Research on Chaotic Time Series Prediction Model for Building Energy Consumption

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Research on Chaotic Time Series Prediction Model for Building Energy Consumption

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Abstract. Aiming the problem that the accuracy of current building energy consumption prediction method depends heavily on environmental parameters (air temperature, air pressure, humidity, etc.), a short-term prediction model of time series building energy consumption based on Chaos-BP is proposed. Firstly, the optimal delay time and embedding dimension of data samples are obtained by CC method. And the small data amount method is used to prove that the building energy consumption has chaotic characteristics. Secondly, the input structure of BP neural network is determined by phase space reconstruction, and again the middle school building is the research object. Finally, the Matlab software is used as the simulation tool to simulate the Chaos-BP prediction model and the BP prediction model respectively. The experimental results show that the building energy consumption has chaotic characteristics. Compared with the BP neural network prediction model, the Chaos-BP model can accurately predict the building energy consumption and provide a scientific basis for the development of building energy conservation work.

1. Introduction

At present, the prediction methods of common building energy consumption can be divided into three categories: 1. Building energy consumption prediction methods based on building energy simulation software, such as DeST, TRNSYS, Energyplus, etc. Although the prediction method is more accurate, it requires detailed meteorological parameters and enclosure parameters, and the modeling is complicated. 2. Building energy consumption prediction methods based on statistical theory, such as regression analysis and prediction method[2], time series prediction method[3], grey theory prediction method[4], etc. Although this method has strong theoretical support, the predictive model is less generalized. 3. Machine learning based energy consumption prediction methods, such as support vector machine prediction method[5], artificial neural network prediction method[6]and combined prediction method, etc. This kind of prediction method has been widely studied because of its high prediction accuracy and good generalization of the model. The combined prediction method mainly improves the accuracy of the original prediction model by reducing the input dimensions of the model (such as PCA, AHP) and optimizing the model parameters (such as GA, PSO), such as GA-BP, PSO-BP, Chaos-BP, etc. The Chaos-BP prediction model does not need to make any assumptions, and only predicts a certain moment in the future based on the time series of historical data, which can avoid human subjectivity. Combined with the good nonlinear approximation ability and fault tolerance of BP neural network, the most important thing is the ability to self-learn[7]. Combining the two methods not only considers the complex characteristics of the prediction object, but also compensates for the shortcomings of the chaotic time series prediction model.

This model has not been applied to the prediction of building energy consumption. Therefore, this paper will introduce the Chaos-BP prediction model to predict the energy consumption of buildings and the specific building energy consumption data are used for simulation experiments.

2. Chaos-BP building energy consumption time series prediction model

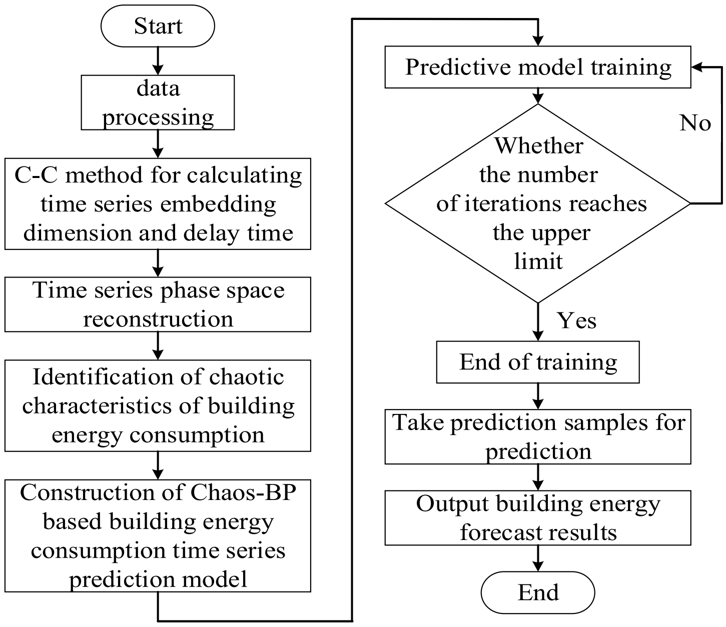

Figure 1. Construction of Chaos-BP Building Energy Consumption Time Series Prediction Model

The neural network model[8]does not require a priori information, has a high degree of self-learning, self-adaptation and fault tolerance. It can be approximated by arbitrary precision for nonlinear functions, and is very suitable for complex nonlinear systems, which can better reflect the chaotic characteristics of the system. The combination of BP neural network and chaos theory overcomes the disadvantage that chaos prediction model has no self-learning ability and improves the prediction accuracy. The basis of chaotic time series prediction is phase space reconstruction theory[9]. The phase space reconstruction is used to find the hidden law of chaotic attractors. Therefore, the model prediction based on Chaos-BP for building energy chaotic time series mainly includes phase space reconstruction. The three parts of chaotic characteristic discrimination and building energy consumption time series prediction are shown in Figure 1.

2.1 Building energy consumption time series phase space reconstruction

Firstly, phase space reconstruction of building energy consumption time series requires taking two parameters of embedding dimension m and delay time τ . At present, methods for obtaining embedded dimensions include pseudo nearest neighbor method, Cao's method, and saturated correlation dimension method (GP algorithm); The methods for obtaining the delay time include autocorrelation function method, average displacement method, and mutual information method[10]. Studies have shown[11]that the main factors affecting the quality of reconstructed phase space are not only the choice of delay time τ and embedding dimension m , but more important is the determination of the embedded window width that combines τ and m . The C-C method[12]forms a statistic by correlating the integrals of the sequence, and simultaneously calculates τ and τ_w by the relationship diagram of the statistic and the delay time, and then finds the embedding dimension according to $\tau_\omega = (m-1)\tau$. The method can effectively reduce the calculation amount of the mutual information method and maintain the nonlinear characteristics of the time series. Therefore, the C-C method is used to obtain the delay time and embedding dimension.

Calculate the following three statistics:

$$\overline{S}(t)=\frac{1}{16}\sum_{m=2}^{5}\sum_{j=1}^{4}S(m,r_j,t) \quad (1)$$

$$\Delta\overline{S}(t)=\frac{1}{4}\sum_{m=2}^{5}\Delta S(m,t) \quad (2)$$

$$S_{cor}(t)=\Delta\overline{S}(t)+\left|\overline{S}(t)\right| \quad (3)$$

When $\Delta\overline{S}(t)$ minimum value is obtained for the first time, the corresponding delay time is τ , and the minimum value obtained by $S_{cor}(t)$ corresponds to the embedded wide window τ_w .

2.2 Identification of chaotic characteristics of building energy consumption

The premise of chaotic time series prediction is to judge the chaotic characteristics of building energy consumption time series[13]. A chaotic system with one or more positive values in its Lyapunov exponent spectrum can affirm the existence of chaotic properties[14]. In this paper, the maximum Lyapunov exponent is calculated by the small data method. The small data method is a method for improving the Wolf method based on the track-tracking method[15]in 1993 by Rosenstein et al. The method can make full use of all the data that can be utilized, is relatively reliable for small data sets, has a small amount of calculation, is relatively easy to operate, and has high precision of calculation results.

For each point $Y_m(t)$ in the phase space, calculate the distance after i discrete time steps of the pair of neighborhood points:

$$L_t(i)=\left\|Y_m(t+i)-Y_m(\hat{t}+i)\right\|, i=1,2,...,\min(N-t,N-\hat{t}) \quad (4)$$

Find the $\ln L_t(i)$ average $y(i)$ of all t for each i :

$$y(i)=\frac{1}{q\Delta t}\sum_{j=1}^{q}\ln L_t(i) \quad (5)$$

Where q is the number of non-zero $L_t(i)$, Δt is the sample period, and a $y(i)$ regression line is made by least squares, and the maximum Lyapunov exponent is the slope of the line.

The flow chart of the small data volume method is shown in Figure 2:

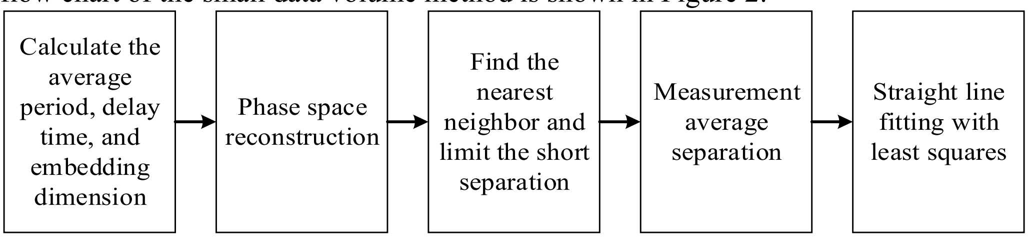

Figure 2. Small data volume method flow chart

2.3 Establishing a Chaos-BP Time Series Prediction Model

The establishment and prediction process of Chaos-BP model is as follows:

Normalize the original data, use the first N data of the sample, perform phase space reconstruction, get the best embedding dimension m , delay time τ , and the m -dimensional phase number of the reconstructed phase space is $M = N-(m-1)\tau$;

Constructing a prediction model and using the $m\times(N-1)$ vector matrix in the reconstructed phase space as training data;

The minimum error of setting the training target is 0.001, the training times are n, the momentum factor is 0.9, and the learning rate is 0.05;

Perform network loop learning to correct the output and weight of the BP neural network until the error control is within the allowable range or the number of iterations reaches the upper limit, and the training ends.

The Q data points after the first N data are sampled as prediction data, and the model is predicted. The output value of the network is the predicted value, and the predicted value is inversely normalized to obtain the predicted actual value.

3. Building energy consumption data collection

This paper uses the building energy consumption data of a middle school in Hefei as the research object. The main target of collection is building electricity consumption. The collected indicators are mainly divided into four categories: lighting socket, air conditioning power, power consumption and special power[16].

Through the energy consumption monitoring platform of a middle school in Hefei, the hourly electricity consumption from 0:00 on November 22, 2017 to 23 o'clock on December 31, 2017 was collected, and 700 groups of continuous time were randomly selected as sample data, and the trend of energy consumption changes is shown in Figure 3.

4. Experimental process and results

In order to verify the prediction effect of Chaos-BP building energy consumption time series prediction model, this paper uses matlab2016a as the simulation experiment platform to achieve the above process.

4.1 Determination of parameters

In this paper, the C-C method is used to obtain the delay time and embedded window width of the building energy consumption data of a middle school in Hefei. The C-C method obtains the statistics as shown in Figure 4. The delay time corresponding to the first zero of $\overline{S}(t)$ or the minimum value obtained by $\Delta\overline{S}(t)$ for the first time is the optimal delay time $\tau = 4$. The delay time corresponding to the minimum value of $S_{cor}(t)$ is the optimal window width $\tau_w = 8$, and the embedding dimension $m \approx 3$ can be obtained according to the embedding time window width formula $\tau_w = (m-1)\tau$.

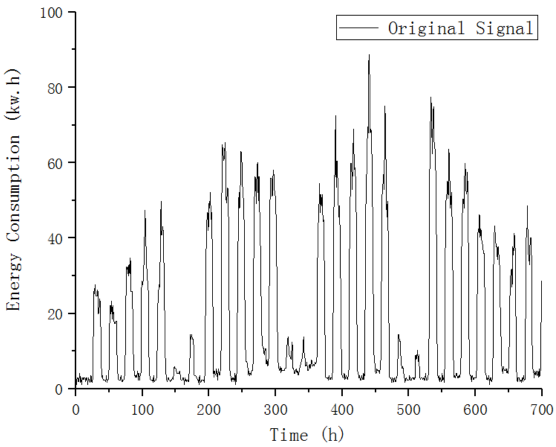

Figure 3. Building energy consumption data of a middle school in Hefei

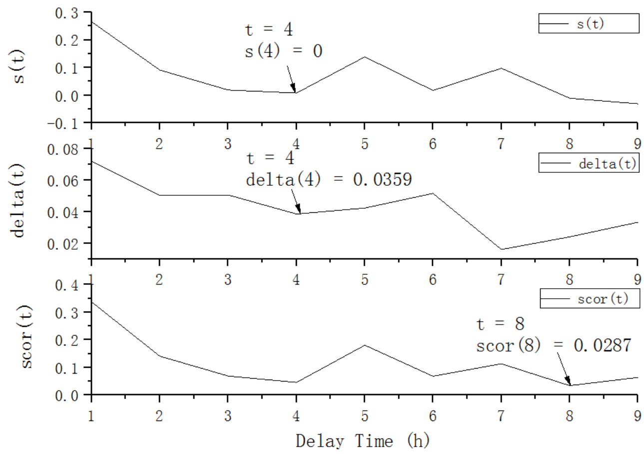

Figure 4. C-C method for reconstructing the time series statistics of building energy consumption

4.2 Proof of chaotic characteristics

This paper uses the small data method to obtain the largest Lyapunov exponent of the building. The least squares fitting straight line of the building energy consumption time series is shown in Figure 5. According to its slope, the maximum Lyapunov value is 0.0832, which proves the existence of chaotic characteristics in building energy consumption.

4.3 Chaos-BP building energy consumption time series forecast results

The Chaos-BP time series prediction model is established. Firstly, the first 500 data points of the sample data are selected for phase space reconstruction, and the model is trained after reconstruction. The training results of the Chaos-BP model are shown in Figure 6 and Figure 7. It can be seen from Figure 6 that the goodness of fit of the model is 0.9807, and the fitting result is shown in Figure 7. The RMSE = 0.7892, and the fitting effect is good.

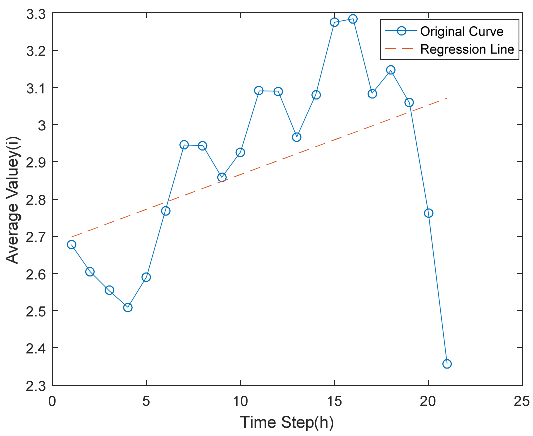

Figure 5. Least Squares Fitting Line

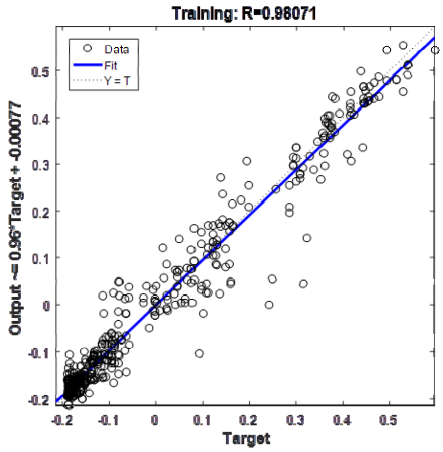

Figure 6. Chaos-BP model training fit Figure

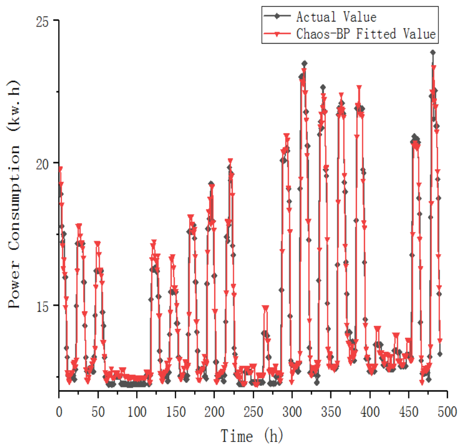

Figure 7. Chaos-BP model training fit value and measured value comparison

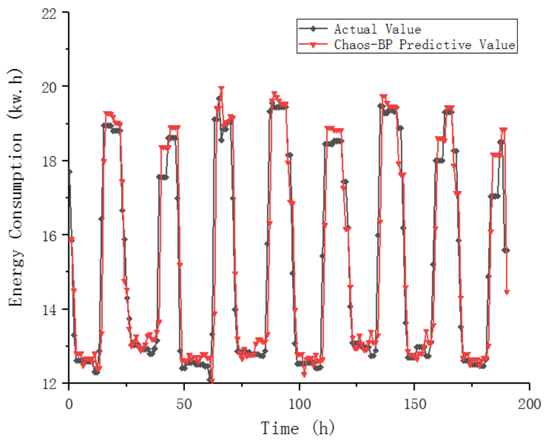

Figure 8. Comparison of predicted and measured values of Chaos-BP model

The last 200 data points in the sample data are selected as the prediction data, and the established Chaos-BP building energy consumption time series prediction model is used to realize the single-step prediction of building energy consumption. The comparison between the predicted value of building energy consumption and the measured value is compared as shown in Figure 8. The root mean square error RMSE between the predicted and measured values is 0.9630. It can be seen that the error is small when the short-term prediction is performed, and the prediction effect is good.

4.4 Comparison of BP and Chaos-BP model prediction results

The BP neural network prediction model is constructed, and the first 500 data points of the sample data are used for model training. The fitting degree of the BP neural network model is 0.9901, and the fitting effect is good. The next 200 data points are selected for prediction. The comparison between the predicted results and the predicted results of the Chaos-BP model is shown in Figure 9. It can be known that the root mean square error of the BP neural network model is RMSE=1.7433. Compared with the prediction results of the Chaos-BP model, the prediction accuracy is lower and the robustness is poor.

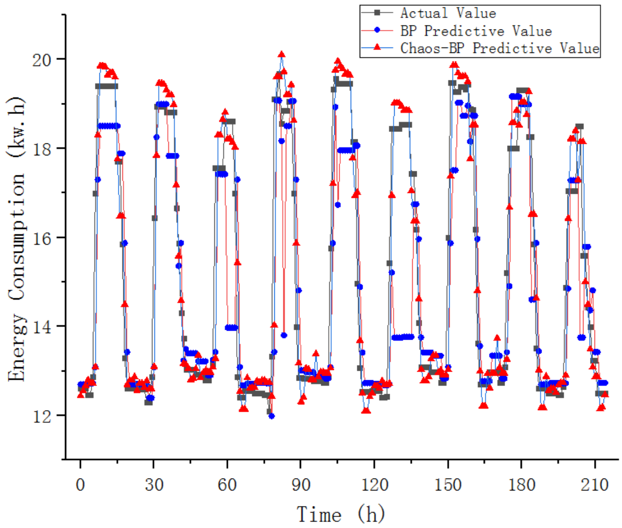

Figure 9. Comparison of predicted and measured values of BP and Chaos-BP models

In order to more accurately evaluate and compare the prediction effects of the two models, this paper evaluates the prediction model by calculating the iteration time and Mean Absolute Percentage Error(MAPE), Root Mean Square Error (RMSE) and Sum of Squared Error(SSE). The results are shown in Table 1:

Table 1. Comparison of BP and Chaos-BP prediction models

Model	Number of iterations	Time/s	MAPE	RMSE	SSE
	600	9.9192	0.0421	1.0210	114.2342
Chaos-BP	800	10.2696	0.0382	0.9630	94.6704
	1000	10.5239	0.0379	0.9239	78.1789
	600	8.7572	0.1247	2.0244	223.8481
BP	800	11.4257	0.1120	1.7433	191.0609
	1000	14.9531	0.1118	1.5084	152.4291

It can be seen from Table 1 that the prediction accuracy of the Chaos-BP model is significantly higher than that of the BP neural network model with the same number of iterations. The results show that the convergence speed of the Chaos-BP model is significantly faster, which greatly shortens the iteration time and improves the prediction accuracy.

5. Conclusions and prospects

At present, the prediction methods for building energy consumption, such as multiple linear regression, artificial neural network, grey theory, time series, etc., need to consider external factors such as meteorological parameters and human subjective factors. Based on the chaotic characteristics of time series, a time series prediction model of building energy consumption based on Chaos-BP is proposed.Through the model test, the following conclusions were obtained:

The C-C method is used to reconstruct the energy consumption data in phase space, and the Lyapunov exponent is calculated to prove the chaotic characteristics of building energy consumption.

The Chaos-BP prediction model is used to predict the building energy consumption data in a short-term and compare with the BP neural network model prediction results. The results show that the prediction accuracy of the Chaos-BP prediction model is significantly higher than that of the BP neural network model. With the increase of the number of iterations, the training time of the Chaos-BP prediction model is significantly shorter than the BP prediction model.

Because the Chaos-BP prediction model has a good predictive effect on building energy consumption, the future can not only provide data support for building energy efficiency improvement, but also provide sufficient decision-making basis for building energy conservation work.

Acknowledgments

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