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The Research on Demand Forecasting of Supply Chain Based on ICCELMAN

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Under the background of the globalization, the competition among the enterprises becomes more and more fierce. And the speed of the product circulation is faster than before. Under this background, if the company forecasts the product demand more accurate, the company can plan the product planning according to the demand. The companies can improve the competitiveness. In this paper, we apply the chaotic forecasting theory to forecast the product demand. Aiming at the defect of the traditional c-c method, we combine the Elam neural network model and put forward a new forecasting method. The method is ICCELMAN. We apply this method to forecast the product demand. Finally, the numerical analysis results show that the method can forecast the trended fluctuation for the actual demand accurately. The method has good forecasting accuracy.

1. Introduction

At present, the forecasting demand of the supply chain has become the key problem of supply chain management. How to forecast the change of the demand information accurately and how to avoid the appearance of the bullwhip effect become a hot issue of the academic research. Forecasting the demand accurately has become the key factor for reducing the lead time of supply, avoiding the out of stock and decreasing the cost loss. Therefore, to forecast the product demand was more and more important.
Demand was the representative of the relationship between the commodity and the quantity. It has become the core driving force of the current supply chain and the operation of the enterprises (M. Kalchschmidt, R. G. Zotteri, 2006). Forecasting Demand was an assessment which was aiming to a product or service. And it was a qualitative and quantitative method for the products which were to sale in future (Huang Xiaoyuan, 2004). Jain (2002) studied the forecasting demand method which was aiming to the enterprise interior. And he found that many enterprises had not the systematic forecasting method. These enterprises adopted the experience, the expert opinion and the historical data to predict. Feng Yun and Ma Haijun (2008) compared the forecasting results among the weight one-rank local-region method, the largest Lyapunov exponent forecasting and the whole domain method of support vector machine. And they predicted the product sales Chaos theory has become one of the commonly used forecasting theories (Farid Tajaddodianfar, Hossein Nejat Pishkenari, 2016). S. Wang etc. (2015) established a polynomial chaos ensemble hydrologic prediction system and Hima Nikafshan Rad etc. (2015) established a rock mass rating prediction system based on chaos theory.
In this paper, we used the improved chaotic forecasting model to predict the product demand. In this paper, we proposed ICCELMAN. And we used the method to predict the product demand. The structure of the paper was as follows. The first part is the introduction. The second part was the improved chaotic forecasting model which was based on the Elman network. In the third part, aiming at the defects of the traditional C-C method, we put forward the improved C-C method. We combined with the Elman model and put forward the ICCELMAN method. The fourth part is the numerical analysis. And the fifth part was the conclusion.

2. The improved chaotic forecasting model which is based on the Elman network

2.1 Elman neural network model

According to storing the internal state, Elman neural network has the function of the mapping dynamic characteristics. Then the system has the ability to adapt the dynamic characteristics. It enhances the computing ability and the stability of the internet. Elman neural network is divided into four layers. They are the

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input layer, the hidden layer, the undertake layer and the output layer. The unit of the input layer only has the function of the signal transmission. The output unit has the function of the weight. The transfer function in the hidden layer can adapt the linear function or the nonlinear function. The undertake layer is used to memory the output value which is output in the hidden layer. In this paper, we combined the characteristics of the Elman neural network and put forward the chaotic forecasting model which is based on the Elman neural network. The nonlinear state space representation of the Elman neural network is as follows.

$$y(k) = g(w^3 x(k)) \tag{1}$$

$$x(k) = f(w \cdot x_c(k) + w^2(u(k-1))) \tag{2}$$

$$x_c(k) = x(k-1) \tag{3}$$

Among them, y is the output node vector of m dimension. x is the node unit vector of the middle layer in n dimension. u is the input vector in r dimension. x_c is the feedback vector in n dimension. w is the connection weight between the undertake layer to the middle layer. w^2 is the connection weight between the input layer to the middle layer. w^3 is the connection weight between the middle layer to the input layer. $g(\cdot)$ is the transfer function of the output neurons and the linear combination of the middle layer. $f(\cdot)$ is the transfer function of the middle layer neurons.

2.2 The determination of the time delay and the embedding dimension

Using the traditional C-C method, we can calculate the embedding dimension m and the time delay τ. However, when calculating the embedding dimension and the delay time, the traditional C-C method exists three deficiencies.

Firstly, for the time series that the sampling period is T, $t = kT$ is the probably to the first zero point of $S(t)$. And it is probably to the global minimum point of $Scor(t)$. Therefore, when we calculate the embedding dimension, we get the contradictory results.

Secondly, for the statistic $S(m, N, r, \tau)$, we adopt the block average strategy. When $t = kT$, $S(t)$ is equal to zero. With the increase of t, $S(t)$ grows which has the high frequency fluctuation. When the optimal delay time is large, it will influence the selection of the first local minima for $S(t)$.

Thirdly, in the ideal case, the global minimum point of $Scor(t)$ is the optimal embedding window τ_w. In fact, $Scor(t)$ has several local minima whose values are close to the global minimum point. It disturbs the interpretation of the optimal embedding window τ_w of the global optimal window. t that τ_w is corresponding may be not global minimum point. Finally, it leads to the error estimation for the interpretation of optimal embedding window τ_w.

Based on the consideration of the shortage for the traditional C-C method, we put forward the following improved C-C method. We reconstruct the phase space of the chaotic time series. Then we determine the embedding dimension m and the delay time τ.

Firstly, the improved C-C method determines again the optimal delay time τ_d. $m = 2, 3, \ldots$

$$S_1(m, N, r, \tau) = C(m, N, r, \tau) - C'(1, N, r, \tau) \tag{4}$$

Among them, we select the maximum and the minimum r. We determine

$$\Delta S_1(m, N, r, \tau) = \max\{S_1(m, N, r_j, \tau)\} - \min\{S_1(m, N, r_j, \tau)\} \tag{5}$$

$$\Delta\overline{S_1}(\tau)=\frac{1}{4}\sum_{m=2}^{s}\Delta\overline{S_1}(m,\tau) \tag{6}$$

$$S_{cor}(\tau)=\left|\overline{S_1}(\tau)-\overline{S_1}(\tau)\right| \tag{7}$$

We make the first local minima point of $\Delta\overline{S_1}(\tau)$ as the optimal delay time τ. Compared with the first local minima point that the original method selects, the new method is more accurate of the selection for the τ. When τ_d gets the larger value, it is more obvious.

Secondly, for the time series that the sampling period is T, when m, r fixes and $N \to \infty$, $t = KT$ is not only the local maxima, but also the zero of the formula. Compared with the traditional C-C method, the periodic point position of $S_{cor}(\tau)=\left|\overline{S_1}(\tau)-\overline{S_1}(\tau)\right|$ exists more obvious local peak. And it makes the selection for the optimal embedding window τ_w more reliable. Therefore, we use the improved C-C method to search the periodic point of $S_{cor}(\tau)=\left|\overline{S_1}(\tau)-\overline{S_1}(\tau)\right|$ as the optimal embedding window τ_w. Then, the embedding dimension is. $m=\tau_w/\tau+1$.

2.3 The chaotic forecasting model which is based on the Elman neural network

Because the Elman neural network can approximate the nonlinear function stably, we select it as the forecasting model of the chaotic time series. In the modeling of the Elman neural network, it is important to determine the input dimension of the model. In this model, we use the optimal embedding dimension as the number of the neural input variables. At the same time, we make the phase space vector of the original time series as the training sample. And we make the original time series as the target sample. Finally, we can establish the chaotic forecasting model of the Elman neural network. The predicted steps are as follows.

Firstly, according to the improved C-C method, we compute the embedding dimension and the time delay of the chaotic time series.

Secondly, we reconstruct the phase space for the original time series.

Thirdly, we normalize the phase space and the original time series.

Fourthly, we use the embedding dimension as the input number of the Elman neural network. And, we make the phase space vector as the training, the original time series as the target sample. Then we construct the neural network.

Fifthly, we train the network and compare the network output value with the target value. If they exists the error, we adjust the network parameter until the error control in the admissible range.

Sixthly, it is the forecasting stage. We put. M value into the neural network. Then the output value is the predicted value.

Seventhly, we make the output values anti normalized. Then we can get the predicted values of the original time series.

The flow chart of the method is as follows.

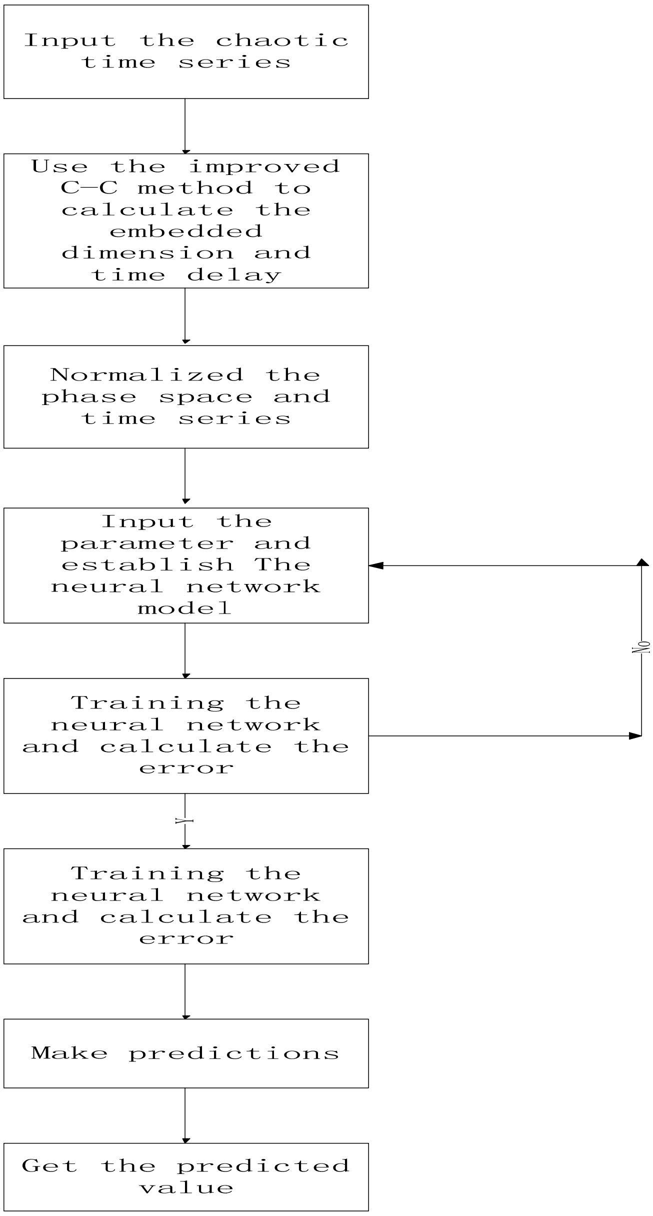

Figure 2: The flow chart of the method

3. Numerical analysis

In order to compare the accuracy of different methods, we select sales data of one commodity in one large supermarket. We select 300 data. The first 250 data is as the training set and the last 50 data is as the test set. Firstly, we compute the Lyapunov index. We get the largest Lyapunov index is 0.0213. It shows that the sequence is chaotic.

Then, we use the improved C-C method to determine the embedding dimension of the phase space. The improved C-C method takes the first extreme 岁. $\Delta\overline{S_1}$ as the optimal delay time of the reconstruction phase space. We take the first periodic point $\left|\Delta\overline{S_1}(\tau)-\Delta\overline{S_2}(\tau)\right|$ as the time window.

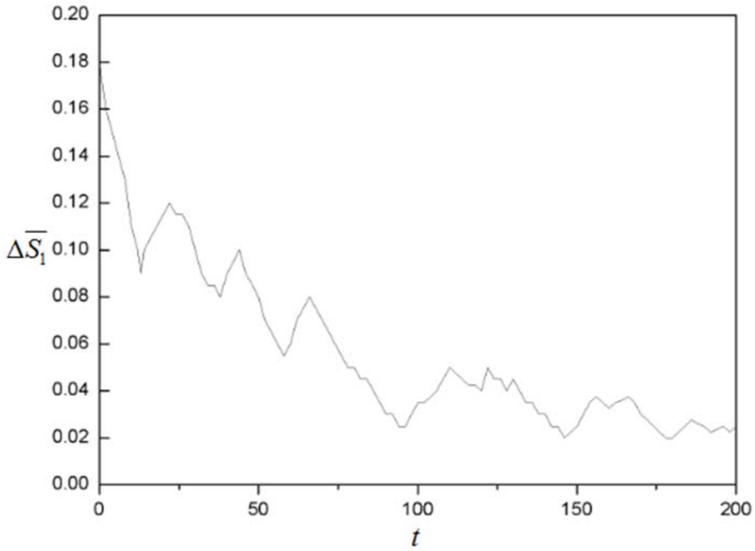

Figure 3: The value of $\Delta\overline{S_1}$

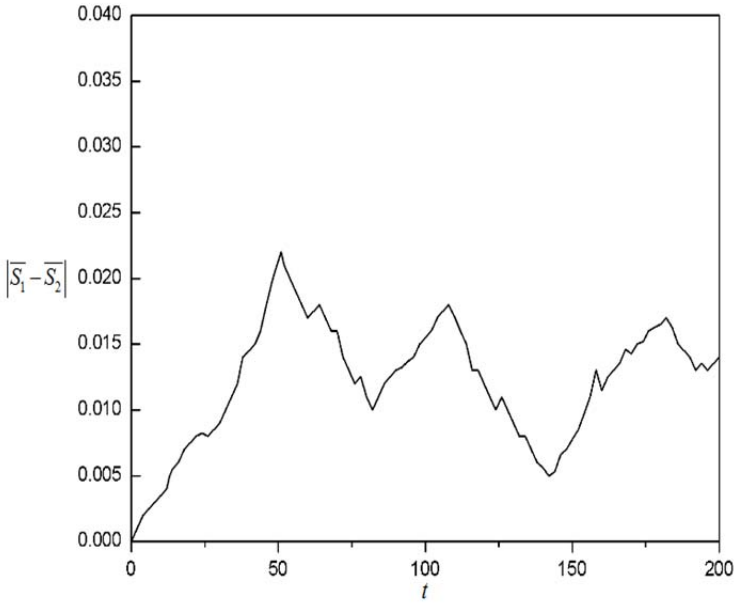

Figure 4: The value of $\left|\overline{S_1}-\overline{S_2}\right|$

From the above figure we can see that the delay time is $\tau = 13$. Form the figure, we can see that the result of the delay time window is $\tau_W = 51$ and the embedding dimension is $m = \tau_W / \tau + 1 = 51/13 + 1 = 4.92$. We take $m = 6$. Then, we use the method which is put forward in this paper to predict the sales data of one commodity in one supermarket. The predicted results are as follows.

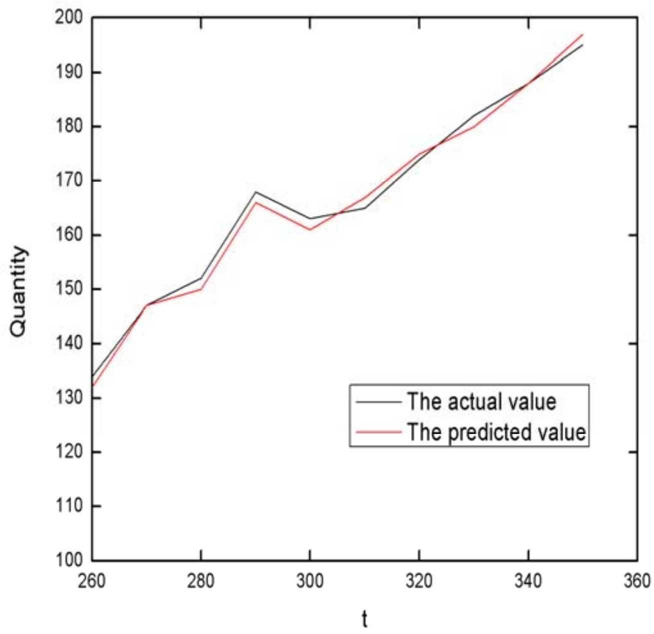

Figure 5: The results of the forecasting value and the actual value

From the above figure, we can see that the ICCELMAN method has good forecasting effect. Its forecasting is more accurate for the demand forecasting of supply chain and has little error. The predicted result is more ideal.

4. Conclusions

In the increasingly competitive environment, all enterprises begin to use supply chain management theory to manage the supply chain. And they also begin to pay more attention on the demand forecasting. In this paper, we apply the chaotic theory to study and predict the demand of supply chain product. This paper has the following work. Firstly, we analyze the present situation of the supply chain demand forecasting and the chaotic forecasting. Secondly, aiming at the shortage of the traditional C-C method, we put forward the improved C-C method. Then, we combine this method with the Elman neural network model and propose the ICCELMAN method. Finally, we apply the ICCELMAN method to predict the product demand and obtain a goof forecasting effect.

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