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(Article begins on next page)

# 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

45 economic growth and carbon emissions in the Yangtze River Delta. Li et al. (2022) studied the regional  
46 carbon emission reduction effect by constructing a theoretical model of spatial emission reduction effect of  
47 digital economy development under the influence of economic agglomeration, and further explored the  
48 link between regional economic development and environmental governance. Zhao et al. (2022) analyzed  
49 the economic and carbon emission status, industrial structure and energy structure characteristics,  
50 inflection point and decoupling, and driving factors of carbon emission of nine provinces and regions in  
51 the Yellow River Basin from 1997 to 2019, and the results showed that the low-carbon evolution trend of  
52 industrial structure in each province was obvious.

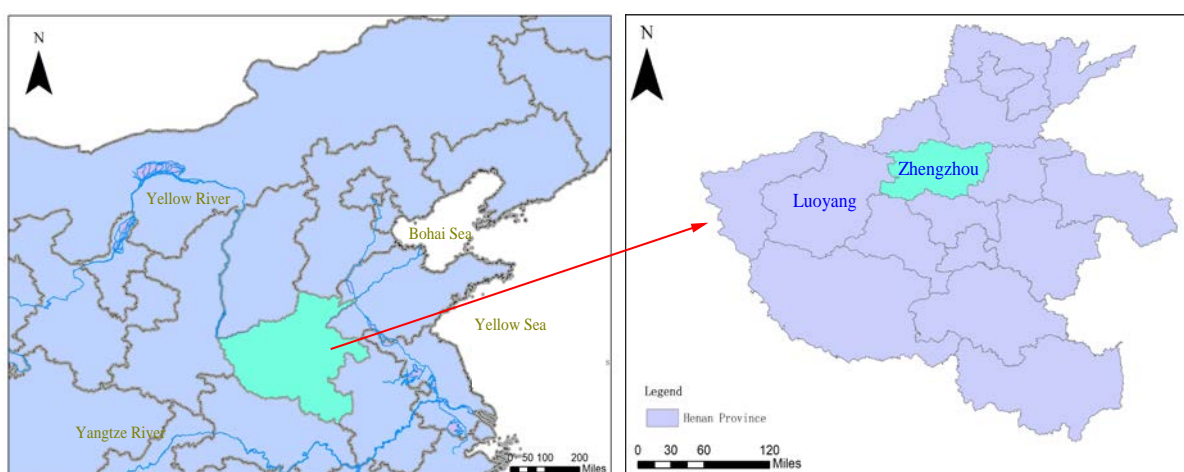
53 With the goal of "carbon peak" and "carbon neutrality" proposed, the prediction of carbon emissions  
54 has also attracted extensive attention from the academic community. Wei et al. (2022) took the accounting  
55 and prediction of building carbon emissions in Baotou, a heavy industrial city in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

73 In the research of carbon emission prediction, neural network and other related models are widely used.  
74 Zhang et al. (2022) established an improved particle swarm optimization algorithm (IPSO) to optimize the  
75 BP neural network model based on the calculation results of carbon emissions and emission intensity in  
76 Shandong Province from 2000 to 2017, and simulated and predicted the carbon emissions and emission  
77 intensity in Shandong Province. The results show that the carbon emission of Shandong Province will  
78 increase slowly in the future. Guo et al. (2020) used BP neural network model for quantitative research,  
79 and also introduced multiple linear regression model for comparison, and finally conducted market test on  
80 the empirical results. The test data show that the error between the predicted value and the actual value of  
81 BP neural network is much smaller than that of the multiple regression model. Yan et al. (2018) used trial  
82 and error method to determine the number of nodes in the hidden layer of the network based on BP  
83 artificial neural network algorithm, established a carbon emission prediction model for maize production in  
84 Hexi oasis, and selected multiple linear regression model and multiple nonlinear regression model to  
85 evaluate the effectiveness of the model. Guo et al. (2022) analyzed the influencing factors of carbon  
86 emissions by STIRPAT model, and predicted the future carbon emissions of Chongqing by GM (1,1)  
87 model. According to the prediction results, the carbon emission reduction scheme of "three-life space" in  
88 Chongqing was proposed. Based on the carbon emission data of building materials from 17 residential

89 buildings in cold areas, Liu et al. (2022) established a carbon emission prediction model of building  
90 materials production stage for residential buildings in cold areas, and adopted linear regression and ridge  
91 regression methods to establish the coupling relationship between residential space, shape design  
92 parameters and carbon emission of building materials. The results showed that: The prediction model has  
93 good fitting effect and low prediction error.

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

103 Henan Province is located in central China, with a total area of 167,000 square kilometers. It is an  
104 important comprehensive transportation hub and an information flow center for people and logistics.  
105 Henan is located at the junction of the coastal open areas and the central and western regions, which is the  
106 middle zone of China's economic development from east to west. As shown in Figure 1. By the end of  
107 2021, the GDP of Henan Province was 5,888741 billion yuan, ranking the fifth in China. With the rapid  
108 development of economic level and the constant adjustment of industrial structure, the total carbon  
109 emissions of Henan Province also fluctuated significantly. With the proposal of "carbon neutrality", it has  
110 become a crucial issue to reduce carbon emissions under the condition of ensuring economic development.  
111 Therefore, this paper takes the carbon emissions and economic development indicators of various  
112 industries in Henan Province from 2005 to 2018 as the research object, and conducts grey correlation  
113 analysis, neural network model, Gaussian multi-peak fitting explored the impact of economic  
114 development and industrial structure change on total carbon emissions, in order to provide reference for  
115 the prediction of "double carbon" (Zhong et al.,2022)target and the formulation of carbon emission  
116 reduction control and other relevant policies in Henan Province.



117  
118

Figure 1. General situation of Henan Province

## 119 2. Carbon emission analysis based on three industries

### 120 2.1 Grey correlation analysis

121 Grey correlation analysis is to calculate the consistency of two factors in the system to judge the

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

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

$$129 \begin{cases} x_0(k) = \{x_0^1, x_0^2, \dots, x_0^m\}, t \in N^* \cap t \in [1995, 2018] \\ x_i(k) = \{x_i^1, x_i^2, \dots, x_i^n\}, t \in N^* \cap t \in [1995, 2018] \end{cases} \quad (1)$$

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

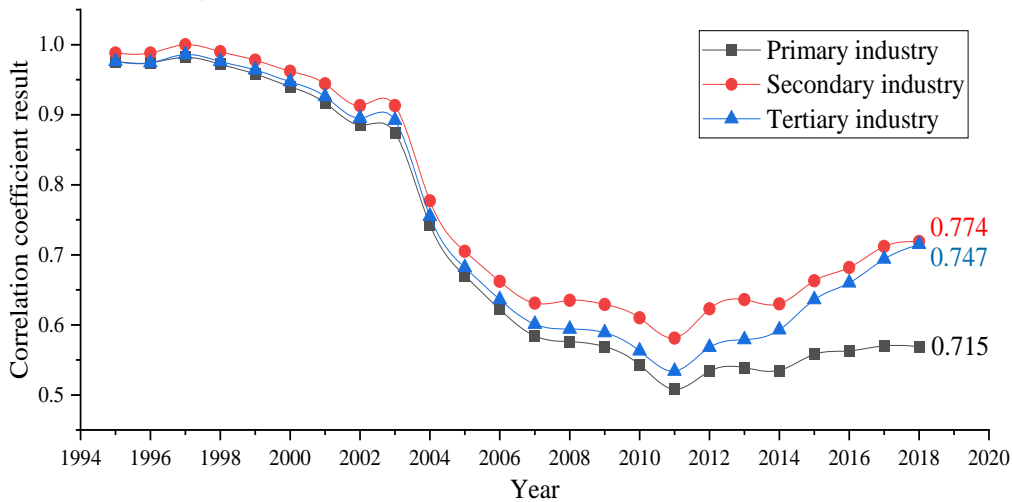
$$138 \xi_{0i}(k) = \left| \frac{\Delta_{min} + \rho \Delta_{max}}{\Delta_{0i}(k) + \rho \Delta_{max}} \right| \quad (2)$$

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

142 According to Equation (2), the gray correlation degree  $\gamma_{0i}$  can be obtained:

$$143 \gamma_{0i} = \frac{1}{m} \sum_{k=1}^m \xi_{0i}(k) \quad (3)$$

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



147  
 148

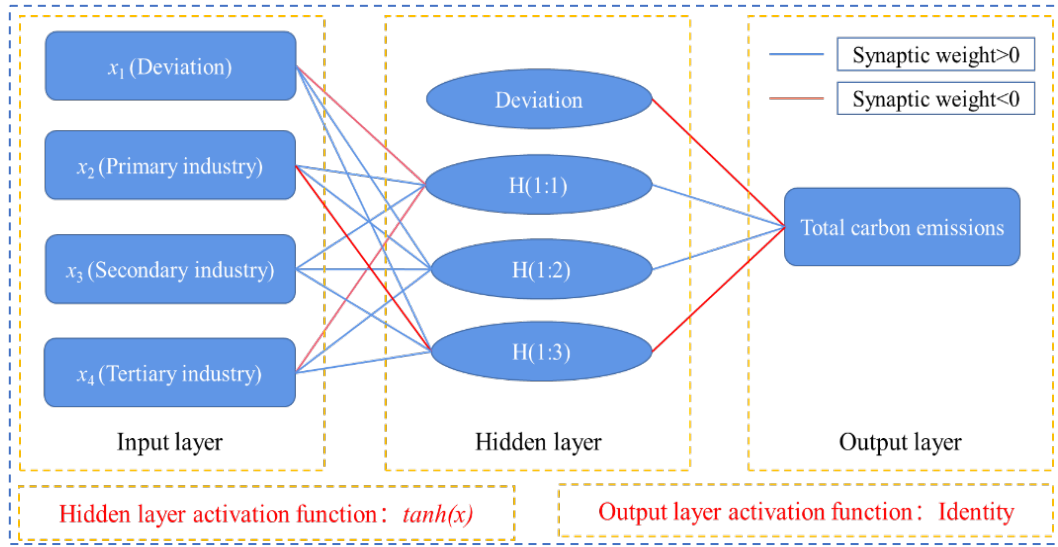
Figure 2. Grey correlation analysis

149 According to Figure 2, the correlation degree between the primary industry and total carbon emissions  
 150 is 0.715, the correlation degree between the secondary industry and total carbon emissions is 0.774, and  
 151 the correlation degree between the tertiary industry and total carbon emissions is 0.747. Relatively

152 speaking, the time series of total carbon emissions in Henan Province has the highest correlation with the  
 153 time series of the secondary industry, indicating that the secondary industry is the biggest factor affecting  
 154 the total carbon emissions. However, the correlation degree between the other two industries and the total  
 155 carbon emissions is also above 0.7, indicating that they also have an important impact on the total carbon  
 156 emissions.

## 157 2.2 Neural network model

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



161

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

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

$$166 \quad \tanh x = \frac{\sinh x}{\cosh x} = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (4)$$

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

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

$$171 \quad \omega_{1n} (1 \times 4) = (0.5, 0.715, 0.774, 0.747) \quad (5)$$

172 Where,  $\omega_n (1 \times 4)$  are the weights of input layer and hidden layer respectively.

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

$$175 \quad P = \begin{bmatrix} x_{11} & & \\ & \ddots & \\ & & x_{17} \end{bmatrix} \times \begin{bmatrix} w_{11} & & \\ & \ddots & \\ & & w_{17} \end{bmatrix} = \begin{bmatrix} w_{11}x_{11} & & \\ & \ddots & \\ & & w_{17}x_{17} \end{bmatrix} = \begin{bmatrix} X_1 & & \\ & \ddots & \\ & & X_7 \end{bmatrix} \quad (6)$$

174 Where,  $x_{1n} (1 \times 7)$  is the influencing factor of input.

- 177 3) Calculate the output result of hidden layer:

$$178 \quad Y_1 = H(1: 1) = \tanh \left( \sum_{n=1}^7 X_n \right)$$

179 (7)

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

$$182 \quad \begin{cases} E = \frac{1}{2} (Y_{target} - Y_{out1})^2 \\ y_{out1} = \frac{e^{y_{net1}} - e^{-y_{net1}}}{e^{y_{net1}} + e^{-y_{net1}}} \\ y_{net1} = \sum_{n=1}^7 X_n \end{cases} \quad (8)$$

181

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

185 5) Update weight:

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

$$190 \quad \frac{\partial E}{\partial w_{12}} = \frac{\partial E}{\partial y_{out1}} \cdot \frac{\partial y_{out1}}{\partial y_{net1}} \cdot \frac{\partial y_{net1}}{\partial w_{12}} \quad (9)$$

189

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

$$194 \quad \begin{cases} \frac{\partial E}{\partial y_{out1}} = Y_{out1} - Y_{target} \\ \frac{\partial y_{out1}}{\partial y_{net1}} = \frac{\partial \left[ \frac{e^z - e^{-z}}{e^z + e^{-z}} \right]_{z=y_{net1}}}{\partial z} = \frac{\partial \left[ \frac{\sinh(z)}{\cosh(z)} \right]}{\partial z} = 1 - \tanh^2(z) = 1 - \left( \frac{e^{y_{net1}} - e^{-y_{net1}}}{e^{y_{net1}} + e^{-y_{net1}}} \right)^2 \\ \frac{\partial y_{net1}}{\partial w_{12}} = \frac{\partial (w_{11}x_{11} + w_{12}x_{12} + \dots + w_{17}x_{17})}{\partial w_{12}} = x_{12} \end{cases} \quad (10)$$

193

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

$$197 \quad \frac{\partial E}{\partial w_{12}} = (Y_{out1} - Y_{target}) \cdot \left[ 1 - \left( \frac{e^{y_{net1}} - e^{-y_{net1}}}{e^{y_{net1}} + e^{-y_{net1}}} \right)^2 \right] \cdot x_{12} \quad (11)$$

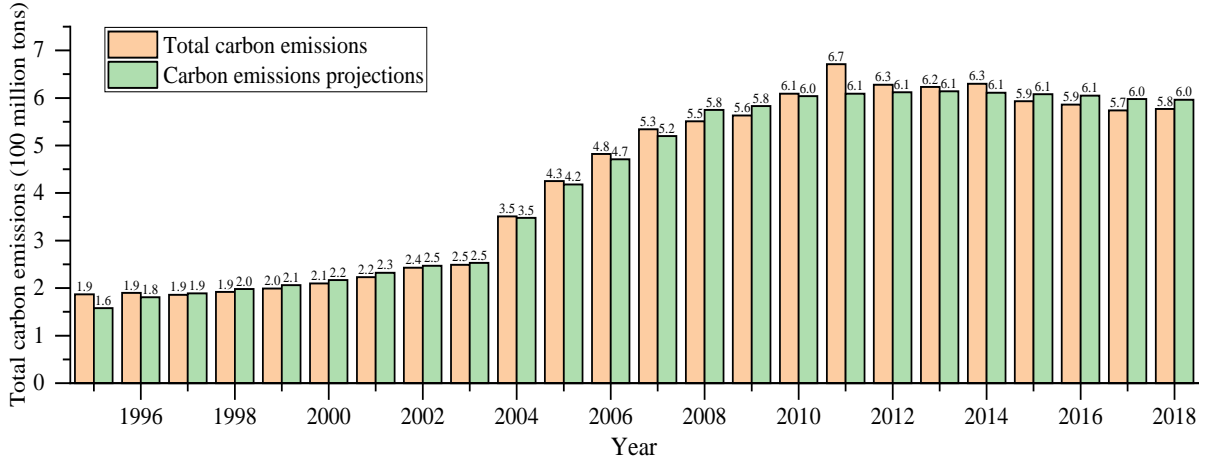
196

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

$$200 \quad w'_{12} = w_{12} - \eta \cdot \frac{\partial E}{\partial w_{12}} \quad (12)$$

199

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



203

204

Figure 4. Neural network model prediction results

205

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:

206

207

208

$$\delta_i = Y_i - y_i \quad (13)$$

209

210

$$\delta_i^* = \frac{\delta_i - \bar{\delta}}{\sigma} \quad (14)$$

211

212

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

213

214

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

215

216

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

217

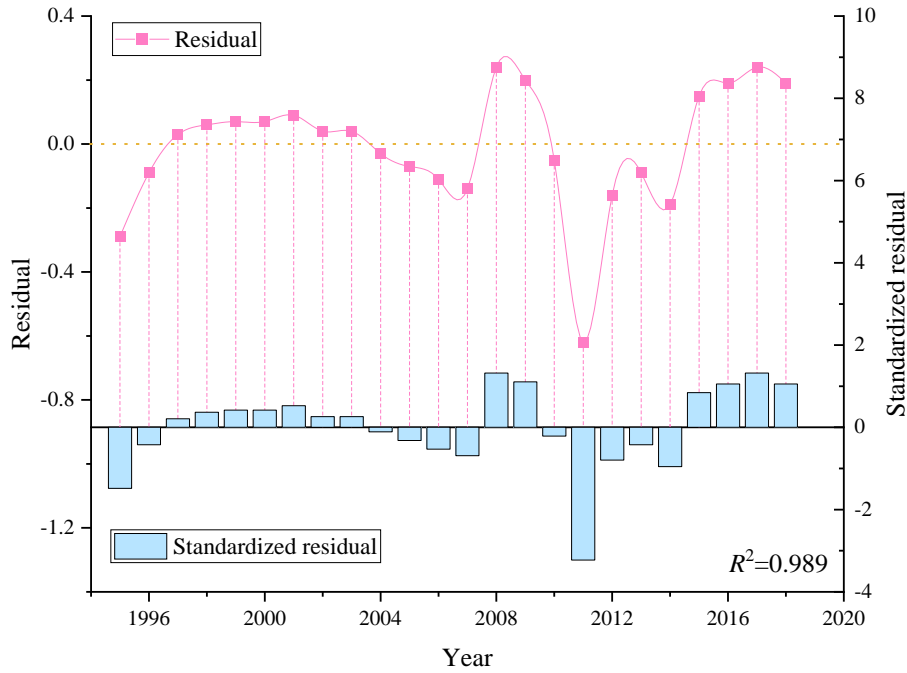
218

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.

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223

Figure 5. Residual analysis of neural network prediction results

224

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.

228

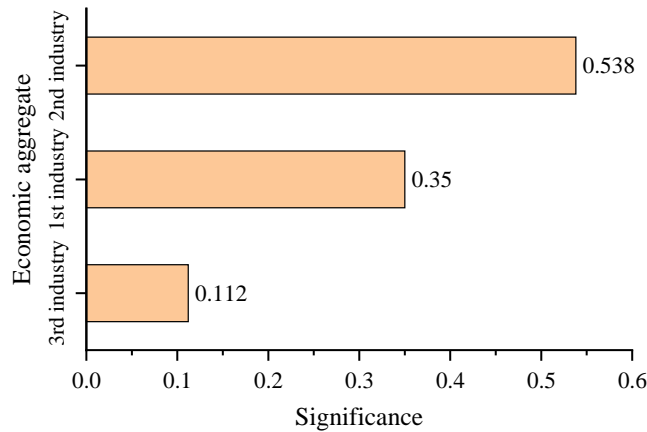
Figure 6 shows the importance of each influence factor under the multi-layer perceptron neural network model, and the sum of the weight of each influence factor is 1. As can be seen from Figure 6, in the multi-layer perceptron model, the ranking of importance of influencing factors is “Secondary industry”, “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.

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Figure 6. Importance analysis of influencing factors

235

### 2.3 Gaussian multi-peak fitting model

236

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:

237

238

239

240

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

241

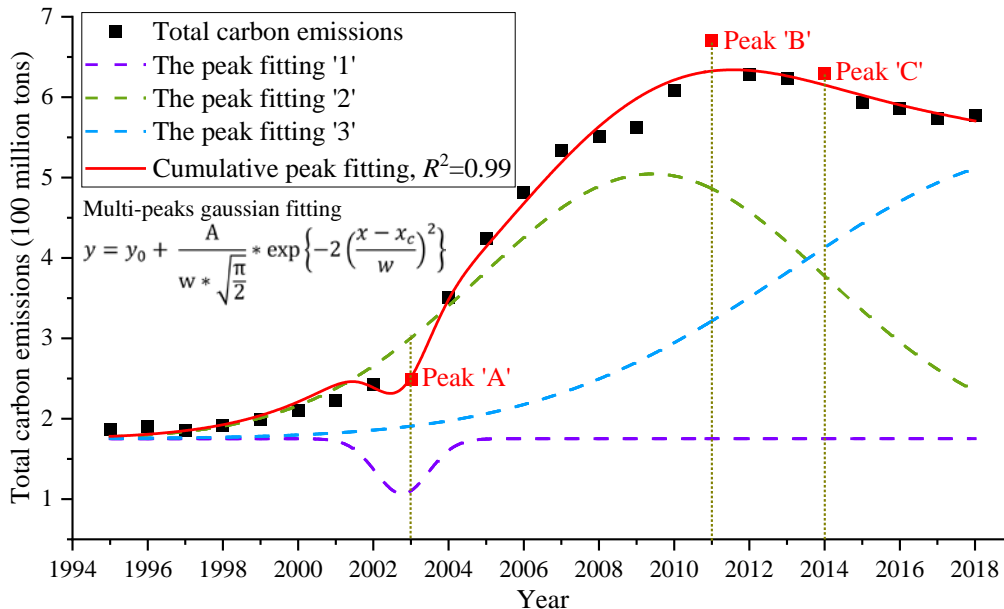
(16)

242

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

243

Figure 10.



244

Figure 7. Gaussian multi-peak fitting

245

246

As shown in Figure 7, 2003, 2011 and 2014 were selected as the local peak centers (the inflection

247

points of the fitting curve of total carbon emissions), and regression fitting was conducted for total carbon

248

emissions. The fitting formula is as follows:

249

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

250

(17)

251

According to Equation (17), the Gaussian fitting curve of total carbon emission (red curve in Figure 10)

252

can be calculated as follows:

253

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

254

(18)

255

After fitting and approximating the total carbon emission curve in Figure 7, the values of each

256

parameter in Equation (18) are:

257

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

258

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

259 required.

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

$$261 \quad \frac{dy}{dx} = -\frac{4(x-x_c)A}{w^2 * \sqrt{\frac{\pi}{2}}} * \exp\left\{-2\left(\frac{x-x_c}{w}\right)^2\right\}$$

262

263

264

(19)

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

$$265 \quad \frac{dy_n}{dx} = \frac{\partial[a(y_1 + y_2 + y_3) + b]}{\partial x} = \frac{\partial y_1}{\partial x} + \frac{\partial y_2}{\partial x} + \frac{\partial y_3}{\partial x}$$

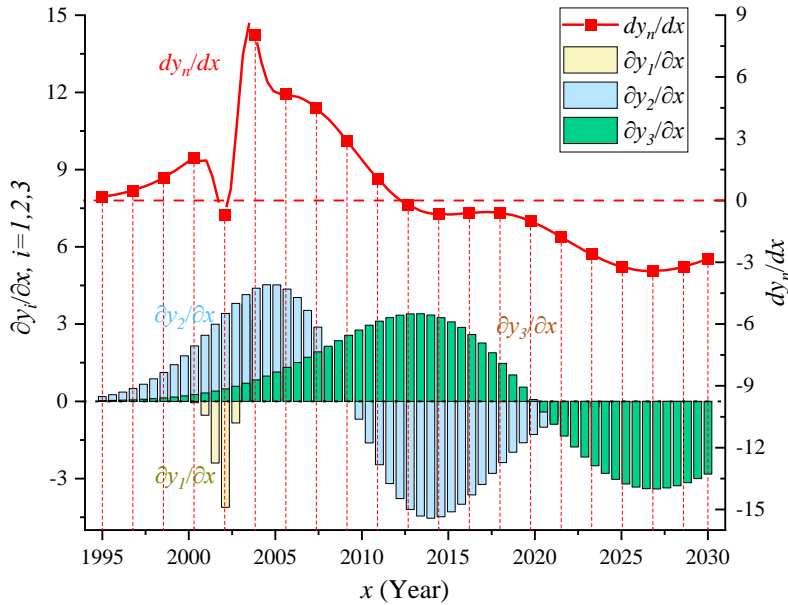
266

(20)

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

$$268 \quad \begin{cases} \frac{\partial y_1}{\partial x} = 1.94(x - 2002.8) * \exp\left\{-2\left(\frac{x - 2002.8}{1.41}\right)^2\right\} \\ \frac{\partial y_2}{\partial x} = -1.42(x - 2009.4) * \exp\left\{-2\left(\frac{x - 2009.4}{9.25}\right)^2\right\} \\ \frac{\partial y_3}{\partial x} = -1.02(x - 2020.0) * \exp\left\{-2\left(\frac{x - 2020.0}{13.7}\right)^2\right\} \end{cases}$$

269 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  
270 the sum of three partial differential curves. It can be seen from Figure 8 that before 2012, the total carbon  
271 emissions showed an increasing trend in other time periods except for a brief downward trend around  
272  $x=2002$ . After 2012, the total carbon emissions showed a downward trend.



273

274

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

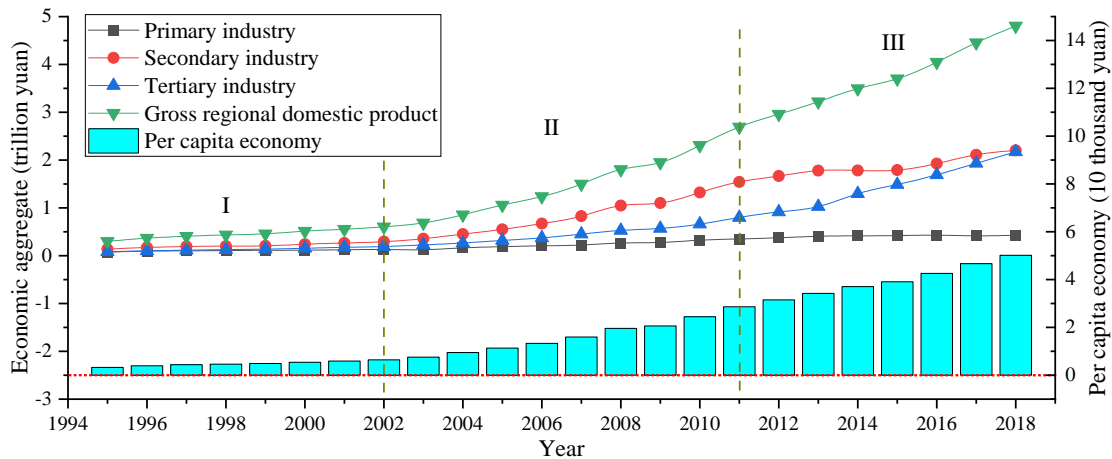
### 275 3. Results analysis and prediction

#### 276 3.1 The impact of three industrial structure changes on carbon emission

277 The rapid growth of economy and the change of industrial structure have an important influence on  
278 carbon emission. The growth trend of total carbon emission in Henan Province has a strong  
279 correspondence with the trend of economic growth. Figure 9 shows the growth trend of gross domestic

280 product and per capita gross domestic product of the tertiary industries in Henan Province from 1994 to  
 281 2018. As can be seen from Figure 9, in the 25 years, all kinds of gross product of Henan Province showed  
 282 an increasing trend and developed well. The growth of regional GDP in Henan Province can be divided  
 283 into three stages: slow development stage, rapid growth stage and adjustment development stage.

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



290  
 291 Figure 9. Economic growth trend of Henan Province from 1995 to 2018

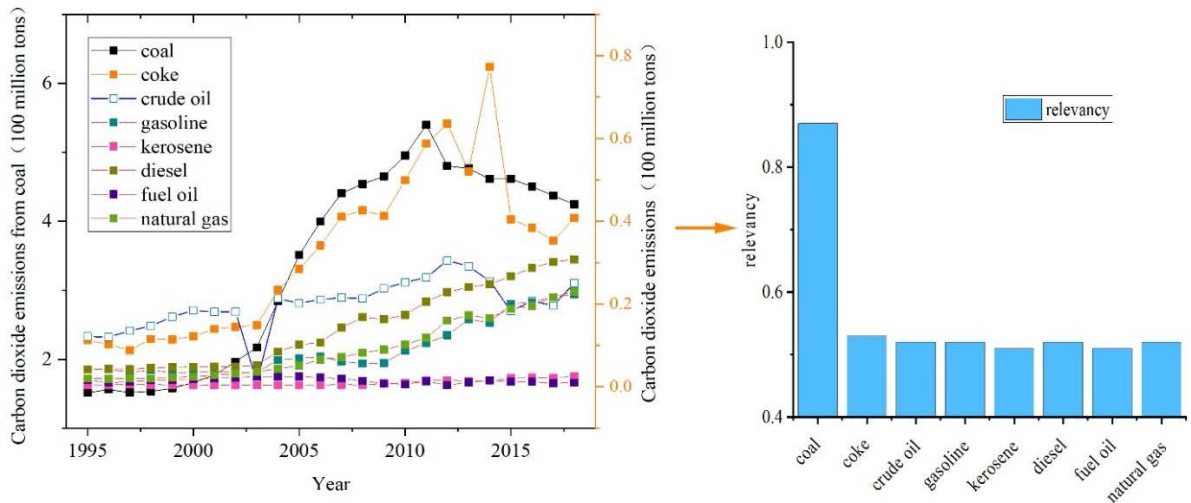
292 2) Rapid growth stage from 2002 to 2011: During this stage, Henan Province vigorously developed the  
 293 secondary and tertiary industries in order to promote economic growth. Economic aggregate then presents  
 294 the trend of rapid growth. It can be seen from the figure that after 2002, the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

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

313 **3.2 Analysis of relationship between energy structure and carbon emission in Henan Province**

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

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



329  
330 Figure 10. Energy carbon emissions change and Carbon emission correlation of various energy sources

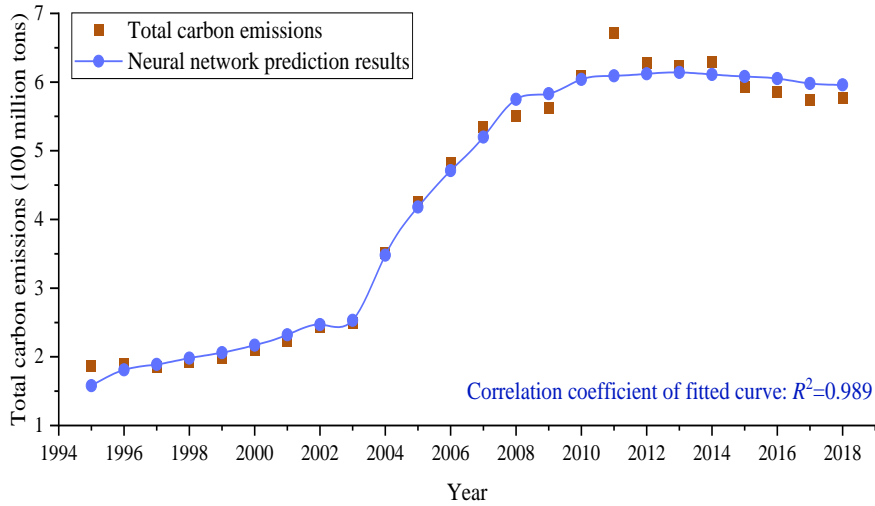
331 In order to further analyze the main influencing factors of carbon emissions in Henan Province, gray  
332 correlation analysis was conducted between carbon dioxide emissions from various energy sources and  
333 carbon emissions in Henan Province, and the correlation results between various energy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

341 **3.3 Total carbon emission prediction**

342 Figure 11 shows the calculation results of the total carbon emission neural network model and  
343 Gaussian multi-peak fitting model. It can be seen from Figure 11 (a) that the prediction of the neural  
344 network model is very accurate thanks to the gray correlation analysis carried out in the early stage,

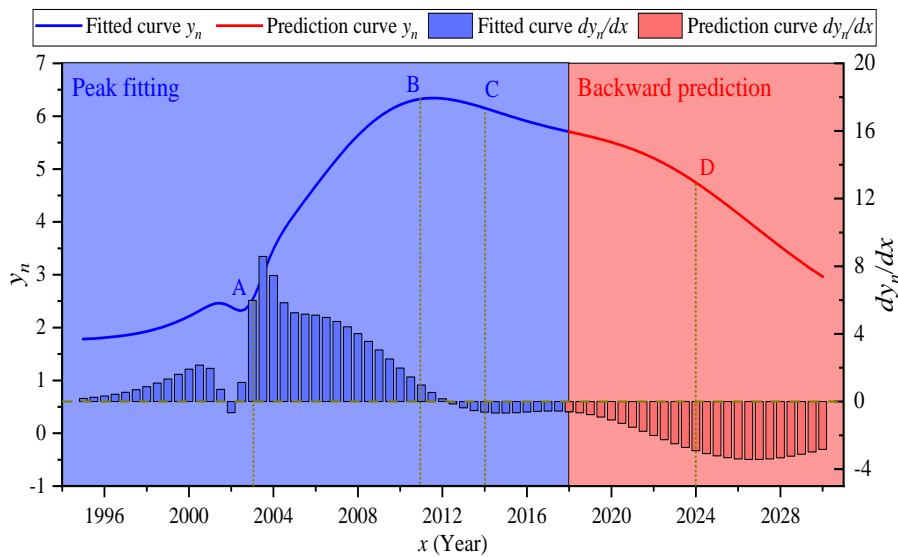
345 especially from 1996 to 2006, the prediction curve almost coincides with the original curve. The separation  
 346 between the prediction curve and the original curve is mainly from 2008 to 2018. This is because there are  
 347 only 24 groups of statistical samples, limited by the limited samples, which makes it impossible for the  
 348 neural network model to conduct further training and learning, resulting in a decline in the prediction  
 349 accuracy of the latter part. However, it is worth noting that the so-called accuracy decline is relative. Even  
 350 during 2008 to 2018, the absolute value of residual error of the prediction model remains below 0.7, and  
 351 the curve correlation coefficient is as high as 0.989, which is enough to prove the accuracy and reliability  
 352 of the prediction model.

353 According to Figure 11(b), the Gaussian multi-peak fitting model accurately restored the carbon  
 354 emission time series of Henan Province from 1996 to 2018, and predicted the total carbon emission of  
 355 Henan Province in the next 12 years. Points A, B and C in Figure 11 (b) are the value points of multi-peak  
 356 fitting. Point D in Figure 11 (b) is the cut-off point of the prediction curve. Before point D, that is, before  
 357 2024, the decline rate of total carbon emissions in Henan Province is similar to that in the BC section, with  
 358 an overall linear downward trend. After point D, the total carbon emission curve of Henan Province will  
 359 enter the stage of rapid decline.



360  
361

(a)



362  
363

(b)

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

## 366 **4. Conclusions and policy implications**

### 367 **4.1 Conclusion**

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

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

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

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

### 402 **4.2 policy implications**

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

408 energy, and accelerating the development and utilization of clean energy are the key factors to achieve the  
409 "double carbon" goal.

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

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

## 424 **5. Statements**

### 425 **5.1 Ethics approval**

426 Consent.

### 427 **5.2 Consent to participate**

428 Agree to participate.

### 429 **5.3 Consent for publication**

430 Agreement for publication.

### 431 **5.4 Author Contributions**

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

### 436 **5.5 Funding**

437 Not applicable.

### 438 **5.6 Competing Interests**

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

### 440 **5.7 Data Availability**

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

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