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A Study on Carbon Emission Forecasting in China Based on PSO-BP Neural Network

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Abstract: *To address the problem that the traditional BP(Back-Propagation) neural network is prone to fall into the local optimal situation for carbon emission prediction, and thus the prediction results have large errors, this paper proposes to improve the BP neural network by using particle swarm optimization algorithm, and conducts simulation experiments with national carbon emission data. The results show that the model has a 12.1% reduction in error compared with the traditional BP neural network model, and has a better prediction effect on carbon emissions.*

Keywords: *Carbon Emissions, Particle Swarm Optimization Algorithm, BP Neural Network*

1. Introduction

Climate change is a global issue that is common to all mankind. With the emission of greenhouse gases, mainly carbon dioxide, from various countries, the earth's ecological environment and life systems are under serious threat[1]. China, as one of the major sources of carbon emissions, clearly stated during the 75th session of the United Nations General Assembly that it would "increase its national contribution, adopt more vigorous policies and measures, and strive to peak its carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060". Therefore, the study of the future trend of China's carbon emissions is of great importance for the adjustment and improvement of national emission reduction measures.

In terms of the application of forecasting models, existing studies have mainly projected carbon emissions in two ways. Firstly, forecasting is done through time series and its combination models based on historical carbon emission data. Secondly, the factors influencing carbon emissions are analysed and predicted in specific contexts. However, most of the existing studies have focused on industries or sectors, and there are few studies on forecasting carbon emissions for the country as a whole, which are context dependent and not generalisable. In this paper, we build a BP neural network model by using the factors that affect carbon emissions, but the initial weights and thresholds of the BP neural network have the problem of randomness, which makes the prediction results lack of rationality and thus affects the prediction effect. Therefore, this paper uses the particle swarm algorithm to improve the optimisation in order to improve the convergence speed of carbon emission prediction and avoid falling into local optimum solutions. The optimised model has a wider range of applicability than the traditional model and is less likely to be constrained by the data of specific influencing factors.

2. Model Principles

BP neural network is one of the most widely used neural network models today. In essence, it is a multi-layer feed-forward network based on error back propagation.

The particle swarm algorithm is an evolutionary computational technique based on the predatory behaviour of birds. A modified BP neural network model is developed by treating each solution to the initial parameters of the neural network as a 'particle' with no mass and no volume, but with an initial position and velocity. By requiring each particle to individually search for the optimal solution in the search space to find the optimal individual extremum, and using this as the current global optimal solution for the entire particle population, iterations are repeated to continuously adjust the velocity and position

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of the particle population to find the global optimum. Assuming that particle i is in n-dimensional space, its velocityV_{in} and positionX_{in} are updated by the following equations.

$$V_{in(\alpha+1)} = V_{in(\alpha)} + c_1 r_1 (P_{in}^{\alpha} - X_{in}^{\alpha}) + c_2 r_2 (P_{gi}^{\alpha} - X_{in}^{\alpha}) \quad (1)$$

$$X_{in(\alpha+1)} = X_{in(\alpha)} + V_{in(\alpha+1)} \quad (2)$$

Where, α is the number of iterations; c_1, c_2 is the learning factor; r_1, r_2 is the random number between [0,1]; P_{in}^{α} and P_{gi}^{α} ,is the position where the individual and group extremes are located, respectively.

The flow of the constructed PSO-BP neural network algorithm is shown in Figure 1.

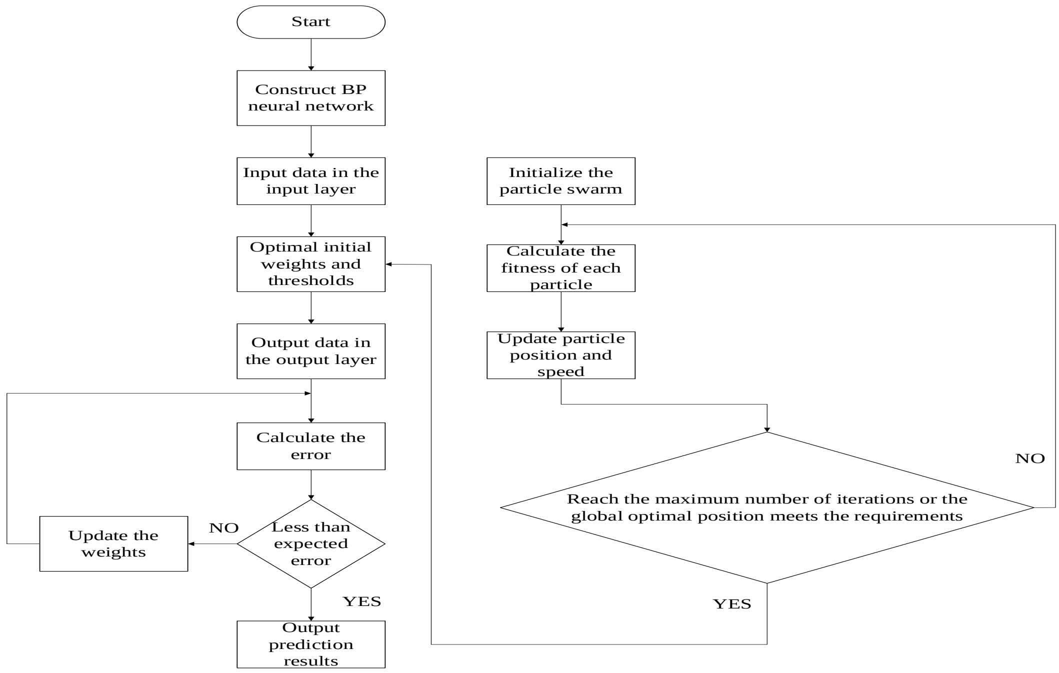

Figure 1: Flow chart of PSO-BP neural network model.

3. Example Application Analysis

3.1. Data Sources

This paper proposes an improved BP neural network forecasting model based on the particle swarm algorithm and uses China's annual carbon emissions as an example for empirical research. The fluctuation trend of carbon emissions in China is shown in Figure 2. The data source is the official Chinese website of the World Bank.

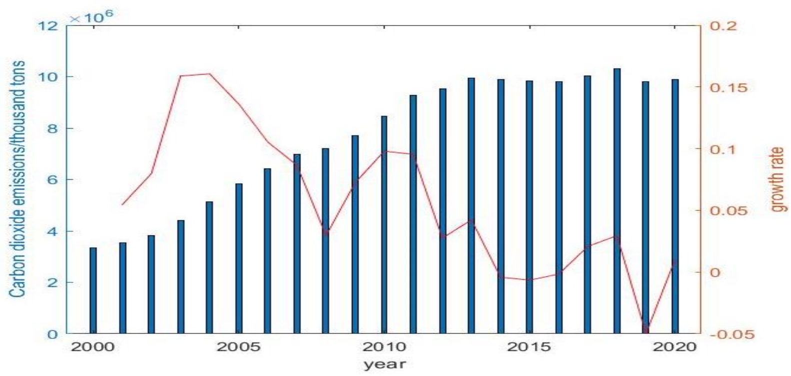

Figure 2: Trends in China's carbon emissions from 2000-2020.

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In terms of the overall trend of fluctuations in China's carbon emissions (see Figure 2), carbon emissions maintained a steady growth trend from 2000 to 2013, but after 2013, the growth rate slowed down significantly, with some years even showing negative growth, i.e. China's carbon emissions gradually shifted from a high growth phase to a fluctuating growth phase. This is mainly due to the rapid development of industry after China's accession to the WTO in 2013, when it rapidly became the "world's factory". However, as China actively promotes the construction of a clean, low-carbon, safe and efficient energy system, the growth rate of carbon emissions has slowed down significantly and is expected to achieve the "double carbon" goal of "peak carbon" and "carbon neutrality" as soon as possible. The "double carbon" target is expected to be achieved soon[2].

3.2. Indicator Selection

(1) Initial Indicator System

Through a review of previous literature[3-6] This paper constructs the initial indicator system as shown in Table 1. The time span of the selected indicators is 2000-2020, and the indicator data are obtained from the official website of the National Bureau of Statistics.

Table 1: Initial indicator system.

Indicators	Unit
GDP per capita	USD
State revenue	RMB 100 million
Total energy consumption	10,000 tons of standard coal
Urban population	10,000 people
Industrial value added	RMB 100 million

(2) Indicator preference

The Pearson correlation coefficient, also known as the Pearson product-moment correlation coefficient, is a linear correlation coefficient and is one of the most commonly used correlation coefficients. It is denoted as r and is used to reflect the degree of linear correlation between two variables X and Y. The value of r ranges from -1 to 1, and the higher the absolute value, the stronger the correlation. In this paper, the correlation analysis of the above indicators was conducted to confirm that they meet the correlation requirements. The results are shown in Table 2.

Table 2: Pearson's correlation coefficient.

Industrial value added (RMB 100 million)	Urban population (10,000 people)	Total energy consumption (10,000tons of standard coal)	State revenue (RMB 100 million)	GDP per capita (USD)
0.942	0.942	0.984	0.927	0.921

3.3. Model Construction

Carbon emissions are influenced by many factors, most of which come from the economy, population, trade and investment, science and technology, etc. There are significant regional differences and temporal variations in the extent and direction of their effects[7]. The degree of influence and direction of effect has significant regional and temporal variation, and therefore BP neural network forecasting models have better accuracy than other models such as time series forecasting models.

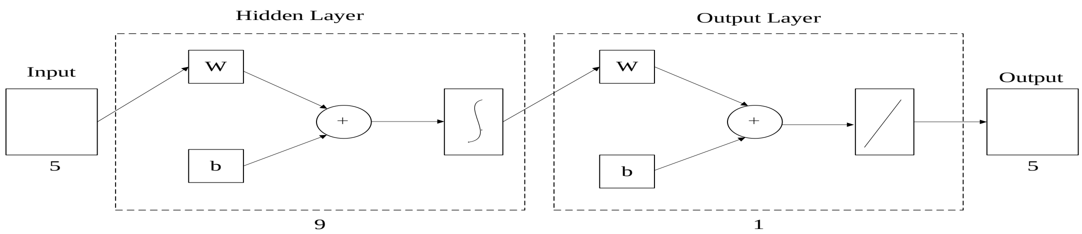

Figure 3: BP neural network structure.

Firstly, the basic structure of the BP neural network was constructed as shown in Figure 3. The number of nodes in the input layer was determined to be 5, and the number of nodes in the output layer was determined to be 1. There is no clear theoretical guidance on the selection and determination of the

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number of nodes in the hidden layer, so the number of nodes in the hidden layer of this model was determined to be 9 through empirical functions and several comparative analyses.

In the particle swarm optimisation BP neural network model, the c_2 particle swarm learning factor c_1 is set to 2, the number of evolutions is set to 100 and the population size is set to 10.

3.4. Simulation Results and Analysis

By training the sample data and using the BP neural network model as well as the optimised PSO-BP model to compare the predicted results with the actual values, the predicted values of the two models are compared with the actual values as shown in Figure 4.

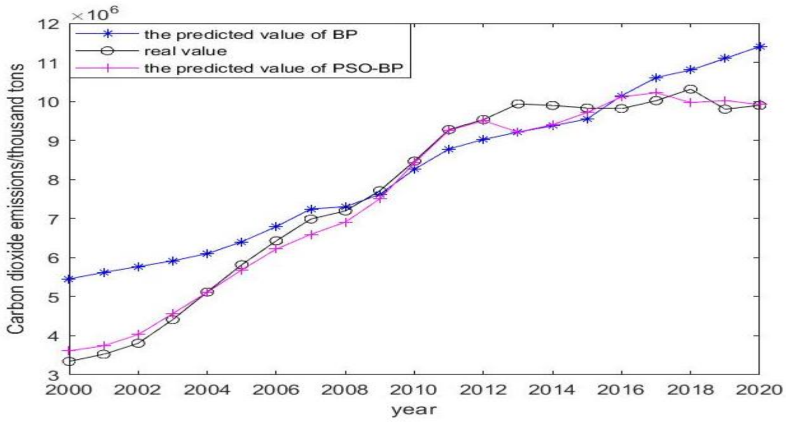

Figure 4: Comparison of model prediction results.

As can be seen from the graphs, the BP neural network model and the particle swarm algorithm optimised model are generally consistent in predicting the trend of carbon emissions, and in some years the predicted values are close to the true values, which indicates that both models have a certain degree of reliability. However, in general, the optimised PSO-BP model is significantly better than the BP neural network model in terms of prediction accuracy, as reflected by the fact that the PSO-BP model approximates the true values much better than the BP neural network model in most years. This indicates that the optimised model is effective on the whole.

In this paper, the relative error values and the mean absolute percentage errors are used to evaluate the accuracy of the model predictions. A histogram comparing the relative errors of the two models' prediction results is shown in Figure 5.

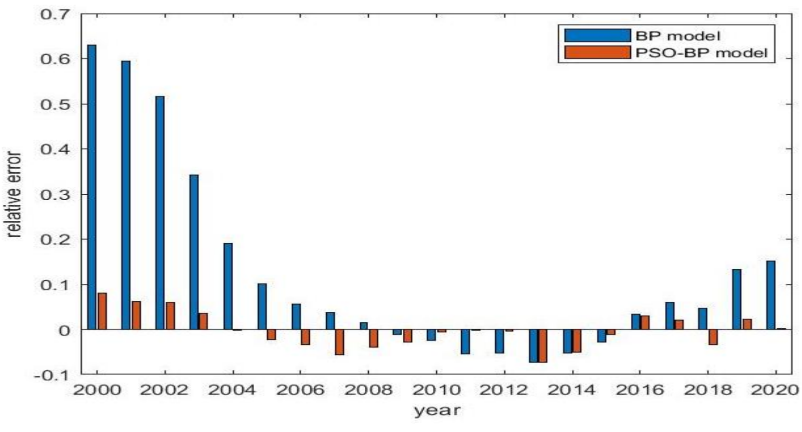

Figure 5: Comparison of relative errors in model prediction results.

From the figure, it can be concluded that the relative error of the PSO-BP model is smaller than that of the BP neural network model in most of the sample years. Specifically, the PSO-BP model had an error of 0.05 in 16 forecasts, accounting for 76.2% of the total, while the relative error was less than 0.02 in 6 years, accounting for more than 28.5%, compared to 9.5% in the BP neural network model. The average absolute percentage errors of the BP neural network model and the optimised PSO-BP model

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were 15.3% and 3.2% respectively, i.e. the latter had 12.1% lower errors than the traditional BP neural network model, which had a better prediction effect on carbon emissions.

4. Conclusions

The optimised model reduces the error by 12.1% compared to the traditional BP neural network model, and the accuracy of the prediction model is greatly improved. It has good applicability to the prediction of annual carbon emission trends in China, and can provide a certain theoretical basis for the adjustment and formulation of further national emission reduction paths and measures.

The selection of factors influencing carbon emissions was limited to a few indicators with a high degree of relevance. This problem will be improved in further research. By establishing a comprehensive database, the weighting of the correlations in the forecasting process will be adjusted according to their strengths and weaknesses to make a more scientific and reasonable forecast of carbon emissions.

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