The Evolutional Prediction Model of Carbon Emissions in China Based on BP Neural Network

Lixin Tian *, Linlin Gao+, Peilin Xu
Nonlinear Scientific Research Center, Jiangsu University
Zhenjiang, Jiangsu, 212013, P.R. China
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Abstract: This paper analyzes and processes the time sequence of carbon emissions from the perspective of the BP neural network, revealing the structure and the law of all kinds of index systems of carbon emissions and describing the dynamic characteristics of carbon emissions system. Based on the synthesis of the energy structure factors, energy efficiency factors, economic development factors, population factors, per capita consumption factors and population urbanization rate factors as the main influencing factors, the author tries to establish the neural network prediction model of carbon emissions in China, simulating it with MATLAB, and forecast carbon emissions of the next decade with three exponential smoothing methods. The simulation results show that the selected input index plays an important role in the carbon emissions. This article adopts the improving BP neural network LM algorithm to predict the carbon emissions in China, with an interesting finding that the predicted carbon emissions and the actual ones are so close that the relative error can be controlled within three percent, which shows that this neural network of carbon emissions forecast can be adopted by the macro economic department as a reliable basis for decision-making. The above result is achieved in the existing policies and measures conditions of energy conservation and emission reduction, but to achieve the carbon emissions proposed by 2050 in Copenhagen world climate summit, the control policy and the related factors of internal and external model need to be analyzed. This paper analyzes the energy conservation and emission reduction concretely by 2050 and designs three scenarios, corresponding to the low, medium and high energy conservation and emission reduction policy. They are forecasted respectively with the forecasting results that in the situation of low energy conservation and emission reduction, that is if any new climate change countermeasure is not taken, the prediction of carbon emissions is 84.7598 billion tons; In the situation of medium energy conservation and emission reduction, that is, in the premise of considering the requirements of the sustainable development, energy security, domestic environment and low carbon conditions in the economic society, the prediction values of carbon emissions is 68.6690 billion tons; In the situation of high energy conservation and emission reduction, that is, with the consideration of the domestic economy and social development and the demand of environment development, the technology of non-fossil energy and emission reduction makes a key breakthrough. It forecasts the carbon emissions of 46.4767 billion tons. Simulation shows that using the improved model of neural network method to predict carbon emissions in 2050, with the analysis of the main factors of carbon emissions, the results can be more accurate and comprehensive.

Keywords: BP neural network; carbon emission; three exponential smoothing prediction; MATLAB; evolving analysis

1 Introduction

With the continuing growth of the world population and the acceleration of industrialization and urbanization, the recent two centuries has witnessed a dramatic increase of the consumption of energy and worsening of the ecological environment. What’s worse, the global warming has become a big threat to the sustainable development of human beings. One of the major challenges the world faces is the global climate change, which is mainly caused by emissions of the greenhouse gases. According to fourth assessment report of the IPCC in 2007, burning fossil fuels is the main source of greenhouse gases, which causes emissions of carbon dioxide in 2004 close to 95.3% of the total carbon emissions (not including the
carbon emission for deforestation and biomass reduction). At present, China’s emissions of carbon dioxide rank the second in the world, following the amount of the United States [8]. Therefore, how to control and reduce carbon emissions has become one of the hottest issues discussed at home and abroad.

In recent years, many scholars have studied the problems of carbon emissions. Guoquan Xu adopted Logarithmic mean Divisia weight decomposition method to quantitatively analyze the influence of energy structure, energy efficiency and economic development on China’s per-capita emissions [8]. Through the extension of STIRPAT model, Qin Zhu analyzed the influence of population, consumption and technical factors on carbon emissions with management regression method [9]. Xiangzhao Feng deployed structure factor analysis of CO$_2$ emissions during the year 1971-2005 by combining Kaya identities with China’s macroeconomic environment change, he tried to explore factors to reduce greenhouse gas emissions and achieve a sustainable development strategy of an economic-energy-complex system [10]. The variation trend of carbon emissions in 1990-2006 suggests that as a large CO$_2$ emission country, China is likely to increase its CO$_2$ emissions quickly in the future 50 years, but China has a greater chance to control it and makes it decline after the year 2030[2]. At present, China has researched on CO$_2$ emission reduction policies and discussed how CO$_2$ emission reduction will influence Chinese economy. But most of these studies are the static analysis based on the CGE models, without considering the factors which have influences on carbon emissions. In addition, some macroeconomic models about China’s CO$_2$ emission have shortcomings. The influenced factors they considered are limited, which are only for prediction of some simple mathematical models and not enough accurate for the prediction on the carbon emission model. This paper simulates and analyzes CO$_2$ emissions scenarios in 2050 using the improved neural network algorithm on the basis of the changes of various influential factors. In order to control carbon emissions and achieve sustainable development, qualitative and quantitative predictions can be made to help the administration in adjusting the macroeconomic strategy.

Neural network is a nonlinear system which is made up of a large number of simple calculated units (neurons), which imitates information processing, storage and function of the human’s brain nerve system to a certain degree. Its unique capability of adapting information processing nonlinearily can overcome the defects of the traditional processing method for data, and then apply successfully in the field of prediction. Among them, the BP neural network is representative of neural network, whose structure is simple, easy to understand. It has an excellent non-linear approximation ability, and obvious advantages in dealing with missing values and the nonlinear problem. The BP neural network has a wide range of applications in function approximation, pattern recognition and intelligent control, etc., especially in the economic forecast. Wei Sun selected an appropriate BP neural network to establish the neural network forecasting model of Anhui province’s GDP [11]. Bin Lv forecasted the power load with artificial neural network [6]. Many scholars predicted energy with neural network. Ying Liu established an energy consumption forecasting model by timing-neural network model in Fujian province, and by using this model forecasted the energy consumption of the next 15 years in Fujian province [14]. Yue Wang established a nonlinear predictive model of energy demand in China based on wavelet neural network [13]. Zong Woo Geem pointed out that the neural network model is superior to linear regression model and the exponential smoothing prediction methods has many limits. But the method of neural network can realize good nonlinear predictions through the analysis of the main six factors influencing the carbon emission comprehensively. Compared with the other econometric method, it has a higher prediction accuracy and its relative error can be controlled within 3%, which proves that artificial neural network has extensive practical application in the macroeconomic prediction.

The improved BP neural network model (LM) proposed in this paper overcomes the time series analysis difficulty in solving mathematic solutions and better reveals the structure and laws of carbon emissions system itself. At the same time, it also makes full use of the characters of the artificial neural network, such as strong ability of information processing, highly nonlinear mapping, good fault-tolerance and associative memory capacity, strong ability of self-study and adaptive ability of environment, etc. Since carbon emissions are influenced by multiple factors which have complicated relationships each other, the prediction is a highly uncertain nonlinear system. To depict it with the traditional forecasting methods has many limits. But the method of neural network can realize good nonlinear predictions through the analysis of the main six factors influencing the carbon emission comprehensively. Compared with the other econometric method, it has a higher prediction accuracy and its relative error can be controlled within 3%, which proves that artificial neural network has extensive practical application in the macroeconomic prediction.

With a systematical analysis of the factors influencing Chinese carbon emissions, the paper briefly introduces the BP neural network and the improved BP neural network algorithm by using the improved BP neural network, taking the influencing factors: energy structure, energy efficiency, economic development (per capita GDP), population, per capita consumption level and population urbanization rate as input information, the paper establishes the carbon emissions model. In this model, the data from the year 1990 to the year 2008 are divided into two parts: fitting the data from 1990 to 2006 and predicting the data from 2007 to 2008, in order to validate the consistency of the model’s fitting degree and the model prediction. Then the paper forecasts China’s future carbon emissions in the year of 2010, 2015 and 2020 using the three exponential smoothing prediction methods. Finally, for the carbon emissions by 2050, the author analyzes three possible energy-saving scenarios and gets three values of carbon emissions in different situations. The three kinds of circumstances correspond to the low, medium and high saving energy level. In different energy structures, energy
efficiency, per capita GDP, etc. using the improved BP neural network model the amount of the carbon emissions in 2050 is predicted.

2 The influenced factors of carbon emissions

Because the carbon emissions are susceptible to change due to the influence of various factors, after analyzing and summarizing, this article obtains six main influencing carbon emissions factors.

According to China’s existing resources and the proportion of coal in energy production and consumption structure, the coal-based energy consumption structure will not change in a long period. In this paper the energy structure $x_1$ refers to the share of coal in energy consumption. Data suggest that when the coefficient of the country’s energy consumption structure change is higher, the carbon emissions growth will slow down, thus the adjustment of fossil energy structure and the use of renewable energy will reduce the growth rate of carbon emissions so that the goal of transferring high carbon emissions to low carbon emissions will be realized.

From the collected data, the contribution value of energy efficiency, namely energy intensity (technology) to reduce China’s per capita carbon emissions is expanding. But in recent years, compared to the contribution of the economic development which increases China’s per capita carbon emissions, the growth trend of the contribution of energy efficiency reducing China’s per capita carbon emissions slows down significantly. It also causes the rapid growth. In this paper, the energy efficiency refers to the energy consumption of per unit of GDP $x_2$ to measure energy efficiency impact on China’s carbon emissions.

The increase of economic development factors, namely, the per capita GDP, is the major source of increasing per capita carbon emissions. There exists a very complex mutual interaction and restrictions relationship between Chinese carbon emissions and the economic growth. First, the diversified development of economic structure leads to the slowing down of the growth of country’s energy consumption demand. Second, the diversified development of the energy consumption structure will cause a decline in nation’s carbon emission levels. So the evolution of the structure diversity of both the economy and energy consumption will eventually realize the change of the nation’s energy consumption from mainly high carbon-based fuels to low carbon-based fuels. In this paper, we use per capita GDP $x_3$ is used to measure the economic impact on carbon emissions.

Birdsall[18] believes that population growth shifts its influences on greenhouse gas emission in two ways. One is that a large population needs much energy, so a great deal of greenhouse gas emissions will be produced by energy consumption; The other is that the rapid growth of population causes deforestation and changes the way of land use, which will lead to the increase of greenhouse gas emissions. Knapp[19], etc. researched the causality relationship between global $CO_2$ emissions and the world’s population from the perspective of Granger causality test. He believed that long cointegration relationship didn’t exist between them, but the global population was the reason of the growth of world’s $CO_2$ emissions. In this paper, population $x_4$ is used to measure population impact on carbon emissions.

The human factors such as consumption level of individual residents, consumption patterns and so on have become the new growth point of Chinese carbon emissions. The behaviors of consumers such as purchasing the private cars, services can affect about 45-55 percent of the total energy consumption. Lenzen[4], Weber [5] etc. established evaluation model respectively and quantitatively analyzed the impacts of consumer behaviors and lifestyle factors on energy consumption and emissions in Australia, Germany, France, the Netherlands and other countries of and so on; Kim [16] studied the changes of Korean residents’ consumption patterns which influenced $CO_2$ and SO2 emissions between 1985 and 1995. The research shows that the direct energy consumption of people’s living and the demand on strong emission consumer goods are the main factors of greenhouse gas emissions. In this paper variables $x_5$ is used to measure the impact of population urbanization rate on carbon emissions.

Currently population urbanization rate influences significantly on China’s total carbon emissions. Urbanization rate reflected in the differences of traffic orientation, energy consumption varieties, energy-using conception and energy-using habits between urban and rural residents. The living standards of people directly affects the selection of travel mode and the change of travel rate, thereby affecting the carbon emissions changes. In this paper, variable $x_6$ is used to measure the impact of population urbanization rate on carbon emissions.

3 BP neural network algorithm

The BP neural network (back propagation network) also called back propagation neural network, is one of the most widely used neural networks, which consists of input layer, hidden layer and output layer. Hidden layer can be made up of one
or more layers, adjacent to the lower realized between all the connections of all neurons. All connections can be realized between each neuron adjacent to the lower level, and each layer has no connections between neurons, which is the most widely used neural network prediction model.

By training the sample data, it constantly modifies the network weights and thresholds, so as to make the error function decline along the negative gradient direction and approach the desired output. Training data transmitted from the input layer to hidden layer, through the hidden layer, treated one by one and then transmitted to the output layer. Finally it produced the output mode after the process of the output layer. If there exits the error between the output pattern and the desired output pattern, the error value will be sent along the connection path layer and the connection weights of each layer will be modified, which is network status prior to the update and back-propagation of the error. The minimum error function is achieved through back propagation error function, by continuously adjusting network weights.

Back Propagation (BP) algorithm is a training algorithm of non-loop multi-level network. In 1986, the PDP research group by UCSD independently gave clear and simple descriptions of BP algorithm. After BP algorithm was put forward, the history which multilayer network had no training algorithm ended, and it was considered to be the training method of multi-level network systems. Soon it became the most widely used training algorithm of multi-level network, and has played an important role in promoting the application of artificial neural networks. Assume that there are three layers of BP network input nodes are \( x_i \), hidden nodes are \( y_k \), and output nodes are \( z_l \). The network weights between the input nodes and the hidden nodes are \( w_{ij} \). The network weights between the hidden nodes and the output nodes are \( v_{lj} \). Choosing logsig function as transfer function, namely, \( f(x) = \frac{1}{1+e^{-x}} \). When the expected value of the output node is \( t_l \), the algorithm is as follows:

The output of hidden nodes: \( y_j = f(\sum_i w_{ji}x_i) = f(\text{net}_j), \text{where } \text{net}_j = \sum_i w_{ji}x_i. \)

The calculation output of the output node: \( z_l = f(\sum_j v_{lj}y_j) = f(\text{net}_l), \text{where } \text{net}_l = \sum_j v_{lj}y_j \)

The error of output node: \( E = \frac{1}{2} \sum_l (t_l - z_l)^2 = \frac{1}{2} \sum_l (t_l - f(\sum_j v_{lj}y_j))^2 = \frac{1}{2} \sum_l (t_l - f(\sum_j v_{lj}f(\sum_i w_{ji}x_i)))^2 \)

Through the error function, the derivation of the output nodes and hidden layer nodes:

\[
\begin{align*}
    w_j(t + 1) &= w_j(t) + \Delta w_j = w_j(t) + \eta \delta_j y_j \quad x \in R, \quad t \geq 0. \\
    w_{ji}(t + 1) &= w_{ji}(t) + \Delta w_{ji} = w_{ji}(t) + \eta \delta_j x_i \quad x \in R, \quad t \geq 0.
\end{align*}
\]

where \( \delta_t = -(t_l - z_l) \cdot (1 - z_l) \), \( \delta_j = y_j \cdot (1 - y_j) \cdot \sum_l \delta_l v_{lj} \Delta v_{lj} \), \( \Delta w_{ji} \) indicate changes in weight, \( \eta \) indicates learning factors of network.

Although the traditional BP network algorithm is an outstanding step in the development of artificial neural network, it is not quite perfect with the following main deficiencies: (1) learning convergence is too slow and it often needs many learning times. Moreover, the study of complex systems sometimes can not be converged. (2) It can not guarantee convergence to be the global minimum. In the learning process, it often appears local minimum points, which make the network stop learning. (3) The learning outcome is not stable enough. When adding new learning mode, it must be re-learning with the original mode of the network. (4) There is no theoretical guidance in the selection of the layers and cell numbers of the network’s middle layer, usually in the light of experience. Therefore, the network often has great redundancy, and increases learning time potentially. In this paper, the Levenberg-Marquardt optimization method (the LM algorithm) is adopted to model. In the process of training network in this paper, the method of increasing the momentum item is first used as improved BP algorithm. Although the predicted values by this algorithm are very similar to the predicted values obtained by LM algorithm, the training time required for a longer time in the process of network training and the number of required training times reaches up to 20,000 times to complete. Therefore, we choose more optimal improved BP network algorithm-LM algorithm, and the practice has proved that LM method is much faster than the traditional BP algorithm and momentum-learning rate adaptation method using gradient descent method.

4 The Chinese carbon emissions prediction model based on improved BP neural network

Based on the improved BP neural network model, this paper divides the year 1990-2008 carbon emissions sequences into two parts. The 1990-2006 data is used to predict the network, and the 2007-2008 data is used to inspect the network accuracy and test the model. According to China statistical yearbook 2008 from the national bureau and the related data,
the original data is shown in Table 1:

<table>
<thead>
<tr>
<th>Year</th>
<th>Proportion of coal in energy consumption(%)</th>
<th>Energy efficiency</th>
<th>Population (10^8)</th>
<th>Per capital GDP (yuan)</th>
<th>Per capital consumption (yuan)</th>
<th>Population urbanization rate(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>0.762</td>
<td>52871.79</td>
<td>11.43</td>
<td>1644</td>
<td>833</td>
<td>26.41</td>
</tr>
<tr>
<td>1991</td>
<td>0.761</td>
<td>47655.12</td>
<td>11.58</td>
<td>1893</td>
<td>932</td>
<td>26.94</td>
</tr>
<tr>
<td>1992</td>
<td>0.757</td>
<td>40559.36</td>
<td>11.71</td>
<td>2311</td>
<td>1116</td>
<td>27.46</td>
</tr>
<tr>
<td>1993</td>
<td>0.747</td>
<td>32829.66</td>
<td>11.85</td>
<td>2998</td>
<td>1393</td>
<td>27.99</td>
</tr>
<tr>
<td>1994</td>
<td>0.75</td>
<td>25457.54</td>
<td>11.99</td>
<td>4044</td>
<td>1833</td>
<td>28.51</td>
</tr>
<tr>
<td>1995</td>
<td>0.746</td>
<td>21581.18</td>
<td>12.11</td>
<td>5046</td>
<td>2355</td>
<td>29.04</td>
</tr>
<tr>
<td>1996</td>
<td>0.747</td>
<td>19514.84</td>
<td>12.24</td>
<td>5846</td>
<td>2789</td>
<td>30.48</td>
</tr>
<tr>
<td>1997</td>
<td>0.717</td>
<td>17449</td>
<td>12.36</td>
<td>6420</td>
<td>3002</td>
<td>31.91</td>
</tr>
<tr>
<td>1998</td>
<td>0.696</td>
<td>15663.08</td>
<td>12.48</td>
<td>6796</td>
<td>3159</td>
<td>33.35</td>
</tr>
<tr>
<td>1999</td>
<td>0.691</td>
<td>14920.2</td>
<td>12.58</td>
<td>7159</td>
<td>3346</td>
<td>34.78</td>
</tr>
<tr>
<td>2000</td>
<td>0.678</td>
<td>13959.64</td>
<td>12.67</td>
<td>7858</td>
<td>3632</td>
<td>36.22</td>
</tr>
<tr>
<td>2001</td>
<td>0.667</td>
<td>13059.12</td>
<td>12.76</td>
<td>8622</td>
<td>3869</td>
<td>37.66</td>
</tr>
<tr>
<td>2002</td>
<td>0.663</td>
<td>12615.02</td>
<td>12.84</td>
<td>9398</td>
<td>4106</td>
<td>39.09</td>
</tr>
<tr>
<td>2003</td>
<td>0.684</td>
<td>12884.43</td>
<td>12.92</td>
<td>10542</td>
<td>4411</td>
<td>40.53</td>
</tr>
<tr>
<td>2004</td>
<td>0.68</td>
<td>12709.67</td>
<td>13</td>
<td>12336</td>
<td>4925</td>
<td>41.76</td>
</tr>
<tr>
<td>2005</td>
<td>0.691</td>
<td>12264.12</td>
<td>13.07</td>
<td>14053</td>
<td>5463</td>
<td>42.99</td>
</tr>
<tr>
<td>2006</td>
<td>0.694</td>
<td>11622.12</td>
<td>13.14</td>
<td>16165</td>
<td>6138</td>
<td>43.9</td>
</tr>
</tbody>
</table>

4.1 The model of Chinese carbon emission prediction

Since the data collected in practical applications have different dimensions, in order to facilitate the network training, and prevent the calculation process “over fitting” and other problems, the data must first be normalized and the normalized formula is as following:

\[ x^1_k = \frac{x_k - x_{\min}}{x_{\max} - x_{\min}}, \quad k = 1, 2, ... , 7, \quad x \in R, \quad t \geq 0. \] (3)

where \( x_{\min} \) indicates the minimum of \( x_k \), \( x_{\max} \) indicates the maximum of \( x_k \). The normalization is embodied in the process of the MATLAB program in this paper.

In this paper, the improved BP neural network is adopted with three layers. The nodes of the input layer is 6 (just as the six factors); The output nodes is 1 (the prediction value of the carbon emission); but the determination of the neurons numbers in the hidden layer relates to whether the model is able to effectively complete the mapping. If the number of neurons is too big, then the training time will greatly increase, and it may appear “over-match” problem; If the number of neurons is too small, then there is too little information for the model to solve application problems. This paper uses “experiment-test method” to determine with this size of the error that the neuron number of hidden layer is 13 and the selected learning step is 0.01.

4.2 Network Testing

Table 2 and Fig.1 are the training results of the improved BP neural network (The prediction value is the average of 20 experiment results)

The above training results show that BP neural network model has a higher degree of data fitting. And the data of influencing factors in 2007 and 2008 are obtained by related calculation and sorting from the 2009 statistical bulletin, the National 11th five-year plan, ”the 11th Five-Year” plan of energy development and the National S’tatistics Bureau, the National Energy Bureau. These data are seen in Table 3.

IJNS homepage: http://www.nonlinearscience.org.uk/
Table 2: The training results of neural network

<table>
<thead>
<tr>
<th>Year</th>
<th>Prediction Value (million tons)</th>
<th>Practical Value (million tons)</th>
<th>Relative Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>2301.7</td>
<td>2288.95</td>
<td>1.23%</td>
</tr>
<tr>
<td>1991</td>
<td>2351.8</td>
<td>2389.19</td>
<td>-2.10%</td>
</tr>
<tr>
<td>1992</td>
<td>2501.5</td>
<td>2469.8</td>
<td>-0.34%</td>
</tr>
<tr>
<td>1993</td>
<td>2652.3</td>
<td>2648.54</td>
<td>2.75%</td>
</tr>
<tr>
<td>1994</td>
<td>2818.9</td>
<td>2855.31</td>
<td>-2.46%</td>
</tr>
<tr>
<td>1995</td>
<td>2918.2</td>
<td>2885.42</td>
<td>0.47%</td>
</tr>
<tr>
<td>1996</td>
<td>2911.8</td>
<td>2917.34</td>
<td>-0.02%</td>
</tr>
<tr>
<td>1997</td>
<td>3095.2</td>
<td>3106.99</td>
<td>0.36%</td>
</tr>
<tr>
<td>1998</td>
<td>3038.4</td>
<td>2991.36</td>
<td>-2.55%</td>
</tr>
<tr>
<td>1999</td>
<td>2951.0</td>
<td>2908.61</td>
<td>1.44%</td>
</tr>
<tr>
<td>2000</td>
<td>2827.2</td>
<td>2871.53</td>
<td>-1.57%</td>
</tr>
<tr>
<td>2001</td>
<td>3005.8</td>
<td>2992.38</td>
<td>0.45%</td>
</tr>
<tr>
<td>2002</td>
<td>3514.7</td>
<td>3492.25</td>
<td>0.64%</td>
</tr>
<tr>
<td>2003</td>
<td>4131.7</td>
<td>4102.46</td>
<td>0.71%</td>
</tr>
<tr>
<td>2004</td>
<td>5096.0</td>
<td>5131.85</td>
<td>-0.70%</td>
</tr>
<tr>
<td>2005</td>
<td>5549.2</td>
<td>5558.48</td>
<td>-0.17%</td>
</tr>
<tr>
<td>2006</td>
<td>5878.2</td>
<td>5861.96</td>
<td>0.28%</td>
</tr>
</tbody>
</table>

Carbon emissions in 2007 and 2008 can be obtained by putting the value of each factor in 2007 and 2008 into the trained BP neural network in China as 6284.8 and 7198.6 million tons. While from International Statistical Yearbook in 2009, the actual value of carbon emissions in China are 6283.56 and 7219.2 million tons respectively in 2007 and 2008, so a good effect can be expected in prediction. Therefore, the trained network can be used as a better way to predict carbon emissions.

5 The forecast of China’s carbon emissions over the next decade

As the improved BP neural network gets the predicted value by entering the relevant variables, and the exact value of the impact factors of carbon emissions after 2008 are not available, here from the China Statistical Yearbook in 2009 and the asymptotical optimality of three exponential smoothing method, this prediction method is used to predict China’s carbon emissions for the 2010, 2015 and 2020 respectively.

Table 3: The training results of neural network

<table>
<thead>
<tr>
<th>Year</th>
<th>$x_1$</th>
<th>$x_2$</th>
<th>$x_3$</th>
<th>$x_4$</th>
<th>$x_5$</th>
<th>$x_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>0.695</td>
<td>10244.59</td>
<td>13.21</td>
<td>19524</td>
<td>7103</td>
<td>44.94</td>
</tr>
<tr>
<td>2008</td>
<td>0.687</td>
<td>9478.83</td>
<td>13.28</td>
<td>22698</td>
<td>8183</td>
<td>45.68</td>
</tr>
</tbody>
</table>
From the result in Table 4, parameters $a_1$, $b_1$ and $c_1$ are obtained respectively, which are 6439.594, 999.3629 and 11.93973. After many debuggings, the weighted coefficient is selected as 0.53, and the carbon emissions of the year 2010, 2015 and 2020 are 21449.13, 9832.24 and 15516.29 million tons respectively, which is very close to 201.3 billion tons in 2020 proposed in the eleventh five-year plan.

China’s carbon emissions can be divided into two stages from 1990 to 2008: the first stage (1990-2000), the declining stage of China’s carbon emission; The second stage (2000-2008), the sharp rising stage of China’s per capita carbon emissions. In order to slow down the risen sharply trend of the carbon emissions, China has taken a series of national
macroeconomic measures to control carbon emissions, such as energy conservation and emission reduction and adjusting coal-based energy structure, etc. which has cut down the carbon emissions to a certain extent. If the carbon are still emitted in this trend in the next decade, the selected weighting coefficient 0.53 in the three exponential smoothing model indicates that the recent data greatly influence the prediction, so the prediction of carbon emissions in 2010, 2015 and 2020 is based on the existing energy-saving policy conditions.

6 Three scene analysis of carbon emissions prediction in 2050

In accordance with the main factors, such as future energy needs and Carbon emissions, we design three scenarios are designed to explore the sustainable development scenarios under the established economic and social development goals, maybe considered as the scenario of reducing future $CO_2$ emissions. Through different scenarios coefficient selected in different scenarios, China’s carbon emissions are predicted in 2050, and these different scenarios coefficients represent different emission reduction measures and strategies.

1) The first scenario is the low energy emission reduction scenario, which does not adopt new climate change countermeasures. This scenario may occur on energy demand and carbon emission in the future. On the premise of realizing the established objectives of economic and social development, the shift of economic development mode is paid attention. The current energy conservation and emission reduction policy are going to continue, and the economy, society and energy, environment are in the “tight balance” status. The promotion of comprehensive national strength, high investment of technology, and rapid progress in technology lead to the rapid depletion of unit GDP energy consumption with an estimation of 2234.15 tons standard coal / yuan [21], but transformation in lifestyles, the consumption patterns close not appear. Considering the three-step development strategies by government in the economic development model, that is, per capita GDP in 2050 reached 10,000 U.S. dollars (referred to the exchange rate of RMB prices and U.S. dollar against the RMB prices in 1990 at that time), in this scenario, the estimation of per capita GDP is 205,000 yuan [14], and the people’s living standard reaches the level of moderately developed countries. According to the national population plan, population development model will reach its peak with 1.46 billion population between 2040 and 2050, and in 2050 the industrialization and implement the modernization will be completed. On the optimization of energy supply structure, the proportion of fossil fuels should be reduced as soon as possible and the share of the renewable energy and clean energy must be increased. Industrial structure optimization particularly the optimization within the industrial structure is a necessary measure in taking a new road to industrialization. Thus the proportion of coal in the energy consumption will reduce to 41.1%. Through the literature [21] the value of the six factors are obtained in the paper, which are $x_1 = 0.411, x_2 = 2234.15, x_3 = 14.6, x_4 = 205000, x_5 = 59619, x_6 = 79$ respectively. The above given improved BP neural network algorithm shows that the carbon emissions can reach 8,475,98 billion tons standard coal under this scenario by 2050.

2) The second scenario is medium energy emission reduction scenario. This main scenario mainly considers China’s integration into global climate change cooperation system and will achieve emission reduction targets of the different emission reduction scenarios in China. It is a scenario of energy demand and carbon emissions considering the demands of sustainable development, energy security, domestic environment and low-carbon road in economic society and making efforts in strengthening technological progress, changing economic development model, changing consuming pattern, achieving low consumption and emitting low greenhouse gas. The scenario envisaged significant changes in the economic development mode, energy structure optimization, energy conservation technology and even aspects of people’s lifestyle. It also expects a more harmonious state between the economic and social development, and between the energy consumption and environment protection. It expects the nation to depend on their own efforts and achieve low-carbon development scenario as soon as possible. Based on the baseline scenario, the scenario further considers energy conservation and the optimization of energy supply structure. By 2050 the proportion of fossil fuels falls from the baseline scenario 77.5% to 64.0%, of which the proportion of coal drops from the energy-saving scenario 41.1% to 36%. Under this scenario, the energy intensity in 2050 falls to 1858.34 tons/yuan GDP [21]. Through the literature [21], the value of the six factors are obtained in the paper, which are $x_1 = 0.36, x_2 = 1858.54, x_3 = 14.6, x_4 = 205000, x_5 = 59619, x_6 = 79$ respectively. The above given improved BP neural network algorithm shows that the carbon emissions can reach 6,866,90 billion tons standard coal under this scenario by 2050.

3) The third scenario is the high energy emission reduction scenarios. It takes into account of China’s national energy security, domestic ecological environment and low-carbon development requirements. It mainly introduces the energy and emission in the premise of a key breakthrough of domestic economy, environment, development needs, strengthening technical progress and non-fossil energy and emissions reduction technologies. The scenario envisages that joint efforts
of the world, the technological progress will be further strengthened and the technology costs will have a significant decline. After 2030 China’s comprehensive national strength could be expected to rank the No. 1 in the world, it can further increase investment in low carbon economy and promote economic social development by making better use the opportunities provided by low-carbon economy. Meanwhile China leads technology development in some areas of the world, such as cleaning coal technology and CCS Technology which has got a large-scale application. Through literature [21], the value of the six factors can be obtained in the article, which are $x_1 = 0.286, x_2 = 1678.05, x_3 = 14.6, x_4 = 205000, x_5 = 59619, x_6 = 79$ respectively. From the above given improved BP neural network algorithm shows that the carbon emissions can reach 4.64767 billion tons standard coal under this scenario by 2050. Through the above prediction of carbon emissions by 2050, the fourth assessment report of the IPCC revealed that in order to minimize the need of implementing reduction in Chinese economic climate investment and from the perspective of China’s economic impact, it is better for China to choose the scheme that the $CO_2$ emissions by 2050 will be controlled to the 253% $CO_2$ emissions in 2000 which is 72.6497 billion tons carbon emissions through calculation. This value is very similar to the medium energy conservation and emission reduction scene. If China implements the low intensity energy saving, it will indirectly affect the development of China’s economy, and make China’s economic climate investment beyond the scope of endurance.

7 Conclusions

This article selects energy structure, energy efficiency, economic development, population, per capita consumption and the urbanization rate as the factors of carbon emissions. Combined with the actual data of 1990-2008, the paper establishes the improved BP neural network model in China. With MATLAB simulation, the prediction values is so close to the practical data that its relative error of carbon emissions is controlled in 3%, showing that the prediction ability of the model is good. The carbon emission of the next decade are forecasted with the three exponential smoothing methods. Finally the paper forecasts the carbon emissions in 2050 under the background of three different levels of energy conservation and emission reduction using the established artificial neural network model. The simulation results show that only if the current energy conservation and emission reduction policy continue to take effect, and the national’s macro reduction measures and technique is strengthened intensely, can the carbon emissions be slowed down effectively. The establishment of this model has certain practical significance for national energy policy and the implementation of national energy macro-control.

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IJNS homepage: http://www.nonlinearscience.org.uk/


IJNS email for contribution: editor@nonlinearscience.org.uk