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Prediction Simulation Study of Road Traffic Carbon Emission Based on Chaos Theory and Neural Network

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Abstract

Study the road traffic carbon emission and accurately predict the problems, the road traffic carbon emission has the complex systems of chaos and nonlinearity, the traditional method ignores the chaos of the road traffic carbon emission change, and it is so difficult to precisely control the rules of the road traffic carbon emission change that the precision of the of traffic carbon emission prediction is lower. In this study, it proposes the road traffic carbon emission prediction model based on the chaos theory and neural network and improves the prediction precision of the road traffic carbon emission time sequence. First of all, it reconstructs the time sequence data of the road traffic carbon emission change through the space, and sorts out the chaos change rules hidden in the time sequence data and then uses the BP neural network to study and carry out the modeling of the time sequence data of the road traffic carbon emission, and optimize the neural network parameter in order to improve the prediction precision of the road traffic carbon emission time sequence. The simulation result shows that, Chao-BPNN has overcome the deficits of the traditional method and could precisely and comprehensively reflect the change rules of the road traffic carbon emission time sequence, and effectively improved the prediction precision of the road traffic carbon emission.

Keywords*: road traffic carbon emission; Chaos theory; neural network; nonlinear prediction*

1. Introduction

The Chinese road traffic has been continuously developed and the road traffic carbon emission has accumulated large numbers of data during the continuous change, the data is a category of time sequence data. The development of road traffic carbon emission has been comprehensively influenced by various factors, and it has the change features of nonlinearity, time-variation, randomness and chaos, carrying out the precise prediction to the time development tendency of nonlinear and chaos road traffic carbon emission is a hot issue in the study of the road traffic carbon emission field, and there are wide application values to improve its prediction precision[1].

For the study for the prediction issues of road traffic carbon emission, large numbers of scholars have made many studies and proposed many prediction methods for the road traffic carbon emission[2]. The traditional prediction methods for the road traffic carbon emission mainly include: CAR, CARMA and *etc*., they have all played certain roles in the time sequence predictions of the liner road traffic carbon emission, however most of the road traffic carbon emission time sequences have the randomness, nonlinearity and time-variation, which results in the low precision of the road traffic carbon emission of the traditional method[3] [4]. At present, the road traffic carbon emission prediction methods mainly include: SVM, Gray System Prediction method, Neural Network Method, and these methods are mostly nonlinear, and each method has its own application range, for instance, SVM's training speed is relatively slower; the Gray System Predication Method is applied to the data prediction of the exponential growth pattern; and the Neural

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Network has the deficits that it is easy to fall into the local optima and difficult to be optimized[5] [6] . The present prediction algorithms lack considerations to the chaos properties of the development and change of road traffic carbon emission; hence there is room for improvement in the prediction precision of the road traffic carbon emission[7].

For the present road traffic carbon emission change ignores the chaos properties of the road traffic carbon emission change, in this article, it introduces the phase space reconstruction algorithm of the chaos theory into the road traffic carbon emission prediction, and combines it with the neural network of powerful nonlinear prediction abilities, and proposes the road traffic carbon emission prediction model (Chao-BPNN) in combination of chaos theory and neural network, and carries out verifications to its performances through two specified road traffic carbon emission prediction experiments.

2. Prediction Theoretical Framework of Road Traffic Carbon Emission Prediction

2.1 Prediction Principles of Road Traffic Carbon Emission

The road traffic carbon emission prediction is to collect the history data and impact factor of the road traffic carbon emission, and then analyze the data to select the most suitable prediction method and establish the most suitable prediction model, and finally adopt the established road traffic carbon emission prediction model to predict the development tendency of the road traffic carbon emission at a certain moment in the future, and the prediction results provide the reference for the government and enterprise to make plans and decisions[8] [9]. The mathematical model is:

$$y = f(x_1, x_2, ..., x_n) \tag{1}$$

In the formula, x_i impacts the factor of the road traffic carbon emission change, y is the prediction result, and $f()$ is the prediction function.

2.2 Difficulty Analysis of Road Traffic Carbon Emission Prediction

From formula（1）it could be seen that height of the road traffic carbon emission prediction result is to establish a relation to predict the result and impact factor through $f()$, and there are as much as several hundreds of rod traffic carbon emission methods at present, however, in the actual applications, none of them has comprehensively considered the chaos properties, nonlinearity and time-delay of the road traffic carbon emission change, hence it is difficult to establish the accurate road traffic carbon emission prediction model.

For this difficulty, in this article, it uses the chaos theory to mine the chaos properties hidden in the road traffic carbon emission data and adopts the neural network to mine the nonlinearity and time-delay in the road traffic carbon emission data to improve the prediction precision of the road traffic carbon emission.

3. Construction of Road Traffic Carbon Emission Prediction Model

3.1 Linear Data of Nonlinear Road Traffic Carbon Emission Change

The road traffic carbon emission time sequence data is impacted by the various factors such as policy, climate, agricultural processing enterprise, population, land and *etc*, it has obvious upward or downward tendency, and shows the rules of nonlinear change, and stabilization treatments should be carried out before establishing the road traffic carbon emission prediction model. Assume the road traffic carbon emission time sequence as y_t , and then:

$$\ln y_t = a + bt \tag{2}$$

The road traffic carbon emission time sequence after the pretreatment is:

$$y_t^{'} = \ln y_t - (a + bt) \tag{3}$$

Analyze the traffic carbon emission time sequence after the stabilization treatments.

3.2 Data Mining of Chaos Properties of Road Traffic Carbon Emission

The study shows that, the road traffic carbon emission time sequence data has the chaos properties, hence analyze the chaos properties strengths of the road traffic carbon emission time sequence data, and then carry out the phase pace reconstruction to it to reveal the change rules hidden in the road traffic carbon emission time sequence data. Assume the rod traffic carbon emission time sequence as $\{x(t)\}$; $t = 1,2,...,n$, in which n means the sample amount. Use the Takens theorem to select the suitable τ and m to reconstruct the time of the road traffic carbon emission time sequence as:

$$X_t = [x_t, x_t + \tau, ..., x_t + (m-1)\tau]^T \tag{4}$$

In which, τ means the time-delay, and m means the embedding dimensions.

Form formula （4） it could be seen that, it could fully mine the chaos properties hidden in the road traffic carbon emission time sequence by selecting the reasonable delay time and embedding dimensions.

3.3 Construction of Road Traffic Carbon Emission Prediction

Assume a road traffic carbon emission time sequence data with nonlinearity properties, and it uses the BP neural network to establish the nonlinear prediction function $f()$ in order to establish the road traffic carbon emission time sequence prediction model. The input vector amount of the BP neural network is the embedding dimension m of the road traffic carbon emission time sequence, and the hidden layer is p, the output amount is 1, and then the BP neural network finishes the mapping $f: R^m \to R^1$, and the input of each node in the hidden layers is:

$$S_j = \sum_{i=1}^{m} w_{ij} x_i - \theta_j \tag{5}$$

In which, w_{ij} is the connection weight from the input layer to the hidden layer, θ_j is the threshold value of the node in the hidden layer.

BP neural network transfer function adopts Sigmoid function, and Sigmoid function is defined as:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{6}$$

The output of the node in the hidden layer is:

$$b_j = \frac{1}{1 + \exp(\sum_{i=1}^{m} w_{ij} x_i - \theta_j)}, j = 1,2,..., p \tag{7}$$

The input and output of the node in the output layer separately are:

$$\begin{cases} L = \sum_{j=1}^{p} v_j b_j - \gamma & (8) \\ x_{i+1} = \dfrac{1}{1+\exp(\sum_{j=1}^{p} v_j b_j - \gamma)} & (9) \end{cases}$$

In which, v_j is the connection weight from the hidden layer to the output layer; γ is the threshold value f the output layer.

The performances of BP neural network are impacted by the connection weight (ω) and threshold value (θ), so far, ω and θ mainly use the gradient descent algorithm, and this gradient descent algorithm is easy to have the deficit of local optima, hence in this article, it selects the genetic algorithm to optimize the BP neural network parameter, in order to improve the prediction precision and performance of the BP neural network, and the BP neural network optimized by the genetic algorithm is as shown in Figure 1.

3.4 Road Traffic Emission Prediction Processes of Chaos Theory and Neural Network

(1) Carry out constructions to a certain carbon emission index of the road traffic carbon data which needs to be predicted, and then carry out the road traffic carbon emission data collection according to the established index system.
(2) Eliminate the abnormal data in the collected road traffic carbon emission data, and adopt the average method for replacement, and then adopt the formula (1) and (2) to carry out the pretreatments to the data.

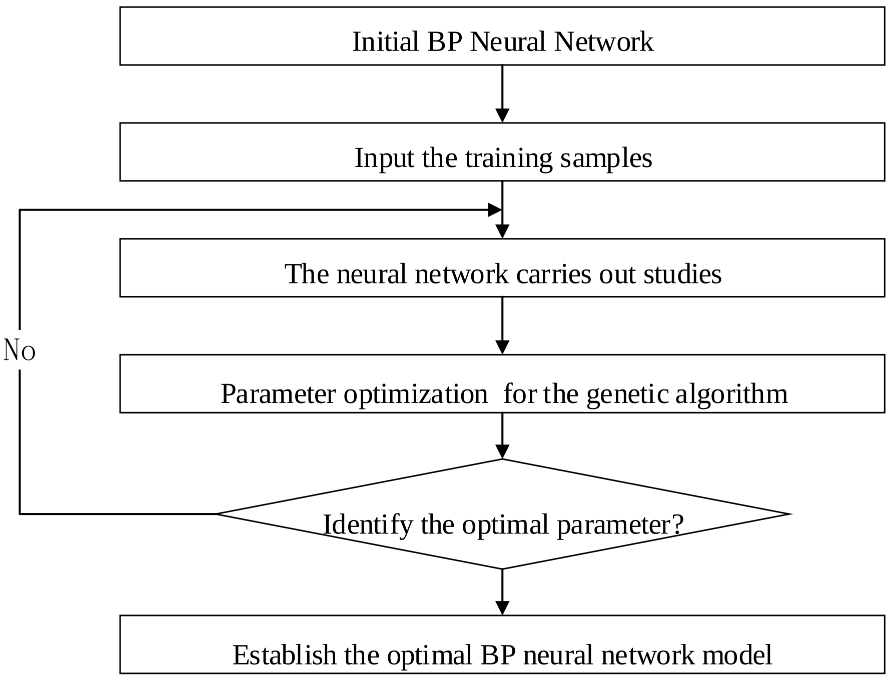

Figure 1. BP Neural Network Parameter Optimization

(3) In order to carry out the phase space reconstruction to the pretreatment data, in this article it adopts the C-C method to determine the delay time (τ) and embedding dimension (m) of the road traffic carbon emission time data sequence, and carry out reconstruction to the road traffic carbon emission time sequence, and through the reconstruction, it could restore the chaotic road traffic carbon emission time sequence into the regular road traffic carbon emission tme sequence.

(4) Divide the reconstructed road traffic carbon emission time sequence data into two parts as the training samples and test samples, the training samples are mainly used to construct the road traffic carbon emission prediction model, while the test samples are mainly used to test the road traffic carbon emission model.

(5) Input the training samples into the BP neural network for study, and use the genetic algorithm to optimize the parameter connection weight (ω) and threshold value (θ) of the BP neural network to guarantee the optimality of the road traffic carbon time serial nonlinear prediction model.

(6) Adopt the established optimal nonlinear road traffic carbon emission prediction model to carry out prediction to the test samples of the road traffic carbon emission time sequence, and the model is tested as effective; finally carry out prediction to the development levels of the road traffic carbon emission in the future moment.

4. Simulation Study

4.1 Simulation Data

In order to prevent the prediction result contingency of some single data set, select two different road traffic carbon emission time data as the simulations, and the data in Table 1 are the road traffic carbon emission index（y）and average GDP（X_1, US dollar）,oil product consumption（X_2,M toc）,car amount(X_3,10^5) in 1981-2010 of China. And the data in Table 2 are the car amount （y,105) and average disposable income（X_1,US dollar）, oil product price（X_2,yuan/L）, car production amount（X_3,10^5） and carport amount（X_4,10^5） in 20 years of a certain place.

Table 1 Road Traffic Carbon Emission Value and Factor in 1951-1980 of China

Year	X_1	X_2	X_3	y
1951	479	0.94	1.05	100.0
1952	537	1.13	1.58	107.8
1953	554	1.21	1.89	115.4
1954	558	1.29	2.45	125.1
1955	575	1.33	2.81	137.2
…	…	…	…	…
1976	852	7.12	18.24	985.1
1977	895	7.49	19.65	1078.5
1978	979	7.78	21.37	1249.3
1979	1040	8.02	26.11	1379.2
1980	1067	8.43	31.42	1518.9

Table 2. Car Amount and Factor in 20 Years of A Certain Place

Number	X_1	X_2	X_3	X_4	y
1	436	1.6	2	1	4
2	527	1.7	3	1	6
3	743	1.7	4	2	7
4	861	1.8	4	3	9
5	942	1.9	5	3	12
…	…	…	…	…	…
16	2262	6.1	17	25	44
17	2496	6.5	18	28	48
18	2694	7.1	19	30	50
19	2946	7.5	21	33	53
20	3157	7.9	21	35	55

4.2 Evaluation Standard and Contrast Model

The application value of the road traffic carbon emission prediction model should be its independent prediction precision but not the back substitution fitting precision. Hence in this article, it uses the one-step prediction method to carry out inspections to the performances of the road traffic carbon emission prediction model, that is to say, when it predicts the No. i+1 sample, the No. i sample needs to be added, and take the prediction result MSE as the measure index of the prediction performances of the road traffic carbon emission model, that is to say,

$$MSE = \frac{\sum (y_i - \hat{y}_i)^2}{n} \tag{10}$$

In the formula, y_i is the actual value of the road traffic carbon emission, and $\hat{y}_i$ is the model prediction value, n is the number of the test samples.

In order to make the prediction result of Chao-BPNN more precise and convincing, in this article, it uses the BP neural network （BPNN1） without the chaos process as the contrast model, and these contrast models mainly include: Multiple Liner Regression model （MLR）, CAR model, moving average model （ARMA） and nonlinear road traffic carbon emission prediction model.

4.3 Determinations of the Optimal Delay-Time and Embedding Dimensions

Carry out pretreatment to the road traffic carbon emission data set 1 and 2, and then use the c-c method to carry out the phase space reconstruction to the road traffic carbon emission data with the chaos properties to confirm that their optimal delay-time (τ) and embedding dimension (m) as: $\tau = 1$, $m = 6$ in data 1; $\tau = 1$, $m = 3$ in data 2 are as shown separately in Figure 2 and 3. For data 1, adopt $\tau = 1$, $m = 6$ to reconstruct the data; and for data 2, adopt $\tau = 1$, $m = 5$ to reconstruct the data; and then separately input them to the BP neural network for optimizations, and establish the optimal prediction models of data 1 and 2. They are as shown separately in Figure 2 and 3.

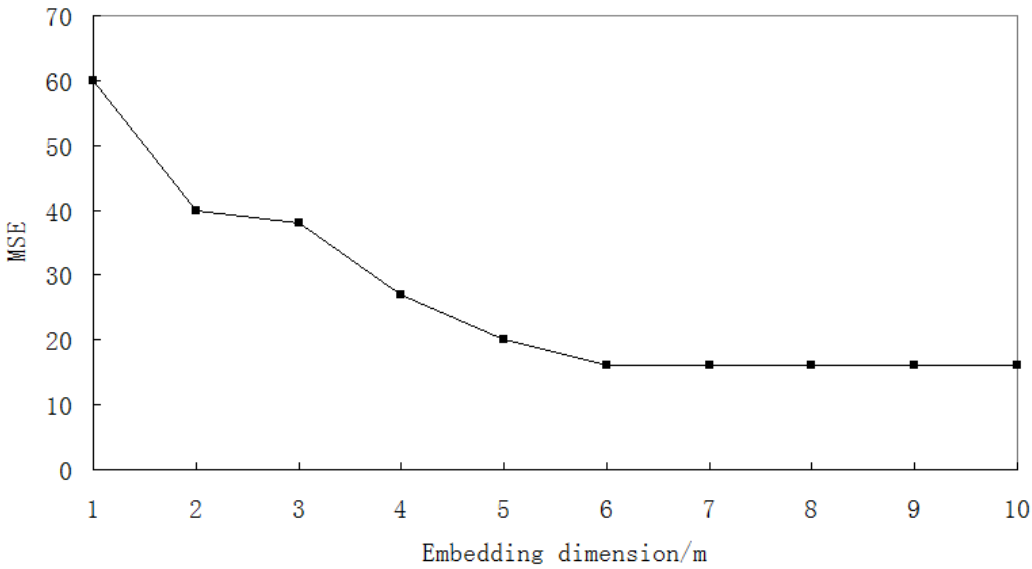

Figure 2. Optimal Embedding Dimensions of Data 1

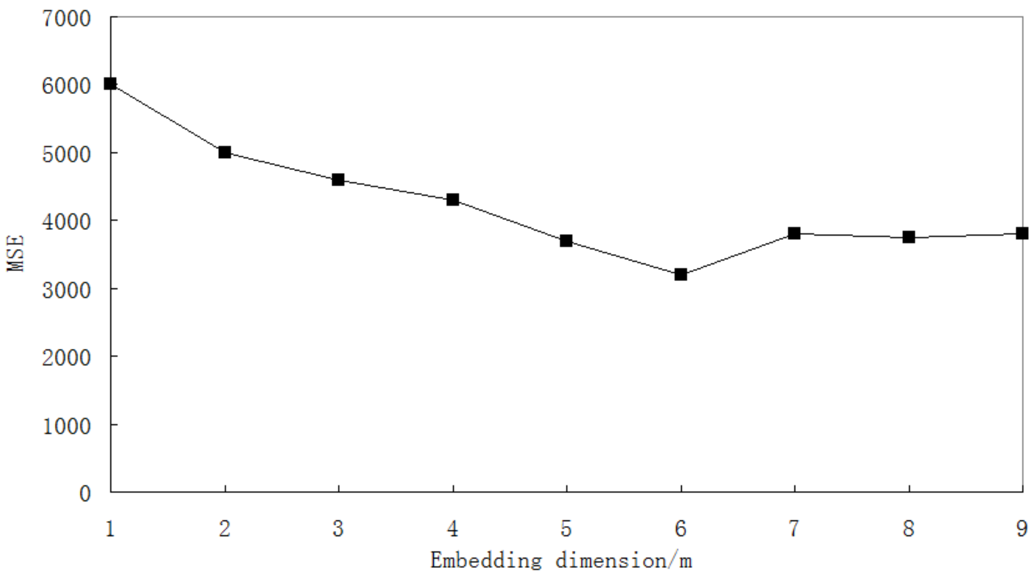

Figure 3. Optimal Embedding Dimensions of Data 2

4.4 Result and Analysis

Take the last 5 samples of data 1 and data 2 as the test samples and adopt the established optimal prediction model to carry out separate predictions to them, and the prediction result obtained is as shown in Table 3 and Table 4.

Table 3. Prediction of Road Traffic Carbon Emission Index

Year	True value	MLR	CAR	ARMA	BPNN1	Chao-BPNN
1976	985.1	58.92	58.92	58.92	58.92	58.92
1977	1078.5	58.92	58.92	58.92	58.92	58.92
1978	1249.3	58.92	58.92	58.92	58.92	58.92
1979	1379.2	58.92	58.92	58.92	58.92	58.92
1980	1518.9	58.92	58.92	58.92	58.92	58.92
	MSE	58.92	58.92	58.92	58.92	58.92

Table 4. Prediction of Car Amount

Year	True value	MLR	CAR	ARMA	BPNN1	Chao-BPNN
14	44	46.72	51.34	69.87	43.72	46.93
15	48	46.02	50.39	41.82	43.08	46.92
16	50	54.94	52.58	49.82	53.92	48.13
17	53	52.31	31.94	51.30	52.19	54.64
18	55	55.92	58.41	53.45	57.83	53.72
	MSE	256.82	231.93	267.82	245.12	73.79

It could be seen from Table 3 and Table 4 that for data 1, the MSE of Chao-BPNN is 58.92, which is lower than the contrast model; and for data as well, the MSE of Chao-BPNN is also the lowest, and the lowest average error of the prediction result means the highest prediction accuracy of the road traffic carbon emission model, which could accurately describes the change rules of the road traffic carbon emission time sequence data. It could be seen from Table 3 and Table 4 that the prediction errors of the liner model MLR, CAR and ARMA are larger than the nonlinear model BPNN1 and the prediction model proposed in this article, which means that the change rules of the road traffic carbon emission time sequence have nonlinear properties, hence there exists the problem of lower accuracy if it uses the linear model to carry out the prediction to the road traffic carbon emission; while the prediction accuracy of the BPNN1 model without chaos analysis is lower than that of the prediction model with the chaos analysis, which means that it fail to accurately and comprehensively describe the time-delay, chaos and nonlinearity of the road traffic carbon emission time sequence without carrying out the chaos analysis to the road traffic carbon emission time sequence and phase space reconstruction, hence through the contrast result it shows that the road traffic carbon emission time sequence prediction model proposed in this article is quick, accurate, effective and of high accuracy.

5. Conclusion

The road traffic carbon emission time sequence data is the common result of various factors which has the features of chaos, nonlinearity, complexity and dynamicity. The traditional prediction method could only carry out predictions on the partial changes, hence there exists the problems of low prediction accuracy and huge error, it is because of this the road traffic carbon emission prediction model combining the chaos theory and neural network has been proposed. The simulation results show that Chao-BPNN has improved the prediction accuracy of the road traffic carbon emission time sequence and reduced the prediction error, and it has wide application prospect in the field of road traffic carbon emission prediction.

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