* released by the Institute of Population and Labor Economics of the Chinese Academy of Social Sciences predicts that China will have an "inflection point" of urbanization from high-speed advancement to gradual slowdown during the 14th Five-Year Plan period. After 2035, it will enter a relatively stable development stage, and the peak of China 's urbanization rate will probably occur at 75 %–80 %. Referring to Ouyang et al. [31] on the prediction of the change trend of urbanization rate, it is predicted that the average annual growth rate of China's urbanization rate will remain at about 0.71 percentage points during the 14th Five-Year Plan period, which is gradually slowing down compared with the growth trend before the 14th Five-Year Plan period. Based on this, this paper sets the average annual growth rate of China's urbanization rate at 0.71 % during the 14th Five-Year Plan period.The growth rate of urbanization rate is set as shown in Table 8.

Table 7
Set values for the growth rate of energy consumption.

	Growth rate	2021–2025	2026–2030	2031–2035	2036–2040
Energy Consumption	medium	2 %	1.9 %	1.7 %	1.4 %
	slow	1.6 %	1.5 %	1.3 %	1 %

According to *the Medium and Long-term Goals, Strategies and Paths of China's Economic and Social Development,* the share of China's service sector in the economy is expected to keep rising, which is the key to the overall transformation and upgrading of China's economy. The growth and decrease rates of the share of the secondary and tertiary industries are determined according to the forecasts presented earlier in a reference scenario, as specified in Table 9.

According to *the China Labor Statistics Yearbook*, the proportion of employment growth in the three major industries in 2011 and 2021, as well as the existing average growth rate of cities along the Yellow River Basin,the growth rate of employees in the primary industry is set.

The average salary of on-the-job employees indicates the level of income of on-the-job employees in a certain period. According to the National Bureau of Statistics, the average wage level of employed persons in the country maintained growth in 2022, but the growth rate declined. Income level is an important factor affecting carbon dioxide.Low-income areas tend to increase carbon emissions to drive economic development, and curbing carbon dioxide emissions in high-income areas is an effective way to achieve carbon dioxide emission reduction (see Table 10).

The average wage growth rate based on the benchmark rate is set in Table 11.

Population density is an important indicator of the distribution of population in a country or region (see Table 12). The population density growth rate is calculated and set based on the existing data.

The growth rate of the built-up area (square kilometers), municipal districts, fixed asset investment (10,000 yuan), the whole city and the total value of foreign trade-import and export (10,000 yuan) is calculated and set through the existing data of cities along the Yellow River Basin.

It should be noted that the growth rate setting values of the above indicators are based on the overall situation in China.For the convenience of research, this paper assumes that the growth rate setting values of the above indicators in cities along the Yellow River Basin are consistent with the overall situation in China.

4.2.2. Path setting

The path selection categorizes twelve influencing factor indicators into four categories: energy, economy, industrial structure, and population. The four classification methods and a single path all have more or less impact on carbon emissions, which is also reflected in the previous literature review [28–31]. Based on the results of carbon emission prediction under different paths, relevant suggestions and opinions are proposed for different fields or development aspects (see Table 13).

The path setting is shown in Table 14.

4.2.3. Prediction results and analysis of carbon peaking under the path setting

Based on the PSO-XGBoost-RF carbon emission prediction model, the carbon emission peak before 2035 is predicted according to the set growth rate of influencing factors and six different pathways with different combinations of factors. The carbon emission prediction results under each path are shown in Fig. 4and Table 15.

We compare and analyze the carbon emission prediction results from Fig. 4 and Table 15. Under different path settings, there are slight differences in the peak and realization of carbon emissions in cities along the Yellow River Basin. From the graph, it can be seen that under the scenarios of economic growth and social population growth, the graph does not show the form of a quadratic function, and there is no peak, that is, carbon emissions have not reached their peak before 2035. Summarize and organize the peak time and peak value of the other four paths, as shown in Table 15.

Cities along the Yellow River Basin in China are under immense pressure to reduce emissions due to the current economic and social development situation. By 2033, carbon emissions will peak at 2051.32 million tons. Given the goal of sustaining rapid economic and social population growth, it may be impossible to reach the carbon peak before 2035, implying that economic and population expansion will postpone carbon peaking.Under the optimization of industrial structure, reduction of energy consumption, and combination path, it becomes feasible to achieve the carbon peak target before 2030, and the time is advanced in turn, with peaks in 2031 and 2029, and peaks of 2019.795 million tons and 1980.835 million tons per year respectively. While maintaining stable economic and social growth, thoroughly enhancing the industrial structure and moderating energy usage, the cities along the Yellow River Basin will reach carbon peak in 2026, with a peak of 1917.132 million tons.

Under the path of optimizing industrial structure, cities along the Yellow River Basin are generally unable to achieve the carbon peak target by 2030, but the carbon peak time is two years earlier and the peak is lower than the benchmark path.Industrial structure optimization means that the development speed of the secondary and tertiary industries is accelerating, while the development speed of the primary industry is slowing down and gradually reducing its share and the number of employees. This may be due to the gradual elimination of high carbon emitting industries during the process of optimizing industrial structure to increase in the proportion of low-carbon industries, and the introduction of more advanced production technologies and equipment to improve production efficiency and reduce carbon emissions. It also means that promoting the application of clean energy and improving energy efficiency. The second and third industries need a lot of energy in operation, and accelerating the development of these industries also provides

Table 8
Setting values of urbanization rate growth rate.

	Growth rate	2021–2025	2026–2030	2031–2035	2036–2040
Urbanization rate	medium	0.71 %	0.61 %	0.53 %	0.47 %
	quick	1 %	0.9 %	0.82 %	0.76 %

Table 9
Set values of the growth rate of secondary and tertiary industries.

	Growth rate	2021–2025	2026–2030	2031–2035	2036–2040
Secondary industry	medium	−0.7 %	−0.6 %	−0.6 %	−0.27 %
	quick	−1.2 %	−1.1 %	−1.1 %	−0.77 %
The tertiary industry	medium	0.8 %	0.75 %	0.75 %	0.4 %
	quick	1.3 %	1.25 %	1.25 %	0.9 %

Table 10
The growth rate of the proportion of employees in the primary industry is set.

	Growth rate	2021–2025	2026–2030	2031–2035	2036–2040
The proportion of employees in the primary industry	medium	−4%	−3.5 %	−3.2 %	−3%
	quick	−5%	−4.5 %	−4.2 %	−4%

Table 11
The set value of the average wage growth rate of on-the-job employee.

	Growth rate	2021–2025	2026–2030	2031–2035	2036–2040
average wage	medium	8.4 %	7.9 %	7.6 %	7.4 %
	quick	11.4 %	10.9 %	10.6 %	10.4 %

Table 12
Population density growth rate set.

	Growth rate	2021–2025	2026–2030	2031–2035	2036–2040
Population density	medium	0.62 %	0.57 %	0.54 %	0.52 %
	quick	0.82 %	0.77 %	0.74 %	0.72 %

Table 13
Setting values of growth rates of other influencing factors.

	Growth rate	2021–2040
Built-up area	medium	5.09 %
Fixed assets Investment	medium	18.86 %
Foreign trade	medium	10.61 %

Table 14
Path combination settings.

Indicator	Benchmark	Economic	Population	Industrial structure	Energy consumption	Combination
Population size	medium	medium	quick	medium	medium	medium
Energy consumption	medium	medium	medium	medium	slow	slow
Average wage	medium	quick	medium	medium	medium	medium
GDP	medium	quick	medium	medium	medium	medium
Population density	medium	medium	quick	medium	medium	medium
Urbanization rate	medium	medium	quick	medium	medium	medium
Built-up area	medium	medium	medium	medium	medium	medium
Secondary industry	medium	medium	medium	quick	medium	quick
Fixed assets investment	medium	medium	medium	medium	medium	medium
Foreign trade	medium	medium	medium	medium	medium	medium
Tertiary industry	medium	medium	medium	quick	medium	quick
Primary industry	medium	medium	medium	quick	medium	quick

opportunities to promote the demand for clean energy and improve energy utilization efficiency, which makes carbon emissions reduce in the process of continuously optimizing energy utilization and gradually replacing traditional energy with clean energy. In addition, industrial development may form a complete industrial chain, and the synergistic effect among various links may drive the overall reduction of carbon emissions. Therefore, upgrading the industrial structure will promote the reduction of carbon emissions and the process of achieving carbon peak to a certain extent.

Under the path of reducing energy consumption, cities along the Yellow River Basin can achieve their carbon peak target by 2030 as

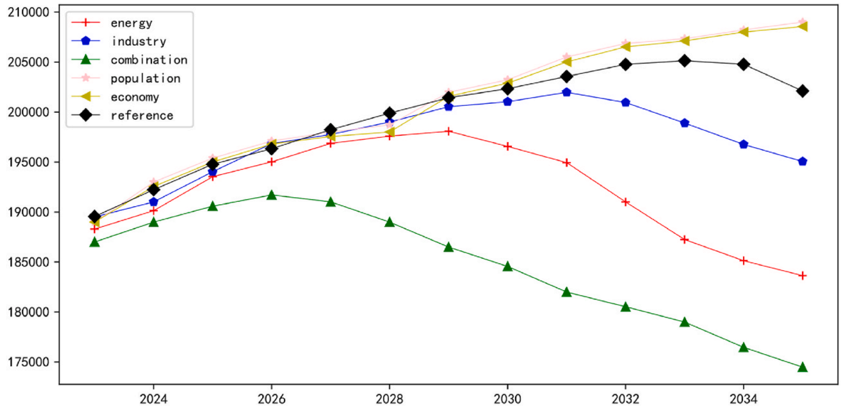

Fig. 4. Trend of carbon emissions under each pathway.

Table 15
Prediction time and peak of carbon peak under each pathway.

path	Peak time	peak (10000 tons)
Reference path	2033	205132.4
Scenario of optimizing industrial structure	2031	201979.5
Scenario of energy consumption reduction	2029	198083.5
Combination scenario	2026	191713.2

Note: The predicted deadline is 2035, so only the peak time and peak value under the carbon peaking path before 2035 are displayed.

a whole. Compared with the peak time of industrial structure optimization, it is two years earlier again and the peak value is lower than the peak value under the benchmark path and the industrial structure upgrading path. This may be due to the fact that the slowdown in energy consumption reduces the consumption and use of fossil fuels from the source, thereby controlling the total carbon emissions. The increase in energy consumption means an increase in the consumption of fossil fuels such as coal, oil, and natural gas, which releases carbon dioxide and exacerbates climate change. In the process of slowing down the speed of energy consumption, the rate of its increase may still continue, but at a decelerated pace, and the growth rate of carbon emissions also decreases, which reduces the negative impact on the atmosphere. Therefore, the delay of carbon peak time is closely related to the increase in energy consumption, thereby promoting the achievement of carbon peak goals on schedule.

Under the path of economic growth, economic growth is usually accompanied by more production and consumption, which requires more energy. The energy used in today's production and life mainly comes from fossil fuels, such as coal, oil, and natural gas. Therefore, economic growth will lead to more energy consumption and combustion, which releases more carbon dioxide into the atmosphere. When carbon emissions increase, the time for carbon peaking will be postponed. Because cities along the Yellow River Basin are still increasing greenhouse gas emissions. It has more negative impacts on climate change. Therefore, as carbon emissions rise with economic growth, the timing of the carbon peak may be postponed.

In the process of population growth and expansion, on the one hand, the increasing population requires more necessities and consumables such as housing, food, and electronic equipment. The production and distribution of these goods and the provision of these services require energy, which increases energy demand and supply. On the other hand, the increase in urbanization rate is often accompanied by the spread of urbanization lifestyles, which means more people use transportation, electricity, and energy intensive facilities. The vast majority of transportation vehicles are powered by oil. Especially if urban planning is insufficient to support sustainable transportation, energy consumption will increase more significantly. Finally, the increase in population and the improvement of urbanization level need to expand urban construction. In this process, the demand for infrastructure will lead to changes in land use involving deforestation, wetland filling, and land landfill, which will disrupt the ecological carbon cycle system and lead to an increase in carbon emissions. And construction, transportation, industry, and commercial activities in urban construction usually require a large amount of energy. Therefore, expanding population size and increasing urbanization rate will lead to more carbon emissions. While other conditions remain unchanged, the final result will delay the time for the total carbon peak of cities along the Yellow River Basin. As a result, the goal of carbon peaking before 2030 will not be achieved under the path of economy growth and population growth. This enlightens us that we cannot blindly pursue rapid economic growth and the improvement of urbanization level in the process of social development. This is an inevitable requirement to adhere to the laws of economic development and uphold continuous and robust economic growth. It is a basic characteristic of China's economic development in the new era. It can assist China and the Yellow River Basin in building an environmentally friendly society and achieving sustainable development.

4.3. Discussion

This article takes 56 cities in the Yellow River Basin as the research object. In the reviewed articles on limited carbon emissions in the Yellow River Basin, the research objects are generally the nine provinces in the Yellow River Basin, such as the article by scholar Zhao et al. [32]; Or all cities in provinces in the Yellow River Basin; The time span studied in this article is different from other articles on carbon emission prediction in the Yellow River Basin, and the data sources are not completely consistent; Therefore, the predicted results may differ from existing articles. There are many factors that may make the research results of this article different from those of other articles. When studying the nine provinces in the Yellow River Basin, scholars such as Zhao et al. [32] selected indicators such as energy consumption intensity and used decoupling models and LMDI models to conduct research. They proposed low-carbon development suggestions that distinguish Shanxi and Inner Mongolia from other provinces, such as increasing energy consumption intensity. This article selects indicators such as population, energy consumption, and industrial structure as influencing factors, predicts based on the set carbon emission growth rate, and finally puts forward relevant policy recommendations. The policy recommendations are universal to cities along the Yellow River Basin and only target the predicted path results, making them targeted. The selection of influencing factors and the setting of ratios will lead to differences in low-carbon policy recommendations and forecast data.

5. Conclusion and policy recommendations

Under the current economic and social development, cities along the Yellow River Basin in China are facing huge pressure to reduce emissions. It is expected to achieve a carbon peak in 2033, with a peak of 2,051,320,000 tons, so the target of reaching the peak of carbon emissions before 2030 will not be accomplished. But through comprehensive optimization of the industrial structure and reduction of energy consumption, cities along the Yellow River Basin as a whole may achieve carbon peak by 2026, with a peak of 1,917,132,000 tons.This paper proposes the targeted suggestions for the Yellow River Basin.

(1) Improving population quality and optimizing urban-rural planning

In Pearson correlation analysis, population size, density, and urbanization rate are the main factors affecting carbon emissions. Therefore, it is necessary to start from the aspects of population quantity, quality, and urban-rural planning to achieve the dual control of population and carbon emissions.

Government departments need to develop clear population policies and urban planning to control the size of the population, to optimize urban planning and to promote sustainable urban-rural coordinated development. Cities in the Yellow River Basin should transform the demographic dividend into a talent dividend. While improving the overall population quality, it is necessary to formulate a talent development strategy to increase high-quality employment opportunities and match talent demand. And they should optimize the spatial allocation of talent resources through policy incentives to promote cross regional talent mobility, to help reduce carbon emissions and to promote the process of carbon peaking.

(2) Reducing energy consumption and optimizing energy structure

Energy consumption is one of the driving factors for carbon emissions in the Yellow River Basin, and resource consuming industrial enterprises are the pillar industries of the Yellow River Basin. Therefore, reducing energy consumption is a basic path choice for achieving the carbon peak goal in the Yellow River Basin.

Government departments should develop and implement stricter energy efficiency standards for various equipment and industrial processes. At the same time, they should promote energy efficiency certification, encourage enterprises to choose more energy-efficient equipment and technologies, conduct regular energy audits, identify and improve energy waste links. And they also should provide corresponding incentive measures and encourage the adoption of clean energy and green low-carbon lifestyles, in order to promote the improvement of energy efficiency. Last but not least, the government should support technological innovation and promote the research and development of more energy-efficient industrial and production technologies. Society and other multiple entities should respond to the national government's policy call and strictly abide by institutional agreements and energy-saving standards. Enterprises should introduce and promote energy efficiency labels to make it easier for consumers to identify and choose products and services with higher energy efficiency, which will stimulate market demand for energy efficiency products.

(3) Optimizing industrial structure and achieving decoupling carbon emissions from economic growth

From the correlation and the prediction results of the single path of industrial structure optimization, it indicates there is a strong correlation between industrial structure and carbon emissions.Attaining optimization in industrial structure holds the potential to expedite the realization of the carbon peak goal in the Yellow River Basin. Consequently, a balanced approach is required in the development of the primary, secondary, and tertiary industries to harmonize economic growth with environmental pollution reduction.

To facilitate this, the government plays a crucial role by steering financial resources towards low-carbon and environmental protection industries. Developing policies that guide industrial transformation and upgrading can help achieve the commitment to achieving both economic goals and environmental sustainability, which makes the carbon peak goal in the Yellow River Basin achieve as soon as possible. Therefore, the development of the first, second, and third industries needs to balance economic growth and environmental pollution reduction simultaneously.

The government guides the flow of funds towards low-carbon and environmental protection industries develop policies to guide industrial transformation and upgrading and encourage high carbon emission industries to transform into low-carbon and green industries. They should provide financial support, technical guidance and training to assist enterprises in adjusting their industrial structure. And the government should guide traditional industries to upgrade towards high value-added and low-carbon emissions. Enterprises and society need to practice the concept of green development, promote resource recycling and reduce waste emissions which will reduce resource waste in the production process. In the process of production and life, enterprises should fully stimulate their interest and vitality in innovation and increase efforts in low-carbon technologies and innovation to promote technological upgrading and transformation of industrial structure.

From the analysis of the prediction results of the combination path, it can be seen that multiple parties need to exert subjective initiative, coordinate and implement the above policy suggestions together, strike a good combination of policy punches, balance multiple factors, consider the interests of all parties, organize and implement policy continuation work, accurately and effectively implement policies to ensure that policy suggestions take root. After policy implementation, it is also necessary to track feedback, timely identify problems to adjust policiesand promote common development of the economy and society to build environmentally friendly and beautiful cities along the Yellow River Basin.

In the future, the field of peak carbon emissions can partially refer to Wang et al. [33] data twin multi perspective bill of materials reconstruction to establish a computable twin model that integrates data and reality, which helps comprehensively, grasp the carbon emissions and energy consumption data of the managed space. We can continuously optimize and learn the data feedback mechanism by introducing machine learning fusion models and artificial intelligence algorithms, in order to observe the implementation effect and construction cost data of various modular energy-saving and carbon reduction measures in real time. Based on the data, it is practical to reach the optimal comprehensive energy efficiency of the entire chain and achieve personalized and economical carbon peak planning through real-time analysis, diagnosis, evaluation, and feedback optimization.

Data availability

The data will be available upon reasonable request through corresponding authors.

CRediT authorship contribution statement

Guangyao Deng: Writing – review & editing, Writing – original draft, Funding acquisition. **Qian Zhu:** Writing – original draft, Data curation. **Yingchen Shen:** Data curation.

Declaration of competing interest

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

Acknowledgments

This work was supported by the Natural Science Foundation of China under Grant [number72363021and 12101279]; Outstanding Youth Fund of Gansu Province[number 20JR5RA206]; Longyuan Youth Talent Project(2022); Double First-class Scientific Research Key Project of Gansu Provincial Department of Education[GSSYLXM-06]; The key scientific research project of the Silk Road Economic Research Institute of Lanzhou University of Finance and economics (JYYZ202102).

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