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The influence and forecast of three industries and energy structure on regional carbon emission

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Abstract: Carbon emission reduction is an important concern of regional low-carbon economic development. Through grey correlation analysis, neural network model, Gaussian multi-peak fitting and other methods, this paper deeply analyzes the relationship between the total carbon emissions of Henan Province and regional economic development, industrial structure, energy consumption. The results show that the secondary industry and coal energy consumption are the biggest sources of carbon emissions in Henan Province. In the neural network prediction model, the correlation coefficient between the prediction curve and the actual total carbon emission curve is 0.989, and the prediction results have a good degree of fit. According to the Gaussian multi-peak fitting process, the fitting curve and prediction curve of carbon emission in Henan province are obtained. The carbon emission prediction curve is divided into two parts: 2018-2024 is a linear decline stage, and after 2024, it enters a rapid decline stage. The research results can provide guidance for the formulation of low-carbon development goals in Henan Province, and the prediction model can formulate emission reduction tasks in line with the current situation for regional economic development, industrial structure and energy consumption.

Keywords: Neural network carbon emission prediction; Grey correlation analysis; Gaussian multimodal fitting.

1. Introduction

Climate warming is an environmental problem resulting from rapid economic development. Greenhouse gas emissions from various industries in the process of social development are an important cause of climate warming. In recent years, the measurement system of carbon emissions has become mature, providing data support for the study of the relationship between carbon emissions and economic development. The internal industrial structure of different regions in China is different, and the impact of economic and social development on carbon emission is not the same (You et al.,2022; Marques, A et al.2019). Therefore, on the basis of regional economy, it is an important basis for promoting green development (Khanna, N et al.2016) and low-carbon economy (Zhao et al.,2022; Yan et al,2022) to explore the total carbon emissions and development trend of various industries (Kwakwa, P et al.2022) at the macro level.

In order to promote the high-quality development of regional economy and achieve the carbon reduction target, many scholars have explored the relationship between economic development and carbon emissions from various aspects. Jing (2022) studied how carbon emission trading pilot policies affect the high-quality development of regional economy by building a high-quality economic development index system and establishing a differential model, and pointed out that carbon emission trading pilot policies can significantly promote the high-quality development of regional economy. Li et al. (2022) studied the spatio-temporal correlation, allometric growth relationship and influencing factors of economic growth and carbon emissions in the Yangtze River Delta, and found that the allometric change of economic growth and carbon emissions was dominated by weak economic expansion. The proportion of secondary industry, tertiary industry, urbanization and population density are the main factors driving the allometric changes of economic growth and carbon emissions in the Yangtze River Delta. Li et al. (2022) studied the regional carbon emission reduction effect by constructing a theoretical model of spatial emission reduction effect of digital economy development under the influence of economic agglomeration, and further explored the link between regional economic development and environmental governance. Zhao et al. (2022) analyzed the economic and carbon emission status, industrial structure and energy structure characteristics, inflection point and decoupling, and driving factors of carbon emission of nine provinces and regions in the Yellow River Basin from 1997 to 2019, and the results showed that the low-carbon evolution trend of industrial structure in each province was obvious.

With the goal of "carbon peak" and "carbon neutrality" proposed, the prediction of carbon emissions has also attracted extensive attention from the academic community. Wei et al. (2022) took the accounting and prediction of building carbon emissions in Baotou, a heavy industrial city in China, as the research object, constructed the LSTM prediction model based on the recurrent neural network model, and made the prediction. The results showed that the carbon emissions of three kinds of buildings in Baotou generally showed a trend of first high and then low. Han et al. (2022) took the Beijing-Tianjin-Hebei region as the research object. By analyzing the relationship between carbon emissions and influencing factors, they constructed a carbon emission system dynamics model and simulated and predicted its impact on the carbon peak time, peak and emission reduction potential in Beijing, Tianjin and Hebei. Hu et al. (2022) used LSTM neural network model and scenario analysis method to simulate the carbon peak-to-peak path and forecast the peak of China's manufacturing industry, and concluded that the overall carbon emissions of China's manufacturing industry would reach the peak in 2029. Hu et al. (2022) deduced and predicted the change trend of China's carbon emission intensity based on the LSTM neural network model. At the same time, the ARIMA-BP neural network model was established as the verification model to directly predict the carbon emission intensity. The comparison and analysis showed that the LSTM model performed better in the prediction accuracy. Lv et al. (2022) measured the decoupling index of carbon emissions and economic growth in 30 provinces, analyzed the decoupling effect and driving factors of each province, calculated and predicted the decoupling index of 2017-2020 and 2020-2023, and pointed out that the effect of per capita R&D expenditure was the main obstacle to decoupling. R&d efficiency effect and energy intensity effect are the main drivers of decoupling.

In the research of carbon emission prediction, neural network and other related models are widely used. Zhang et al. (2022) established an improved particle swarm optimization algorithm (IPSO) to optimize the BP neural network model based on the calculation results of carbon emissions and emission intensity in Shandong Province from 2000 to 2017, and simulated and predicted the carbon emissions and emission intensity in Shandong Province. The results show that the carbon emission of Shandong Province will increase slowly in the future. Guo et al. (2020) used BP neural network model for quantitative research, and also introduced multiple linear regression model for comparison, and finally conducted market test on the empirical results. The test data show that the error between the predicted value and the actual value of BP neural network is much smaller than that of the multiple regression model. Yan et al. (2018) used trial and error method to determine the number of nodes in the hidden layer of the network based on BP artificial neural network algorithm, established a carbon emission prediction model for maize production in Hexi oasis, and selected multiple linear regression model and multiple nonlinear regression model to evaluate the effectiveness of the model. Guo et al. (2022) analyzed the influencing factors of carbon emissions by STIRPAT model, and predicted the future carbon emissions of Chongqing by GM (1,1) model. According to the prediction results, the carbon emission reduction scheme of "three-life space" in Chongqing was proposed. Based on the carbon emission data of building materials from 17 residential buildings in cold areas, Liu et al. (2022) established a carbon emission prediction model of building materials production stage for residential buildings in cold areas, and adopted linear regression and ridge regression methods to establish the coupling relationship between residential space, shape design parameters and carbon emission of building materials. The results showed that: The prediction model has good fitting effect and low prediction error.

Although there are abundant research results on economic development and carbon emissions (Ghosh S et al., 2022; Ren et al.,2021; Xiao et al.,2022), there are few studies on carbon emissions based on regional economic development, industrial structure, energy consumption and other aspects. In this paper, by means of grey correlation analysis, neural network model and multi-peak Gaussian fitting analysis, the influence of three industries and energy consumption on the carbon emissions of Henan Province is analyzed, the carbon emissions are predicted. And the energy saving and emission reduction effect of energy consumption structure is further analyzed. (Huang et al.,2022; Zhang et al.,2022; Chen et al.2022). It will guide the adjustment of industrial structure and energy consumption structure in Henan province and promote the green and coordinated development of industrial economy in Henan Province.

Henan Province is located in central China, with a total area of 167,000 square kilometers. It is an important comprehensive transportation hub and an information flow center for people and logistics. Henan is located at the junction of the coastal open areas and the central and western regions, which is the middle zone of China's economic development from east to west. As shown in Figure 1. By the end of 2021, the GDP of Henan Province was 5,888741 billion yuan, ranking the fifth in China. With the rapid development of economic level and the constant adjustment of industrial structure, the total carbon emissions of Henan Province also fluctuated significantly. With the proposal of "carbon neutrality", it has become a crucial issue to reduce carbon emissions under the condition of ensuring economic development. Therefore, this paper takes the carbon emissions and economic development indicators of various industries in Henan Province from 2005 to 2018 as the research object, and conducts grey correlation analysis, neural network model, Gaussian multi-peak fitting explored the impact of economic development and industrial structure change on total carbon emissions, in order to provide reference for the prediction of "double carbon" (Zhong et al.,2022)target and the formulation of carbon emission reduction control and other relevant policies in Henan Province.

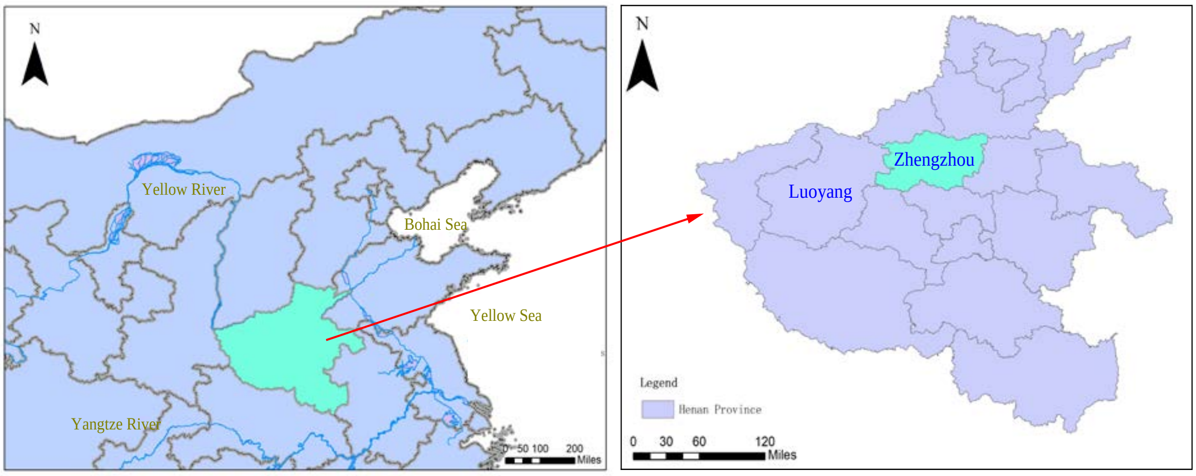


Figure 1. General situation of Henan Province

2. Carbon emission analysis based on three industries

2.1 Grey correlation analysis

Grey correlation analysis is to calculate the consistency of two factors in the system to judge the correlation degree between them (Yang et al., 2022; Xiong et al., 2021; Yan et al., 2021; Ma et al.,2020). The correlation coefficient of each factor is determined by determining the reference sequence and comparison sequence, and the dimensionless processing is carried out to determine the influence degree of the object to be identified on the research object. This section uses the grey correlation analysis method to explore the relationship between the total carbon emissions of Henan province and the three industrial development levels.

In the grey correlation analysis, the reference sequence and the comparison sequence are as follows:

$$\begin{cases} x_0(k) = \{x_0^1, x_0^2, \dots x_0^m\}, t \in N^* \cap t \in [1995{,}2018] \\ x_i(k) = \{x_i^1, x_i^2, \dots x_i^n\}, t \in N^* \cap t \in [1995, 2018] \end{cases} \tag{1}$$

Where, $x_0(k)$ is the reference sequence, here refers to the time series of total carbon emission; $x_i(k)$ is the comparative series, here refers to the time series of regional economic level, $x_1(k)$ refers to the primary industry, $x_2(k)$ refers to the secondary industry, $x_3(k)$ refers to the tertiary industry. Since the dimensions of each factor are not the same, it is necessary to make the sequence dimensionless for direct comparison and calculation. When calculating the grey correlation coefficient, $\{x_0(t)\}$ is the sequence after mean processing, and its subcolumn is $\{x_i(t)\}$. When t=k, calculate the grey correlation degree between $\{x_0(t)\}$ and $\{x_i(t)\}$. The specific formula is:

$$\xi_{0i}(k) = \left| \frac{\Delta_{min} + \rho \Delta_{max}}{\Delta_{0i}(k) + \rho \Delta_{max}} \right| \tag{2}$$

Where, $\Delta_{0i}(k)$ is the absolute difference between two sequences at time k; Δ_{max} is the maximum value of the absolute difference; Δ_{min} is the minimum absolute difference.

According to Equation (2), the gray correlation degree γ_{0i} can be obtained:

$$\gamma_{0i} = \frac{1}{m} \sum_{k=1}^{m} \xi_{0i}(k) \tag{3}$$

According to Equations (2) and (3), the correlation results between total carbon emissions and the three industries are shown in Figure 5.

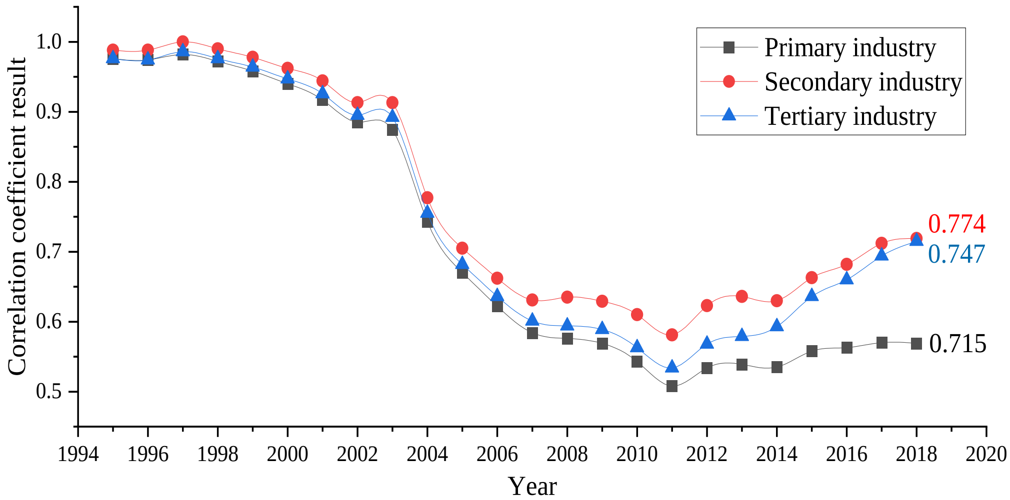


Figure 2. Grey correlation analysis

According to Figure 2, the correlation degree between the primary industry and total carbon emissions is 0.715, the correlation degree between the secondary industry and total carbon emissions is 0.774, and the correlation degree between the tertiary industry and total carbon emissions is 0.747. Relatively speaking, the time series of total carbon emissions in Henan Province has the highest correlation with the time series of the secondary industry, indicating that the secondary industry is the biggest factor affecting the total carbon emissions. However, the correlation degree between the other two industries and the total carbon emissions is also above 0.7, indicating that they also have an important impact on the total carbon emissions.

2.2 Neural network model

Based on the results of grey correlation analysis, the neural network prediction model of multi-layer perceptron is established by SPSS software with three major industries as influencing factors, as shown in Figure 6.

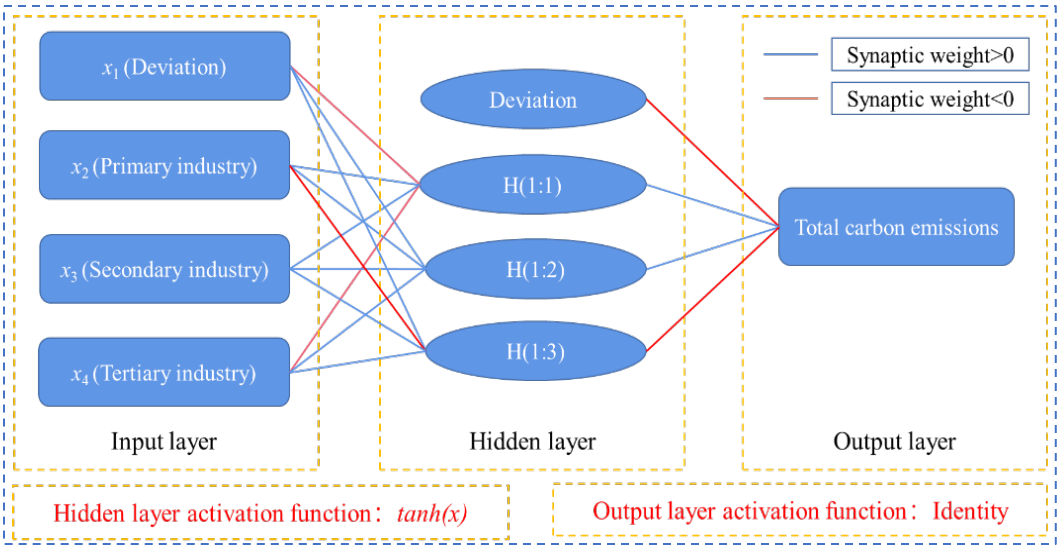


Figure 3. Neural network model of total carbon emission prediction.

In Figure 3, the hidden layer activation function of multilayer perceptron is hyperbolic tangent, namely:

$$tanhx = \frac{sinhx}{coshx} = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{4}$$

The weight calculation method of each input layer is as follows:

1) Set the initial random weight (For the convenience of calculation, we write "deviation" as the first input factor):

$$\boldsymbol{\omega}_{1n}\ (1 \times 4) \ = \ (0.5, 0.715, 0.774, 0.747) \tag{5}$$

Where, $\boldsymbol{\omega}_n(1 \times 4)$ are the weights of input layer and hidden layer respectively.

2) Multiply each factor of the input layer by the weight:

$$P = \begin{bmatrix} x_{11} & & \\ & \ddots & \\ & & x_{17} \end{bmatrix} \times \begin{bmatrix} w_{11} & & \\ & \ddots & \\ & & w_{17} \end{bmatrix} = \begin{bmatrix} w_{11}x_{11} & & \\ & \ddots & \\ & & w_{17}x_{17} \end{bmatrix} = \begin{bmatrix} X_1 & & \\ & \ddots & \\ & & X_7 \end{bmatrix} \tag{6}$$

Where, $\boldsymbol{x}_{1n}\ (1 \times 7)$ is the influencing factor of input.

3) Calculate the output result of hidden layer:

$$Y_1 = \mathrm{H}(1:1) = \tanh\left(\sum_{n=1}^{7} X_n\right)$$

(7)

4) Calculate the error between the output result of hidden layer and the real result:

$$\begin{cases} E = \frac{1}{2}\left(Y_{target} - Y_{out1}\right)^2 \\ y_{out1} = \frac{e^{y_{net1}} - e^{-y_{net1}}}{e^{y_{net1}} + e^{-y_{net1}}} \\ y_{net1} = \sum_{n=1}^{7} X_n \end{cases} \tag{8}$$

Where, E is the error; y_{net1} is the input signal received by the hidden layer, that is, the weighted sum of factors of the input layer. y_{out1} is the output value of the hidden layer after activating the function.

5) Update weight:

Taking w_{12} as an example, the weight is updated after the error backpropagation, and the partial derivative of w_{12} needs to be calculated with the overall error first, namely the value of $\partial E/\partial w_{12}$. For convenient calculation, $\partial E/\partial w_{12}$ can be decomposed into:

$$\frac{\partial E}{\partial w_{12}} = \frac{\partial E}{\partial y_{out1}} \cdot \frac{\partial y_{out1}}{\partial y_{net1}} \cdot \frac{\partial y_{net1}}{\partial w_{12}} \tag{9}$$

According to Equation (8), the values of each split-term are calculated successively, and it can be known that:

$$\begin{cases} \frac{\partial E}{\partial y_{out1}} = Y_{out1} - Y_{target} \\ \frac{\partial y_{out1}}{\partial y_{net1}} = \frac{\partial\left[\frac{e^z - e^{-z}}{e^z + e^{-z}}\right]}{\partial z}\Big|_{z=y_{net1}} = \frac{\partial\left[\frac{sinh(z)}{cosh(z)}\right]}{\partial z} = 1 - tanh^2(z) = 1 - \left(\frac{e^{y_{net1}} - e^{-y_{net1}}}{e^{y_{net1}} + e^{-y_{net1}}}\right)^2 \\ \frac{\partial y_{net1}}{\partial w_{12}} = \frac{\partial(w_{11}x_{11} + w_{12}x_{12} + \cdots + w_{17}x_{17})}{\partial w_{12}} = x_{12} \end{cases} \tag{10}$$

Substituting Equation (10) into Equation (9), it can be known that:

$$\frac{\partial E}{\partial w_{12}} = \left(Y_{out1} - Y_{target}\right) \cdot \left[1 - \left(\frac{e^{y_{net1}} - e^{-y_{net1}}}{e^{y_{net1}} + e^{-y_{net1}}}\right)^2\right] \cdot x_{12} \tag{11}$$

Using the calculation results of Equation (11), update the value of w_{12}:

$$w'_{12} = w_{12} - \eta \cdot \frac{\partial E}{\partial w_{12}} \tag{12}$$

The comparison between the carbon emission results calculated from the neural network model in Figure 3 and the original data of carbon emission is shown in Figure 4.

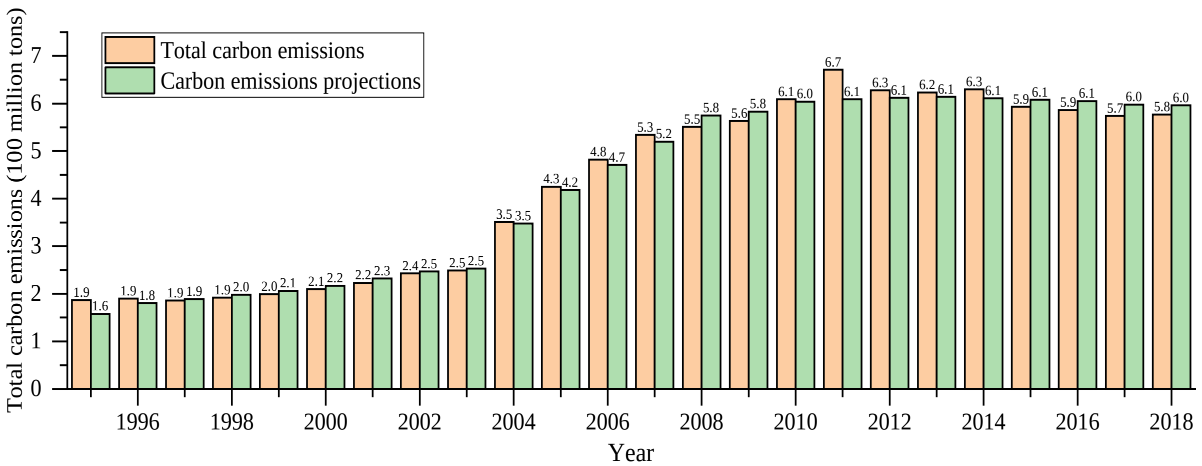


Figure 4. Neural network model prediction results

As can be seen from Figure 4, the carbon emission prediction results obtained by the neural network model of multi-layer perceptron have a high similarity with the original recovery result. In order to analyze the fitting degree of the model in detail, the residual and correlation coefficients of the two prediction results should be calculated. The residual error can be calculated as follows:

$$\delta_i = Y_i - y_i \tag{13}$$

$$\delta_i^* = \frac{\delta_i - \bar{\delta}}{\sigma} \tag{14}$$

Where, δ_i is the residual, Y_i is the predicted value of the neural network, y_i is the original value, δ_i^* is the standardized residual, $\bar{\delta}$ is the average value of the residual, and σ is the standard deviation.

Then, the correlation coefficient R^2 between the total carbon emissions prediction curve and the original curve can be calculated as follows:

$$R^2 = \frac{\sum_{i=1}^{n} \delta_i^2}{\sum_{i=1}^{n} (Y_i - \bar{y})^2} \tag{15}$$

According to Equations (13), (14) and (15), the residual, standardized residual and correlation coefficient of the prediction curve are calculated, and the variance and standardized variance curves of the neural network prediction results are drawn, as shown in Figure 5.

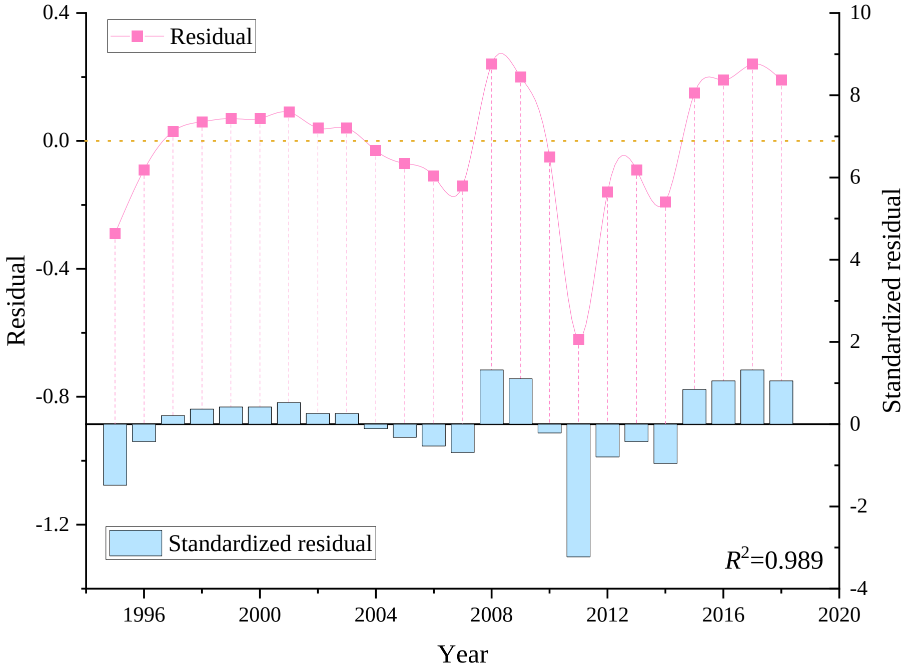


Figure 5. Residual analysis of neural network prediction results

The Figure 5 shows that the absolute value of multilayer perceptron residual $|\delta_i| \in [0,0.7]$. And the correlation coefficient of the prediction curve of total carbon emission also reached 0.989. This shows that the multi-layer perceptron neural network model has a good effect in predicting the total carbon emission in Henan Province.

Figure 6 shows the importance of each influence factor under the multi-layer perceptron neural network model, and the sum of the weight of each influence factor is 1. As can be seen from Figure 6, in the multi-layer perceptron model, the ranking of importance of influencing factors is “Secondary industry”, “Primary industry” and “Third industry”, which is consistent with the results of grey correlation analysis. This shows that the secondary industry has the greatest impact on the total carbon emissions.

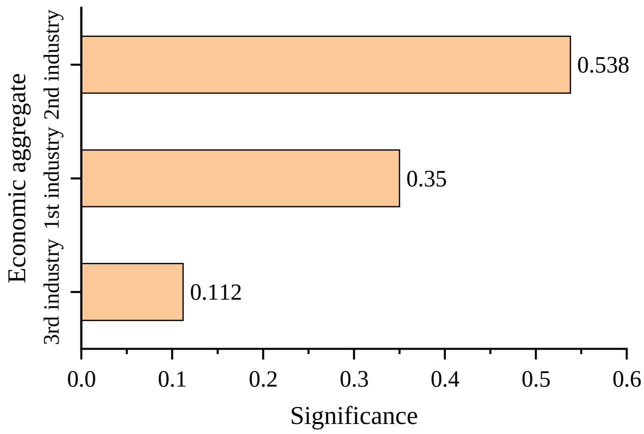


Figure 6. Importance analysis of influencing factors

2.3 Gaussian multi-peak fitting model

Section 2.2 analyzes the total carbon emissions of Henan Province using the neural network model of multi-layer perceptron. In order to further realize the prediction of total carbon emissions, Gaussian multi-peak fitting (Wang 2021; Zhou et al., 2013; Zhao et al., 2011; Jiang et al.,2019) method is used to interpolate and approximate the carbon emission time series. The fitting formula is as follows:

$$y = y_0 + \frac{A}{w * \sqrt{\frac{\pi}{2}}} * \exp\left\{-2\left(\frac{x - x_c}{w}\right)^2\right\}$$

(16)

Equation (16) is used to carry out multi-peak fitting for the carbon emission time series, as shown in Figure 10.

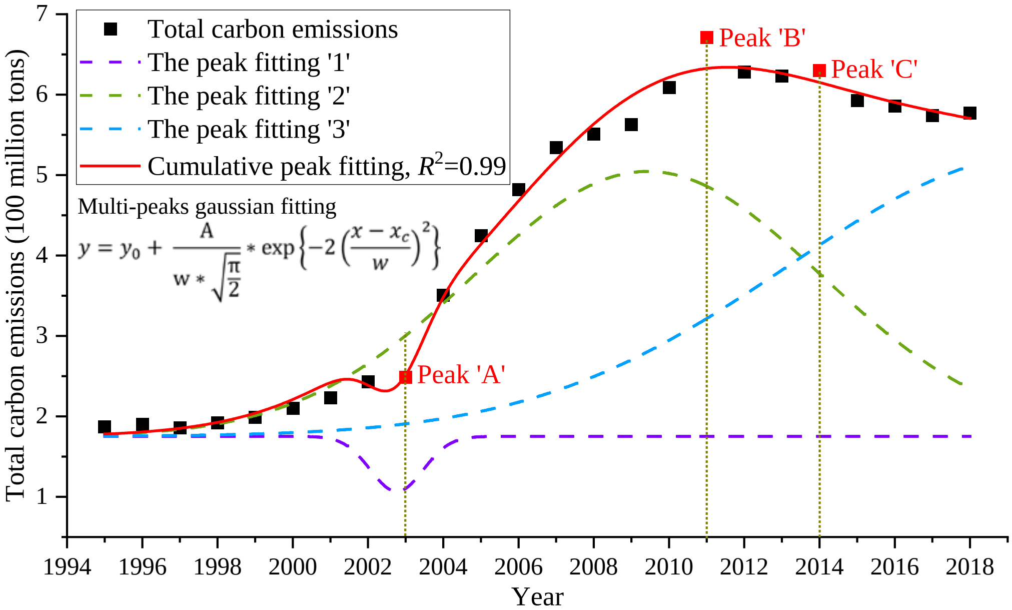


Figure 7. Gaussian multi-peak fitting

As shown in Figure 7, 2003, 2011 and 2014 were selected as the local peak centers (the inflection points of the fitting curve of total carbon emissions), and regression fitting was conducted for total carbon emissions. The fitting formula is as follows:

$$\begin{cases} y_1 = 1.75 + \dfrac{-1.21}{1.41 * \sqrt{\frac{\pi}{2}}} * \exp\left\{-2\left(\dfrac{x - 2002.8}{1.41}\right)^2\right\} \\ y_2 = 1.75 + \dfrac{38.2}{9.25 * \sqrt{\frac{\pi}{2}}} * \exp\left\{-2\left(\dfrac{x - 2009.4}{9.25}\right)^2\right\} \\ y_3 = 1.75 + \dfrac{60.1}{13.7 * \sqrt{\frac{\pi}{2}}} * \exp\left\{-2\left(\dfrac{x - 2020.0}{13.7}\right)^2\right\} \end{cases}$$

(17)

According to Equation (17), the Gaussian fitting curve of total carbon emission (red curve in Figure 10) can be calculated as follows:

$$y_n = a(y_1 + y_2 + y_3) + b$$

(18)

After fitting and approximating the total carbon emission curve in Figure 7, the values of each parameter in Equation (18) are:

$$\begin{cases} a = 1 \\ b = -3.5 \end{cases}$$

In order to better predict the total amount of carbon emissions, the monotonous interval of (18) is required.

It is easy to know that by differentiating Equation (16), we can get:

$$\frac{dy}{dx} = -\frac{4(x - x_c)A}{w^2 * \sqrt{\frac{\pi}{2}}} * \exp\left\{-2\left(\frac{x - x_c}{w}\right)^2\right\} \tag{19}$$

Similarly, to differentiate Equation (18) is to find the sum of partial differentials of the terms of Equation (18) with respect to x (Year), namely:

$$\frac{dy_n}{dx} = \frac{\partial[a(y_1 + y_2 + y_3) + b]}{\partial x} = \frac{\partial y_1}{\partial x} + \frac{\partial y_2}{\partial x} + \frac{\partial y_3}{\partial x} \tag{20}$$

The values of each item in Equation (20) are:

$$\begin{cases} \frac{\partial y_1}{\partial x} = 1.94(x - 2002.8) * \exp\left\{-2\left(\frac{x - 2002.8}{1.41}\right)^2\right\} \\ \frac{\partial y_2}{\partial x} = -1.42(x - 2009.4) * \exp\left\{-2\left(\frac{x - 2009.4}{9.25}\right)^2\right\} \\ \frac{\partial y_3}{\partial x} = -1.02(x - 2020.0) * \exp\left\{-2\left(\frac{x - 2020.0}{13.7}\right)^2\right\} \end{cases}$$

The curve depicted in Equation (20) is shown in Figure 8. In Figure 8, the red dot plot is $\frac{dy_n}{dx}$, which is the sum of three partial differential curves. It can be seen from Figure 8 that before 2012, the total carbon emissions showed an increasing trend in other time periods except for a brief downward trend around x=2002. After 2012, the total carbon emissions showed a downward trend.

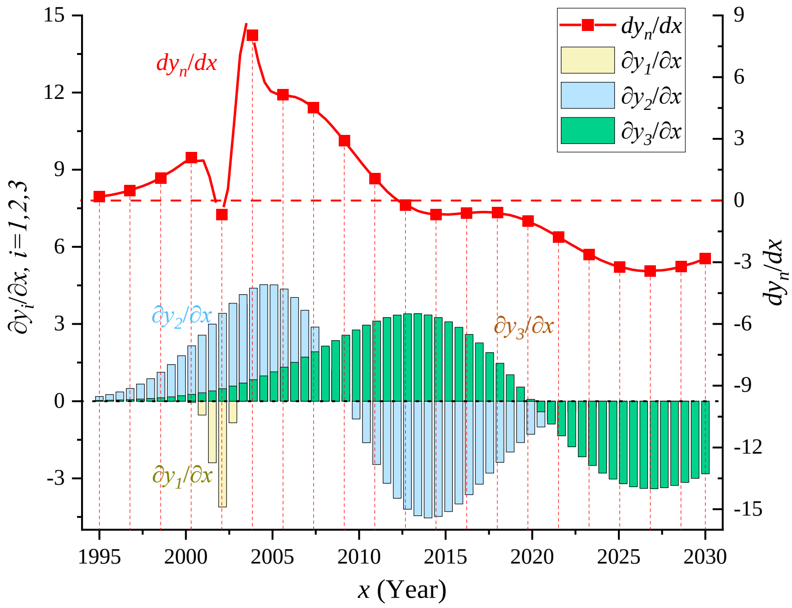


Figure 8. The derivative of the function $y_n(x)$

3. Results analysis and prediction

3.1 The impact of three industrial structure changes on carbon emission

The rapid growth of economy and the change of industrial structure have an important influence on carbon emission. The growth trend of total carbon emission in Henan Province has a strong correspondence with the trend of economic growth. Figure 9 shows the growth trend of gross domestic product and per capita gross domestic product of the tertiary industries in Henan Province from 1994 to 2018. As can be seen from Figure 9, in the 25 years, all kinds of gross product of Henan Province showed an increasing trend and developed well. The growth of regional GDP in Henan Province can be divided into three stages: slow development stage, rapid growth stage and adjustment development stage.

1) Slow development stage from 1995 to 2002: It can be seen from the figure that the scale of the three industries is similar. As a major grain producing province in central China, Henan Province has always occupied an important position in agriculture, and its gross agricultural production accounted for more than 20% of the total local gross domestic product. During this period, the GDP growth of Henan Province was relatively small. Meanwhile, as a province with a large population, the per capita GDP of Henan Province was also very low.

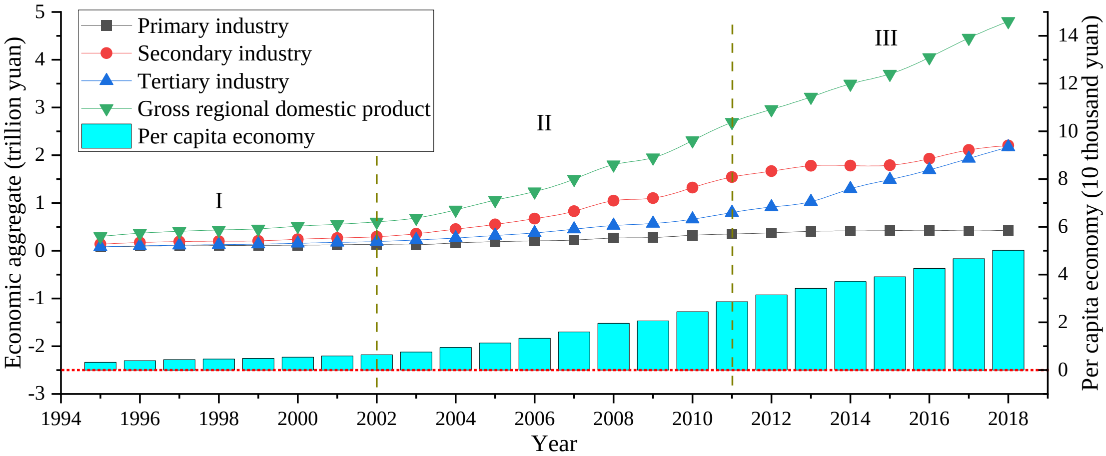


Figure 9. Economic growth trend of Henan Province from 1995 to 2018

2) Rapid growth stage from 2002 to 2011: During this stage, Henan Province vigorously developed the secondary and tertiary industries in order to promote economic growth. Economic aggregate then presents the trend of rapid growth. It can be seen from the figure that after 2002, the continuous promotion of industrialization made the gross product of the secondary industry in Henan Province grow rapidly, while the primary and tertiary industries showed a steady growth trend. In the three industries of this stage, the secondary industry occupies the dominant position, with the highest proportion of total output value. In particular, steel, cement, glass, alumina and electrolytic aluminum, coking, coal chemical and other industries in the secondary industry are enterprises with high energy consumption and high carbon emission, which to some extent increases the contribution rate of the secondary industry to carbon emission.

3) Adjustment and development stage from 2011 to 2018: During this stage, while the economic aggregate of Henan Province maintained rapid growth, the industrial structure changed. The scale of the primary industry remained stable, the growth momentum of the secondary industry was restrained, and the output value of the tertiary industry increased rapidly. By 2018, Henan's tertiary industry had reached parity with its secondary industry. This is due to the continuous improvement of economic strength in Henan Province since the beginning of the 21st century, which has promoted the optimization and upgrading of the industrial structure and the upgrading of the industrial level, and the economic development has strided toward a more reasonable and coordinated direction. At the same time, higher requirements for energy conservation and emission reduction have been put forward, backward production capacity has been phased out, and emerging industries have been developed to promote industrial emission reduction.

3.2 Analysis of relationship between energy structure and carbon emission in Henan Province

The development of the three industries requires a large amount of energy consumption, coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas and other energy consumption is the main source and driving factor of carbon emissions, but also the basis of carbon emission reduction. The following figure shows the trend of carbon dioxide emission of various energy sources in Henan Province. Since carbon dioxide produced by energy consumption is positively correlated with energy usage, the following figure also reflects the development trend of various energy use.

It can be seen from the figure 10 that the carbon emission of coal energy is much higher than that of other energy sources, and the growth trend is obvious before 2011, while the carbon dioxide emission of other energy sources is stable and below 100 million tons. The development of mining industry leads to the increase of coal output and the supply of a large number of coal resources. The growth trend of coal resource consumption of various industrial enterprises is also obvious, and it will reach the peak in 2011. With the improvement of the technology level of energy utilization, the consumption of all kinds of industrial energy also shows a certain upward trend. From the structure of energy utilization in recent years, it can be seen that the industrial development of Henan Province began to change to low-carbon production, from extensive to intensive.

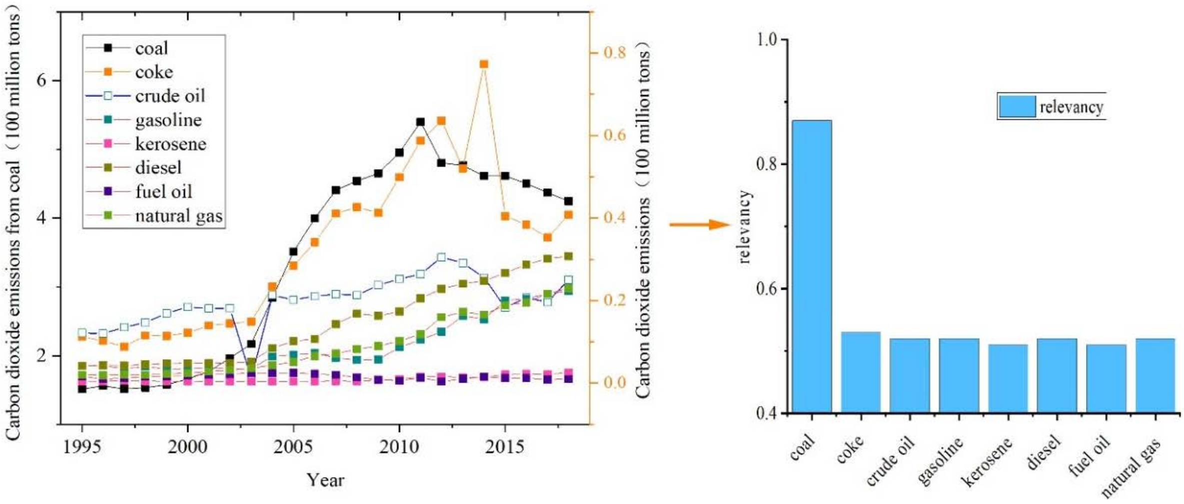


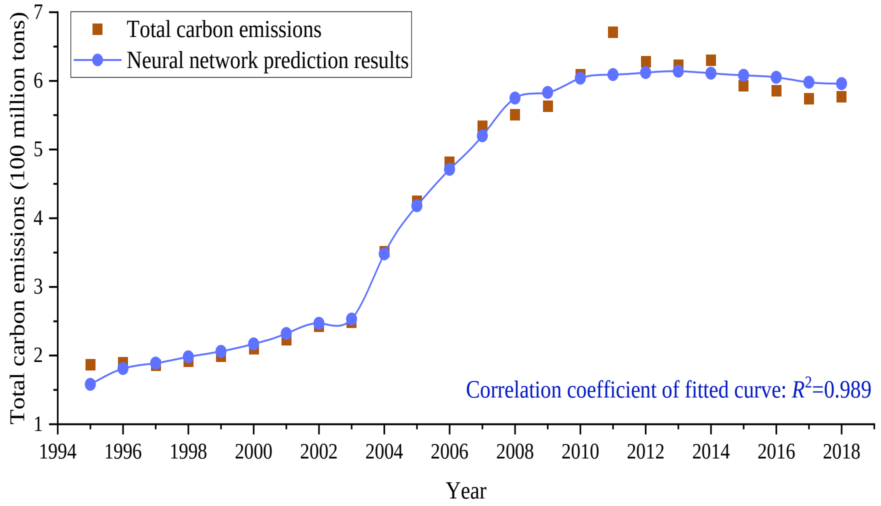
Figure 10. Energy carbon emissions change and Carbon emission correlation of various energy sources

In order to further analyze the main influencing factors of carbon emissions in Henan Province, gray correlation analysis was conducted between carbon dioxide emissions from various energy sources and carbon emissions in Henan Province, and the correlation results between various energy sources and carbon emissions could be obtained (as shown in Figure 10). From the perspective of energy type, the correlation between coal and carbon emissions is relatively high, reaching 0.87, while the correlation between coke, crude oil, gasoline and so on is close to 0.5. It shows that coal consumption is still the main source of carbon emissions in the secondary industry of Henan Province, but the utilization efficiency of coal energy is low, and there is still a lot of room for development in energy conservation and emission reduction. Energy sources such as coke, crude oil and gasoline are also closely related to Henan's carbon emissions, and under the current circumstances these energy sources are more efficient than coal.

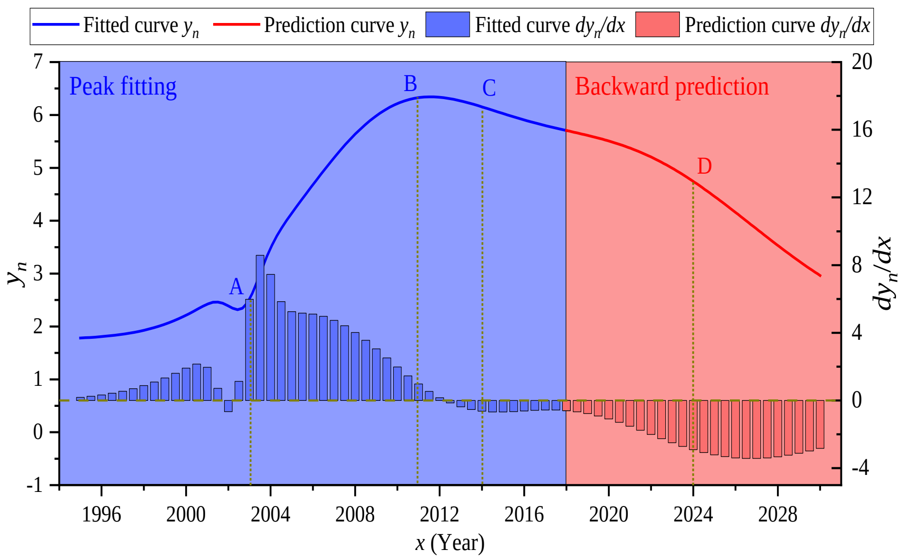
3.3 Total carbon emission prediction

Figure 11 shows the calculation results of the total carbon emission neural network model and Gaussian multi-peak fitting model. It can be seen from Figure 11 (a) that the prediction of the neural network model is very accurate thanks to the gray correlation analysis carried out in the early stage, especially from 1996 to 2006, the prediction curve almost coincides with the original curve. The separation between the prediction curve and the original curve is mainly from 2008 to 2018. This is because there are only 24 groups of statistical samples, limited by the limited samples, which makes it impossible for the neural network model to conduct further training and learning, resulting in a decline in the prediction accuracy of the latter part. However, it is worth noting that the so-called accuracy decline is relative. Even during 2008 to 2018, the absolute value of residual error of the prediction model remains below 0.7, and the curve correlation coefficient is as high as 0.989, which is enough to prove the accuracy and reliability of the prediction model.

According to Figure 11(b), the Gaussian multi-peak fitting model accurately restored the carbon emission time series of Henan Province from 1996 to 2018, and predicted the total carbon emission of Henan Province in the next 12 years. Points A, B and C in Figure 11 (b) are the value points of multi-peak fitting. Point D in Figure 11 (b) is the cut-off point of the prediction curve. Before point D, that is, before 2024, the decline rate of total carbon emissions in Henan Province is similar to that in the BC section, with an overall linear downward trend. After point D, the total carbon emission curve of Henan Province will enter the stage of rapid decline.



(a)



(b)

Figure 11. Calculation results of carbon emission model in Henan Province (a) neural network model (b) Gaussian multi-peak fitting

4. Conclusions and policy implications

4.1 Conclusion

This paper uses grey relation analysis, neural network model and methods of multi-peak gaussian fitting, first analyzed the carbon emissions in henan province and the economic development level, the relationship between different industries is the second industry and the most relevant of the carbon in henan province, on the basis of further analysis of the relationship between energy use and carbon emissions in henan province. The research conclusions are as follows:

1) The results of grey correlation analysis show that the total carbon emission of Henan Province has the highest correlation with the secondary industry, indicating that the secondary industry is the biggest factor affecting the total carbon emission of Henan Province. The correlation degree between the other two industries and the total carbon emissions is also above 0.7, which also has an important impact on the total carbon emissions. According to the neural network prediction model, the importance of the three industries is the secondary industry, the primary industry and the tertiary industry, which is consistent with the results of grey correlation analysis.

2) Energy consumption of coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil and natural gas mainly occurs in the secondary industry. Grey correlation analysis results show that the correlation between coal energy and total carbon emissions is the highest, up to 0.87, and the correlation coefficients of other energy sources are all about 0.5. The large use of coal resources in the secondary industry promotes the high carbon emissions in the secondary industry. With the adjustment of the industrial structure in Henan Province, the proportion of the secondary industry with large energy consumption decreases. The development and use of green energy and the rise of the tertiary industry will make a certain contribution to the realization of energy conservation and emission reduction and the "double carbon target" in Henan Province.

3) The correlation coefficient between the neural network prediction results and the carbon emission curve is 0.989, indicating that the multi-layer perceptron neural network model has a good effect on the carbon emission prediction of Henan Province. In the process of Gaussian multi-peak fitting, three inflection points of carbon emission curve before peak, above peak and after peak were selected for multi-peak fitting, and the fitting curve and prediction curve of carbon emission in Henan province were obtained. It can be seen from the forecast curve that the carbon emission of Henan Province has reached the peak, the tertiary industry keeps developing, and the GDP in 2018 is equal to that of the secondary industry. With the continuous adjustment and optimization of the structure of the primary, secondary and tertiary industries in Henan Province, the economic development is transforming to a low-carbon and green direction. According to the forecast curve, the carbon emission curve of Henan Province after 2018 can be divided into two parts. Before 2024, the total carbon emission of Henan Province showed a linear decline trend, and after 2024, the total carbon emission curve of Henan Province will enter a rapid decline stage.

4.2 policy implications

In view of China's carbon peak and carbon neutral goals, Henan Province has to shoulder important responsibilities in terms of industrial structure, energy structure and environmental protection in order to achieve green development. Among the three major industries, the secondary industry is an important source of carbon emissions. As a major energy consumption province, promoting energy conservation and consumption reduction in the secondary industry, improving the utilization efficiency of traditional fossil energy, and accelerating the development and utilization of clean energy are the key factors to achieve the "double carbon" goal.

Based on the above analysis and the carbon emission prediction curve, it can be seen that according to the current economic development situation, Henan Province will enter a rapid decline stage after 2024. It shows that Henan Province needs to make great efforts in energy conservation and emission reduction, economic development and environmental protection coordination. According to the development trend chart of carbon emissions from energy consumption, the carbon emissions caused by coal consumption showed a downward trend, while the carbon emissions caused by gasoline and natural gas consumption showed an increasing trend. Therefore, Henan Province is still facing great pressure of carbon emissions and energy consumption. Therefore, Henan Province should encourage and support the application of clean energy such as wind, solar and hydropower in the three major industries.

Technological progress can not only promote economic development, but also eliminate backward production capacity. To achieve carbon emission reduction and green development, Henan Province needs to increase investment in technological innovation, industrial upgrading, model innovation and institutional innovation, improve the development and supply capacity of green energy, and finally effectively promote the realization of the goal of "carbon peak" and "carbon neutrality".

5. Statements

5.1 Ethics approval

Consent.

5.2 Consent to participate

Agree to participate.

5.3 Consent for publication

Agreement for publication.

5.4 Author Contributions

Wang Chongyang supervised the research and proposed the research direction. Pan Yisha was responsible for report analysis and paper writing. Wang Yidi and Zhang Yuyang were responsible for data processing. Zhang Shanshan and Wang Penghui were responsible for data collection. Li Pengyang was responsible for method investigation.

5.5 Funding

Not applicable.

5.6 Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

5.7 Data Availability

The datasets generated during and analyzed during the current study are available from the corresponding author on reasonable request.

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