

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

Original

The influence and forecast of three industries and energy structure on regional carbon emission / Pan, Y.; Wang, Z.; Wang, C.; Zhang, Y.. - In: ENERGY SOURCES. PART A , RECOVERY, UTILIZATION, AND ENVIRONMENTAL EFFECTS. - ISSN 1556-7230. - 46:1(2024), pp. 4078-4094. [10.1080/15567036.2024.2323157]

Availability:

This version is available at: 11583/2997264 since: 2025-02-06T14:32:10Z

Publisher:

Taylor and Francis Ltd.

Published

DOI:10.1080/15567036.2024.2323157

Terms of use:

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

Publisher copyright

Springer postprint/Author's Accepted Manuscript

This version of the article has been accepted for publication, after peer review (when applicable) and is subject to Springer Nature's AM terms of use, but is not the Version of Record and does not reflect post-acceptance improvements, or any corrections. The Version of Record is available online at: <http://dx.doi.org/10.1080/15567036.2024.2323157>

(Article begins on next page)

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

Yisha Pan¹, Zhanwu Wang², Chongyang Wang^{3*}, Yuyang Zhang⁴

1. School of Surveying and Land Information Engineering, Henan Polytechnic University, Jiaozuo, Henan 454000, China.

2. Statistics Bureau of Ruzhou City, Pingdingshan, Henan 467000, China.

3. School of Resources and Safety Engineering, Chongqing University, Chongqing 400044, China.

4. School of Economics, Henan University, Kaifeng, Henan 475000, China.

* Correspondence: wcy@cqu.edu.cn.

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.

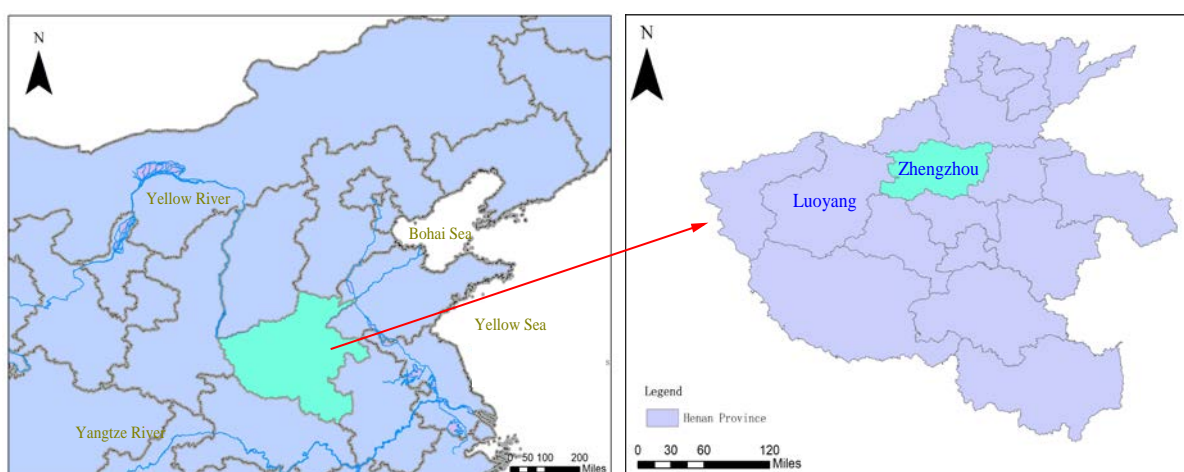
53 With the goal of "carbon peak" and "carbon neutrality" proposed, the prediction of carbon emissions
54 has also attracted extensive attention from the academic community. Wei et al. (2022) took the accounting
55 and prediction of building carbon emissions in Baotou, a heavy industrial city in China, 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:

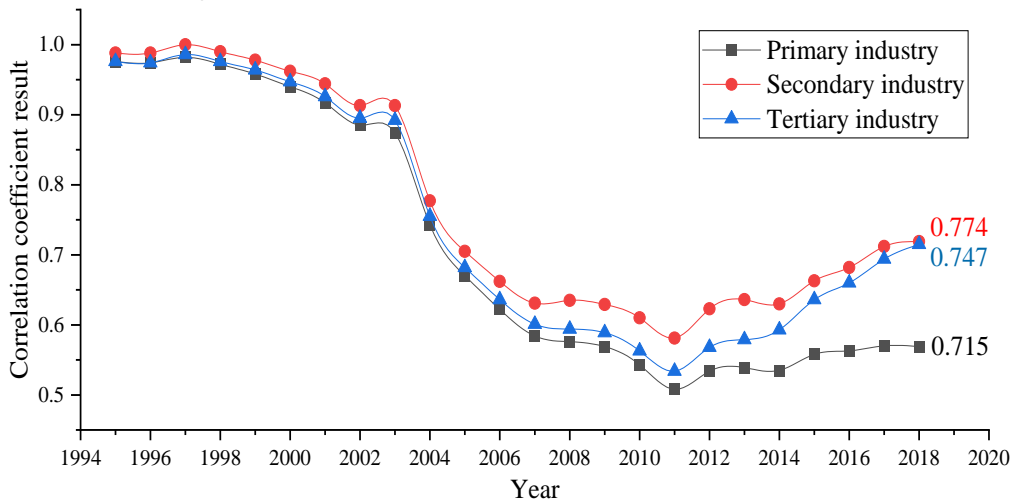
$$138 \xi_{0i}(k) = \left| \frac{\Delta_{min} + \rho\Delta_{max}}{\Delta_{0i}(k) + \rho\Delta_{max}} \right| \quad (2)$$

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

142 According to Equation (2), the gray correlation degree γ_{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

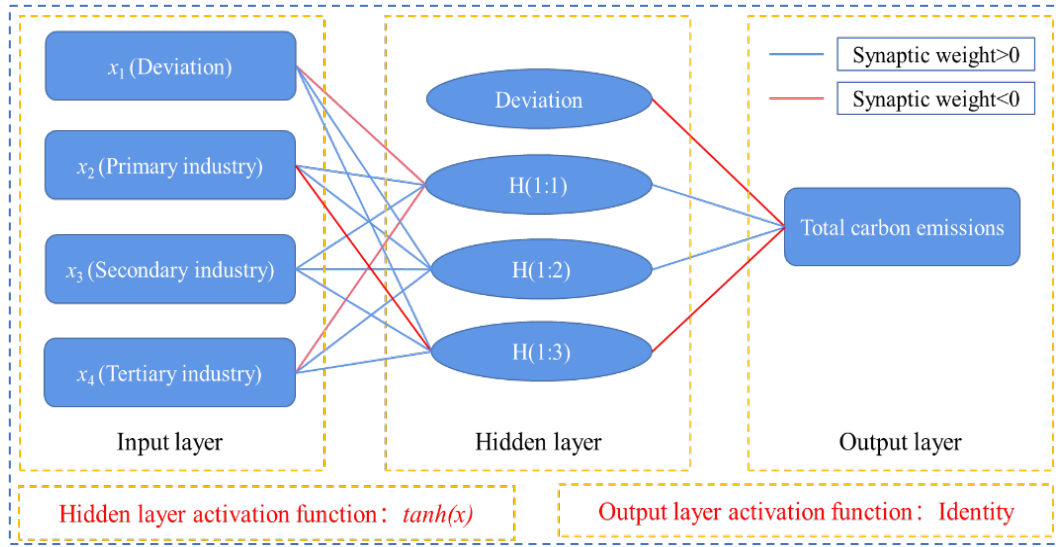
Figure 2. Grey correlation analysis

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

167 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):

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

170

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

176 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:

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

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:

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

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

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

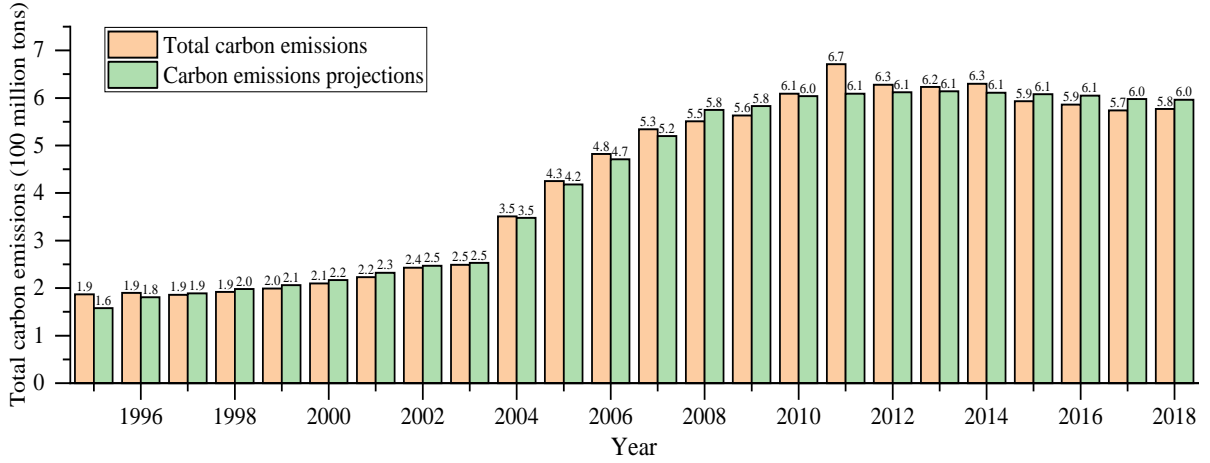
195 Substituting Equation (10) into Equation (9), it can be known that:

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

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

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

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

$$\delta_i = Y_i - y_i$$

209

(13)

210

211

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

212

213

214

215

216

217

218

219

220

221

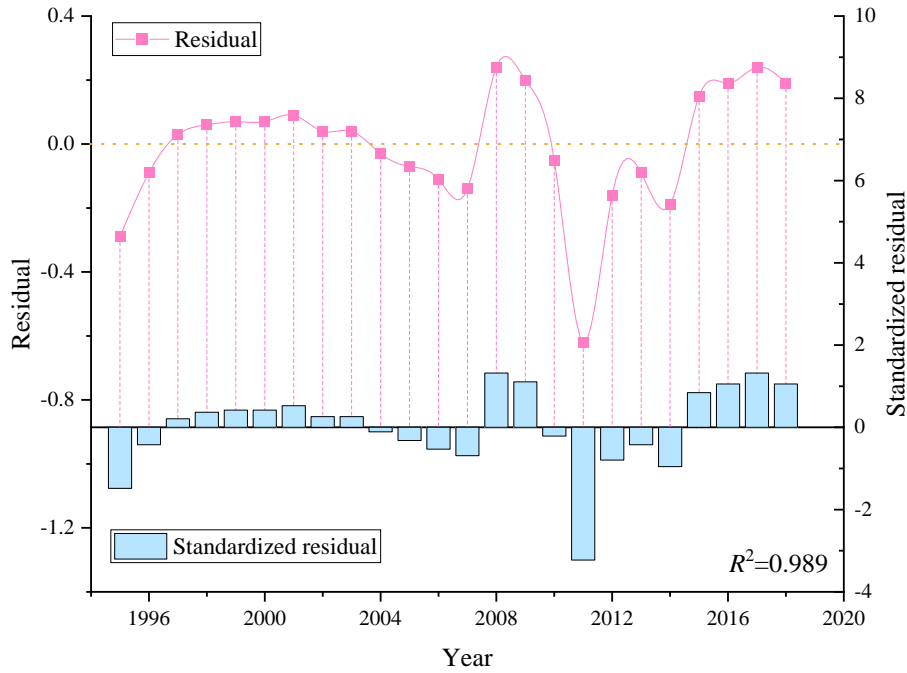
Where, δ_i is the residual, Y_i is the predicted value of the neural network, y_i is the original value, δ_i^* is the standardized residual, $\bar{\delta}$ is the average value of the residual, and σ is the standard deviation.

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

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

(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.



222

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

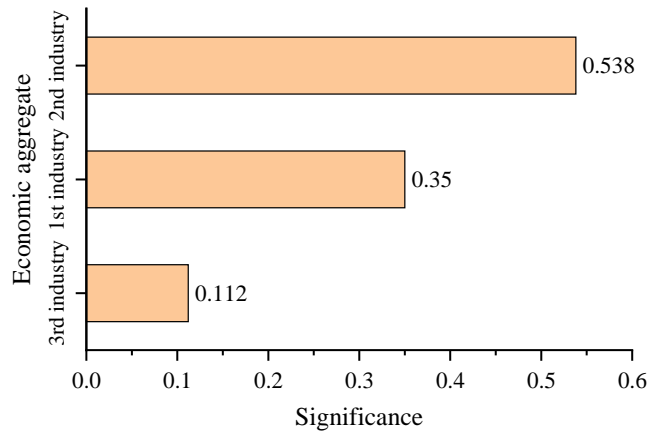
Figure 6 shows the importance of each influence factor under the multi-layer perceptron neural network model, and the sum of the weight of each influence factor is 1. As can be seen from Figure 6, in the multi-layer perceptron model, the ranking of importance of influencing factors is “Secondary industry”,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

229

230

231

232



233

234

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:

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

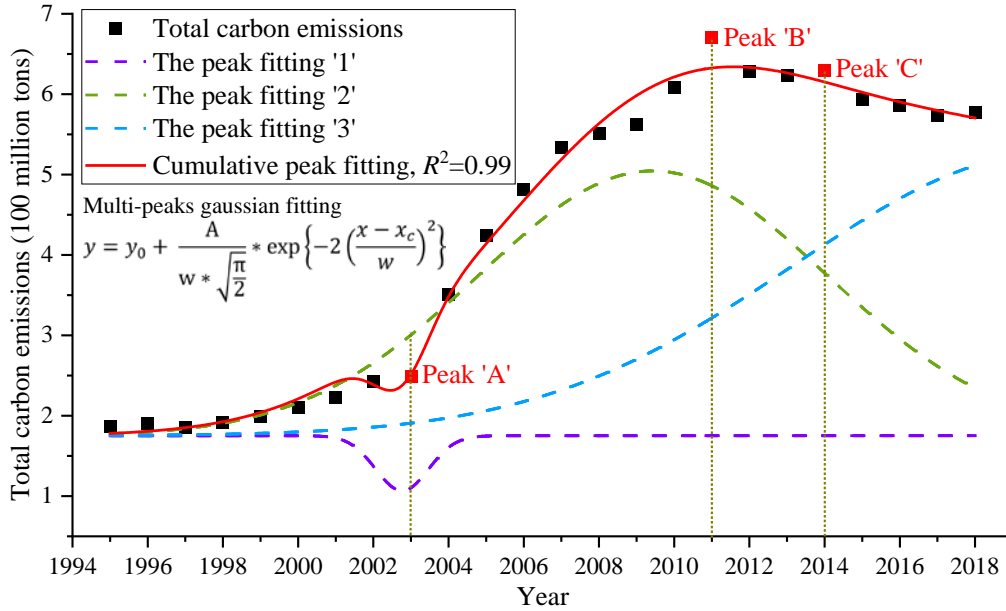
(16)

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:

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

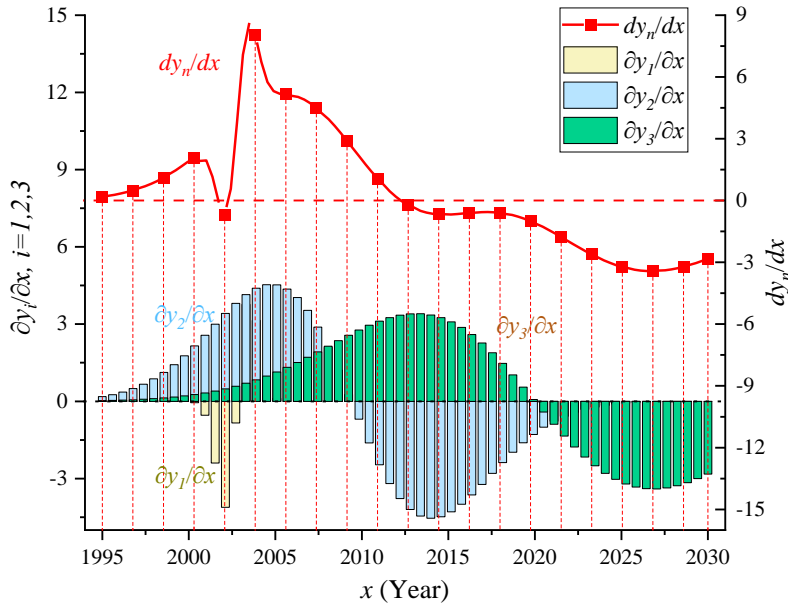
266

(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 $y_n(x)$

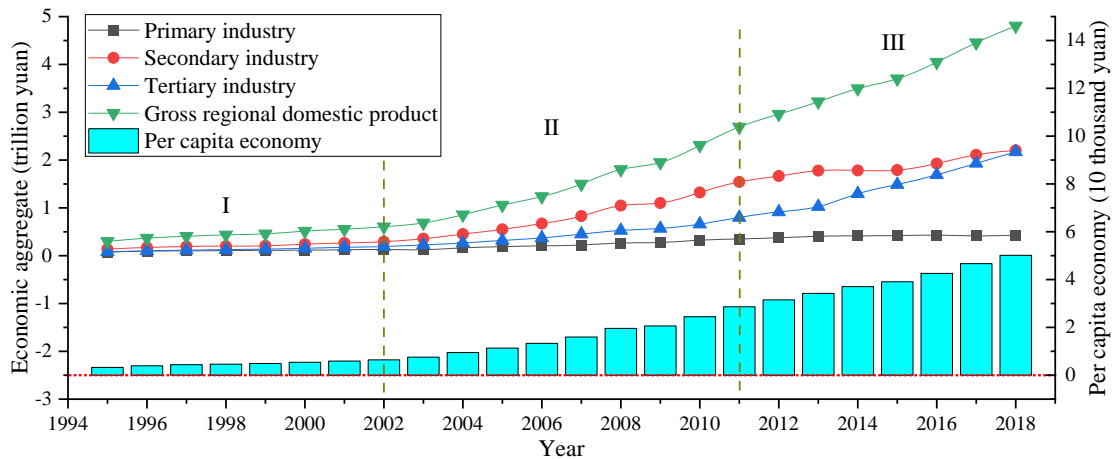
275 3. Results analysis and prediction

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 producti
 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

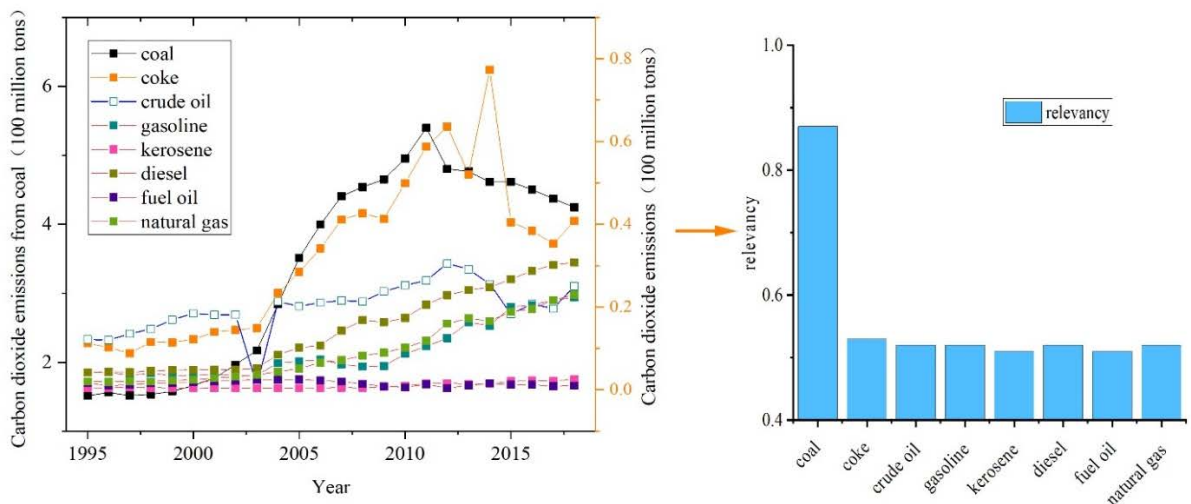
292 2) Rapid growth stage from 2002 to 2011: During this stage, Henan Province vigorously developed the
 293 secondary and tertiary industries in order to promote economic growth. Economic aggregate then presents
 294 the trend of rapid growth. It can be seen from the figure that after 2002, the continuous 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

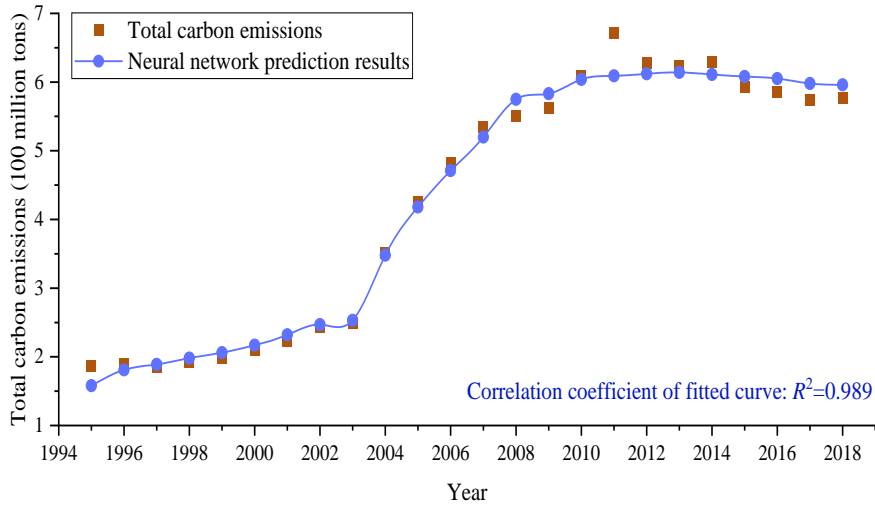
331 In order to further analyze the main influencing factors of carbon emissions in Henan Province, gray
332 correlation analysis was conducted between carbon dioxide emissions from various energy sources and
333 carbon emissions in Henan Province, and the correlation results between various energy sources 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,

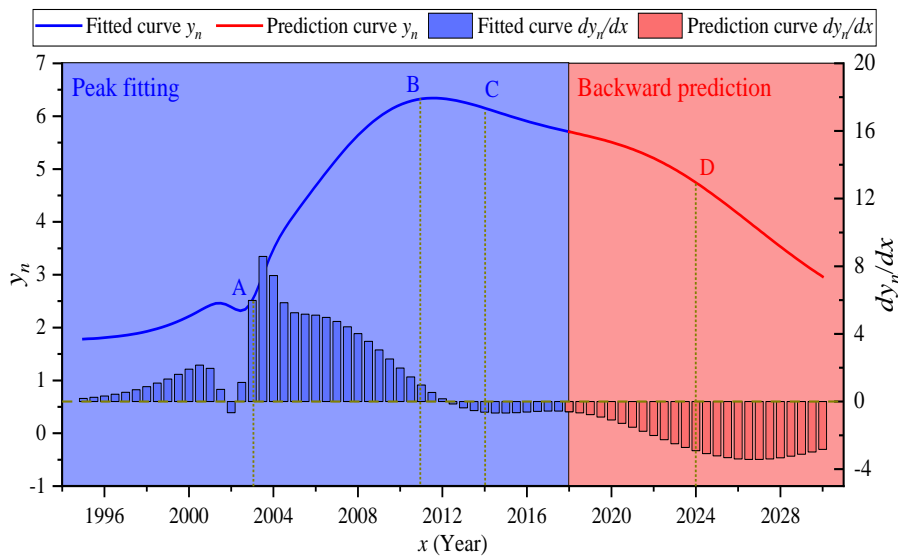
345 especially from 1996 to 2006, the prediction curve almost coincides with the original curve. The separation
 346 between the prediction curve and the original curve is mainly from 2008 to 2018. This is because there are
 347 only 24 groups of statistical samples, limited by the limited samples, which 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.

443 **References**

444 Chen Z, Wu J. 2022, "Evolution of Logistics Industry Carbon Emissions in Heilongjiang Province, China.
445 *Sustainability*, 14.15.

446 Ghosh S, Dinda S, Das Chatterjee, et al. 2022 Spatial-explicit carbon emission-sequestration balance
447 estimation and evaluation of emission susceptible zones in an Eastern Himalayan city using
448 Pressure-Sensitivity-Resilience framework: An approach towards achieving low carbon cities.
449 *Journal of cleaner production*, 336. <https://doi.org/10.1016/j.jclepro.2022.130417>

450 Guo L, Bai L, Wang C, et al. 2022. Growth mechanism and trend prediction of carbon emissions in

451 Chongqing based on "three-life space". *Environmental pollution and prevention*, 44(06):816-823.
452 <https://doi.org/10.15985/j.cnki.1001-3865.2022.06.021>.

453 Guo S. 2020. Carbon emission trading price prediction based on BP neural network. *Zhongnan University*
454 *of Economics and Law*. <https://doi.org/10.27660/d.cnki.gzczu.2020.000775>.

455 Han N, Luo X. 2022. Carbon emission peak prediction and emission reduction potential in
456 Beijing-Tianjin-Hebei region from multi-scenario perspective. *Journal of Natural Resources*,
457 37(05):1277-1288.

458 Huang J, Wen C. 2022, "The impact of private sector energy investment, innovation and energy
459 consumption on China's carbon emissions." *Renewable Energy*, 195. <https://doi.org/10.1016/J.RENENE.2022.06.131>.

461 Hu J, Luo Z. 2022a. Research on energy consumption structure and carbon peak-to-peak prediction of
462 China's manufacturing industry under multi-scenario simulation. *Jiangxi Social Sciences*,
463 42(04):50-60+207.

464 Hu J, Luo Z, Li F. 2022b. Forecast of China's carbon emission intensity under "carbon peak" target:
465 analysis based on LSTM and ARIMA-BP model. *Science of finance and economics*, (02):89-101.

466 Jiang P, Yang H, Ma X. 2019, Coal production and consumption analysis, and forecasting of relat
467 ed carbon emission: evidence from China. *Carbon Management*, 10(2). <https://doi.org/10.1080/17583004.2019.1577177>

468

469 Jing G W. 2022. Carbon emission trading pilot policy and high-quality regional economic develop
470 ment. *Contemporary economic management*, 44(06):50-59. <https://doi.org/10.13253/j.cnki.ddjjgl.2022.06.006>.

471

472 Khanna, N; Zhou, N; Fridley, D; et al.2016, Quantifying the potential impacts of China's power-sector
473 policies on coal input and CO² emissions through 2050: A bottom-up perspective. *Utilities*
474 *Policy*.41:128-138. <https://doi.org/10.1016/j.jup.2016.07.001>.

475 Kwakwa, P, Adjei-Mantey, K , Adusah-Poku, F. 2022, The effect of transport services and ICTs on carbon
476 dioxide emissions in South Africa. *Environmental Science and Pollution Research*, <https://doi.org/10.1007/s11356-022-22863-7>.

477

478 Li Z, Wang J. 2022. How does the development of digital economy affect spatial carbon emissions in the
479 context of economic agglomeration? *Journal of Xi'an Jiaotong University (Social Science Edition)*,
480 1-16. <http://kns.cnki.net/kcms/detail/61.1329.C.20220727.1027.002.html>.

481 Li Z, Yin S, Jiang Y, et al. 2022. Allometric relationship and formation mechanism between economic
482 growth and carbon emissions in Yangtze River Delta. *Journal of Natural Resources*,
483 37(06):1507-1523.

484 Liu Y, Liu N, Xu P. 2022. Carbon emission prediction model for residential building materials production
485 in cold regions. *Journal of Tsinghua University (Natural Science Edition)*:1-9. <https://doi.org/10.16511/j.cnki.qhdxxb.2022.22.044>.

486

487 Lu J, Li J. 2022. Study on the effect, driving factors and prediction of carbon emission decouplin
488 g in China. *Environmental Science and Technology*, 45(02):210-220. <https://doi.org/10.19672/j.cnki.1003-6504.1908.21.338>.

489

490 Ma X, Ping J, Jiang Q. 2020, Research and application of association rule algorithm and an optimized grey
491 model in carbon emissions forecasting. *Technological Forecasting & Social Change*, 158.

492 Ren F, Long D. Carbon emission forecasting and scenario analysis in Guangdong Province based on
493 optimized Fast Learning Network. *Journal of Cleaner Production*, 2021, 317. <https://doi.org/10.1016/J.JCLEPRO.2021.128408>

494

495 Wei G, Kang Y, Fan H, et al. 2022. Study on carbon emission accounting and prediction of construction
496 industry in heavy industrial cities.2022. *Ecological economy*, 1-12. [http://kns.cnki.net/kcms/
497 detail/53.1193.F.20220715.0959.002.html](http://kns.cnki.net/kcms/detail/53.1193.F.20220715.0959.002.html)

498 Wang B. 2021. Traditional Chinese medicine pulse detection system based on multi-peak fitting algorithm.
499 *Northern University for Nationalities* . <https://doi.org/10.27754/d.cnki.gbfmz.2021.000148>.

500 Xiao P, Zhang Y, Qian P. 2022"Spatiotemporal Characteristics, Decoupling Effect and Driving Factors of
501 Carbon Emission from Cultivated Land Utilization in Hubei Province." *International Journal of
502 Environmental Research and Public Health* 19.15. <https://doi.org/10.3390/IJERPH19159326>.

503 Xiong P, Cao S, Yang Z. 2021. Grey correlation analysis of carbon emissions in East China. *Jour
504 nal of Dalian University of Technology (Social Sciences)*, 42(01):36-44. [https://doi.org/10.195
505 25/j.issn1008-407x.2021.01.005](https://doi.org/10.19525/j.issn1008-407x.2021.01.005).

506 Yan C, Hou L. 2021. Research on land use change and carbon emissions in Shaanxi Province based on
507 grey theory. *Journal of Xi'an Polytechnic University*, 37(01):25-31. [https://doi.org/10.19322/j.cnki.
508 issn.1006-4710.2021.01.004](https://doi.org/10.19322/j.cnki.issn.1006-4710.2021.01.004).

509 Yan J, Zhang Z, Chen, M, et al.2022.How will Chinese cities reduce their carbon emissions? Evidence
510 from spatial differences. *Environmental Science and Pollution Research*, 29(48):72461-72479. <https://doi.org/10.1007/s11356-022-20605-3>.

511

512 Yan Z, Li W, Yan T, et al. 2018. Application and effectiveness of BP neural network algorithm in carbon
513 emission assessment of maize production in the oasis of Hebei. *Chinese Journal of Eco-Agriculture*,
514 26(08):1100-1106. <https://doi.org/10.13930/j.cnki.cjea.180084>.

515 Yang J, Chen H, Liu Z, et al. 2022, Analysis and prediction of carbon emission based on information
516 entropy and multi-factor grey system model. *Journal of South-Central University for Nationalities
517 (Natural Science Edition)*, 41(01):123-128.

518 You J, Ding G, Zhang L. 2022, Heterogeneous Dynamic Correlation Research among Industrial Structure
519 Distortion, Two-Way FDI and Carbon Emission Intensity in China. *Sustainability*, (15). <https://doi.org/10.3390/SU14158988>.

520

521 Zhang D, Wang T, Zhi J. 2022. Carbon emission prediction and eco-economic analysis of Shandong
522 Province based on IPSO-BP neural network model. *Ecological science*, 41(01):149-158. <https://doi.org/10.14108/j.cnki.1008-8873.2022.01.017>.

523

524 Zhang L, Mu R, Zhan Y, et al. 2022,Digital economy, energy efficiency, and carbon emissions: Evidence
525 from provincial panel data in China. *The Science of the total environment*, 852. <https://doi.org/10.1016/J.SCITOTENV.2022.158403>.

526

527 Zhao B, Sun, L, Qin, L. 2022, Optimization of China's provincial carbon emission transfer structure under
528 the dual constraints of economic development and emission reduction goals. *Environmental Science
529 and Pollution Research*, <https://doi.org/10.1007/s11356-022-19288-7>.

530 Zhao C, Zhu H, Liu W, et al. 2011. a phase correlation extension method based on multi-peak fitting.
531 *Computer Engineering*, 37(11):228-230. <https://doi.org/10.3969/j.issn.1000-3428.2011.11.079>

532 Zhao Z, Yan Y, Liu J. 2022. The implementation path of the "double carbon" target in nine provinces and
533 regions of the Yellow River Basin. *Journal of Xi'an Jiaotong University (Social Science Edition)*, 1-1.
534 <http://kns.cnki.net/kcms/detail/61.1329.c.20220727.1852.008.html>

535 Zhong C, Dong F, Geng Y, et al. 2022, Toward carbon neutrality: The transition of the coal industrial chain
536 in China. *Frontiers in Environmental Science*. <https://doi.org/10.3389/FENVS.2022.962257>.

537 Zhou Y, Chen Y, Zhang J. 2013, Measurement of acid dissociation constants of acid-base indicators by
538 Gaussian multippeak fitting technique. *Experimental technology and management*, 30(12):58-61. <https://doi.org/10.1016/j.1008-8873.2013.12.005>

