Adaptive Chaotic Prediction Algorithm of RBF Neural Network Filtering Model based on Phase Space Reconstruction

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Abstract—**With the analysis of the technology of phase space reconstruction, a modeling and forecasting technique based on the Radial Basis Function (RBF) neural network for chaotic time series is presented in this paper. The predictive model of chaotic time series is established with the adaptive RBF neural networks and the steps of the chaotic learning algorithm with adaptive RBF neural networks are expressed. The network system can enhance the stabilization and associative memory of chaotic dynamics and generalization ability of predictive model even by imperfect and variation inputs during the learning and prediction process by selecting the suitable nonlinear feedback term. The dynamics of network become chaotic one in the weight space. Simulation experiments of chaotic time series produced by Lorenz equation are proceeded by a RBF neural network.The experimental and simulating results indicated that the forecast method of the adaptive RBF neutral network compared with the forecast method of back propagation (BP) neutral network based on the chaotic learning algorithm has faster learning capacity and higher accuracy of forecast. The method provides a new way for the chaotic time series prediction.**

Index Terms—**Chaos Theory, Phase Space Reconstruction, Time Series Prediction, RBF Neural network, Algorithm**

I. INTRODUCTION

Since the phase space reconstruction theory proposed by Packard et al. in 1980, many scholars at home and abroad to set off a climax of chaotic time series prediction. Prediction for chaotic time series is to approximate the unknown nonlinear functional mapping of a chaotic signal. The laws underlying the chaotic time series can be expressed as a deterministic dynamical system. Farmer and Sidorowich suggest reconstructing the dynamics in phase space by choosing a suitable embedding dimension and time delay [1]. Takens' theorem ensures that the method is reliable, based on the fact that the interaction between the variables is such that every component contains information on the complex dynamics of the system [2].

The neural network [3-6]. not only has the self-adaptive, parallelism and fault tolerance characteristics, but also has the ability to approximate any nonlinear function. Based on these advantages, the neural network model of the nonlinear system has a very wide range of applications [7-10]. In recent years, particular interest has been put into predicting chaotic time series using neural networks because of their universal approximation capabilities. Most applications in this field are based on feed-forward neural networks, such as the Back Propagation (BP) network [11-13], Radial Basis Function (RBF) network [14-15], Recurrent neural networks (RNNs) [16-18], FIR neural networks [19-20] and so on. It is widely used tool for the prediction of time series [21-23].

The RBF neural network model structure is easy to understand, training process stability, training speed is fast, training result is high accuracy and generalization ability is strong. In this paper, the chaotic algorithm is proposed to a RBF neural network filtering predictive model and the model is proposed to make prediction of chaotic time series. The network system can enhance the stabilization and associative memory of chaotic dynamics and generalization ability of predictive model even by imperfect and variation inputs by selecting the suitable nonlinear feedback term. The dynamics of network become chaotic one in the weight space. The model is tested for the chaotic time series which venerated with Lorentz system by on-line method. The experimental and simulation results indicated that the adaptive filtering has a good self-suitable prediction performance and can be successfully used to predict chaotic time series.

II. ESTABLISHMENT OF ADAPTIVE RBF NEURAL NETWORK FILTERING PREDICTIVE MODEL BASED ON CHAOTIC ALGORITHM

A. Model of Chaotic Time Series Prediction

Takens theorem considers evolution of any component of the system is decided by other components interacting with this component, therefore, the information of relevant component imply in the development process of this component, so the original rules of the system can be extracted and restored from a group of time-series data of a certain component. The one-dimensional time series is embedded to multi-dimensional phase space through reconstruction and the new system with same dynamic characteristics as original system can be obtained through the selection of a suitable embedding dimension m and time delay τ. The usual method of selecting time delay

τ includes autocorrelation function method, multiple correlation function method, mutual information method. Embedding dimension m is calculated by the methods of GP algorithm, pseudo-nearest-point method, correlation integral method and Cao method.

The chaotic time series prediction is based on the Takens' delay-coordinate phase reconstruct theory. If the time series of one of the variables is available, based on the fact that the interaction between the variables is such that every component contains information on the complex dynamics of the system, a smooth function can be found to model the portraits of time series. If the chaotic time series are $\{x(t)\}$, then the reconstruct state vector is

$$\mathbf{x}(t) = (x(t), x(t+\tau), \cdots, x(t+(m-1)\tau))$$

where m ($m = 2, 3, \cdots$) is called the embedding dimension ($m = 2d+1$, d is called the freedom of dynamics of the system), and τ is the delay time. The predictive reconstruct of chaotic series is a inverse problem to the dynamics of the system essentially. There exists a smooth function defined on the reconstructed manifold in R^m to interpret the dynamics $x(t+T) = F(x(t))$, where T ($T > 0$) is forward predictive step length, and $F(\cdot)$ is the reconstructed predictive model.

B. RBF Neural Network Function Approximation Theory

Takens embedding theorem states that there is a smooth mapping F of the F makes:

$$x(t+\tau) = F(x(t)) \tag{1}$$

that is,

$$x(t+\tau), x(t), \cdots, x(t-(m-2)\tau) = F\{[x(t), x(t-\tau), \cdots, x(t-(m-1)\tau]\}$$

For purposes of calculation, equation (1) can be rewritten as:

$$x(t+\tau) = F[x(t), x(t-\tau), \cdots, x(t-(m-1)\tau] \tag{2}$$

where, f is the mapping from R^M to R^L. Chaos theory suggests that the chaotic time series is short-term forecast, and the essence of prediction is how to get a good approximation $\hat{f}$ on the function f. Chaotic time series determined by the internal regularity, this regularity comes from the non-linear, it exhibits the time series in the time delay state, this feature makes the system seem to have some kind of memory capacity. The same time, it is difficult to demonstrate such a regularity by using the analytic methods; this type of information processing happens to be the neural network, and the Kolmogorov continuity theorem in the neural networks theory provides a theoretical guarantee for the neural network nonlinear function approximation.

Theorem (Kolmogorov continuity theorem) Let $\varphi(x)$ be a non-constant and bounded monotonically increasing a continuous function; M is a compact sub-set of R^n, and $f(x) = f(x_1, x_2, \cdots, x_n)$ is the continuous real value function on M, then for $\forall \varepsilon > 0$, exists a positive integer N and real numbers C, makes:

$$\hat{f}(x_1, x_2, \cdots, x_n) = \sum_{i=1}^{N} C_i \varphi(\sum_{j=1}^{n} \varpi_{ij} x_j - \theta_j) \tag{3}$$

meet:

$$\max_{M} \left| \hat{f}(x_1, x_2, \cdots, x_n) - f(x_1, x_2, \cdots, x_n) \right| < \varepsilon \tag{4}$$

By the above theorem, the nonlinear time series prediction process using neural network can be considered as dynamic reconfiguration, which is an inverse process. Namely, the existence of a three-layer network, the hidden unit output function, the network input and output function is linear, three-layer network input and output relation f can approximate p.

Therefore, the theorem from mathematics is to ensure the feasibility of chaotic time series prediction by neural network.

C. Realized Architecture of Adaptive RBF Neural Network Filtering Predictive Model

After reconstructing the phase space, the RBF neural networks adopt three layers networks of Figure 1. Where the input layer has m nerve cells, the first layer feed to the second layer directly and it do not need the power processing. r_i ($i = 1, 2, \cdots, L$) is the reference vector and ϖ_k ($i = 1, 2, \cdots, L$) is the adjustable parameters in the adaptive RBF neural network filtering. Thus, the adaptive RBF neural network filtering is more flexible in studying the nonlinear functions. The differentiation between the networks and the traditional neural networks is that the activation function is a RBF function but not the Sigmoid function. The activation function usually choose the Gauss function, the spline function $f(d_i(k))$, where $d_i(k) = \|x(k) - r_i(k)\|$. In the adaptive RBF neural network filtering, $y(k)$ is expressed as

$$\hat{y}(k) = f_2(\sum_{i=0}^{L-1} \varpi_i(k) f(d_i(k))),$$

$$i = 0, 2, \cdots, L-1,$$

where $f_2(\cdot)$ is the activation function of output signal.
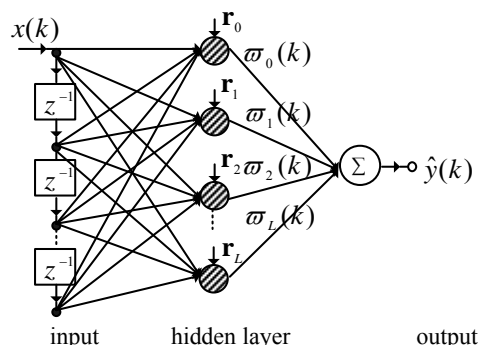

Figure 1. Structure of adaptive RBF neural network filtering

Generally, the learning of the RBF neural network filtering has three steps. If the gradient method and the Gauss activation function are adopted, the regulate formulas of RBF are shown as:

$$\begin{cases} \varpi_i(k+1) = \varpi_i(k) + 2\mu_\varpi e(k) f(d_i(k)) \\ \sigma_i(k+1) = \sigma_i(k) + 2\mu_\varpi e(k) f(d_i(k)) \varpi_i(k) \dfrac{d_i^2(k)}{\sigma_i^3(k)} \\ \mathbf{r}_i(k+1) = \mathbf{r}_i(k) + 2\mu_r e(k) f(d_i(k)) \varpi_i(k) \dfrac{\mathbf{x}(k)-\mathbf{r}_i(k)}{\sigma_i^2(k)} \\ \mathbf{r}_i(k+1) = \mathbf{r}_i(k) + 2\mu_r e(k) f(d_i(k)) \varpi_i(k) \dfrac{\mathbf{x}(k)-\mathbf{r}_i(k)}{\sigma_i^2(k)} \end{cases} \quad (5)$$

$i = 0, 2, \cdots, L-1$.

The RBF neural network system can enhance the stabilization and associative memory of chaotic dynamics and generalization ability of predictive model even by imperfect and variation inputs by selecting the suitable nonlinear feedback term. The dynamics of network become chaotic one in the weight space. Thus, the regulate formula $\varpi(k)$ is shown as

$$\varpi_i(k+1) = \varpi_i(k) + 2\mu_\varpi e(k) f(d_i(k)) + g(\varpi_i(k) - \varpi_I(k-1)) \quad (6)$$

where $g(x) = \tanh(ax)\exp(-bx^2)$, $x = \varpi_i(k) - \varpi_i(k-1)$.

That the feedback function $g(x)$ is chose is because that $g(x)$ can get the difference feedback function corresponding to the dissimilar parameter, such as the staircase function, δ function and so on. If the feedback function is seen as the motion-promoting force, the different feedback parameters a and b corresponding to the amplitude and width of the motion-promoting force. The paper [18] was detailed to discuss the influences by selecting the suitable learning and predictive process. The simulation results indicated that the network system can enhance the stabilization and associative memory of chaotic dynamics and generalization ability of predictive model even by imperfect and variation inputs during the learning and prediction process by selecting the suitable nonlinear feedback term.

III. DETERMINATION METHOD OF THE OPTIMAL DELAY TIME AND MINIMUM EMBEDDING DIMENSION

A. Determination Method of the Optimal Delay Time τ

During Phase Space Reconstruction in the Takens embedding theorem does not make limited to the delay time τ. In theory, when the observational data point is an infinitely long, the effect of embedded not too large. However, in actual operation, τ is caused a great impact. If τ is too small, the chaotic attractor cannot be fully expanded, redundant error is larger; if τ is too large, the no related error is larger. Therefore, in order for complex nonlinear systems, using the mutual information method to determine the optimal delay time τ, the mutual information method using a minimal value of the mutual information function to determine the optimal delay time τ, its expression is as follows:

$$M(x_t, x_{t-\tau}) = \sum_{i,j} P_{i,j}(r) \ln \frac{P_{i,j}(r)}{P_i P_j} \quad (7)$$

where, P_i is the probability of point x_t in the i time interval; $P_{i,j}(r)$ is the joint probability of the point x_t in t moment fall into the i time interval and the $t+\tau$ moment fall into the j time intervals.

B. Determination Method of the Minimum Embedding m

In this paper, the commonly used pseudo-near-point method to calculate the minimum embedding dimension m, set the number of attractor dimension d, then m is just the minimum embedding dimension when the attractor is fully open. When $m < d$, the attractor in the phase space cannot be completely open, the attractor will produce some projection point in the embedded space, the projection point and the other points in the phase space will form the closest point. In the original system, the 2 points are not true nearest neighbors, so called pseudo adjacent points. Assume that any point $y(t)$ in the phase space, the criterion of false neighboring points are as follows:

$$\frac{\left|D_{m+1}^2(t) - D_m^2(t)\right|^{\frac{1}{2}}}{D_m(t)} = \frac{\left|x(t+m\tau) - x(t'+m\tau)\right|}{D_m(t)} > \rho_m \quad (8)$$

Where $D_m(t)$ is the Euclidean distance between the points of $y(t)$ with its nearest neighbor $y^N(t)$ in the phase space when the embedding dimension is m. According to this criterion, the calculation pseudo-nearest neighbor number N when m from small to large, and then calculate the change amount ΔN when the embedding dimension from m to $m+1$. Draw the curve from $\dfrac{\Delta N}{N}$ to m; when $\Delta N = 0$, just $\dfrac{\Delta N}{N}$ dropped to 0, the value m^* of m is seeking the minimum embedding dimension.

IV. ADAPTIVE RBF NEURAL NETWORK RAPID LEARNING ALGORITHM

On the establishment of chaotic time series RBF, Network input the number of neurons, hidden layers and the number of neurons in the hidden layer are to be considered. The following chaotic time series used are from Lorenz chaotic sampling time series. The Lorenz chaotic sampling time series RBF neural network can be constructed: RBF neural network is designed to be three layers: input layer, single hidden layer and output layer; the number of hidden layer wavelet neural taken as 9 by Kolmogorov Theorem, the number of input layer neurons equal to the minimum embedding dimension, the number of output layer is 1, so that the 4-9-1 structure of Lorenz chaotic sampling time series RBF was obtained, specifically shown in Figure 1.

Algorithm The steps of the chaotic time series learning and prediction of the adaptive RBF neural network filtering predictive model are showed:

Step1) Based on the Takens' delay-coordinate phase reconstruct theory, the number of the input nerve cells

M of the adaptive RBF neural network filtering is determined.

The dimension m of chaotic time series is calculated by the way of G- P algorithms, and the delay time τ is calculated by the self-correlation method. For the overall description of the dynamics characteristic of the original system by the Takens' delay-coordinate phase reconstruct theory, a chaotic series demand $m \geq 2d + 1$ variances at least, so the number of the input nerve cells of the adaptive RBF neural network filtering is $M = m$; The reconstruction phase space vector number is 200, Then, the 200 phase space vectors to make a simple normalized, the normalized as $[x(t) - mean(x(t))]/[\max(x(t)) - \min(x(t))]$, $t = 1, 2, \cdots 200$, and making the value is owned by a range of $-1/2$ to $1/2$.

Step2) The adaptive filtering is initialized and the weights are vested the initial values. RBF neural network vector weighting parameters w is initialized, where the weight vector w in each component take random function between 0 and 1; and the learning rate η is initialized at the same time, where $\eta = 0.0002$. β and γ are the learning rate adjustment factors, $0 < \beta < 1$, $\gamma > 1$, for example, $\beta = 0.75, \gamma = 1.05$.

Step3) Using the above the initialization network and the pretreatment traffic flow time series, the first training network is carried out.

Step4) The error is calculated. If the error is in the scope of the permission, the error is calculated and it turns into Step4), otherwise it continues; the error function formula:

$$E(\theta) = \frac{1}{2}\sum_{t=1}^{200}(y(t) - \hat{y}(t))^2 \qquad (9)$$

Set the maximum error is $E_{\max} = 0.035$, if $E < E_{\max}$, the storage RBF neural network parameter use w; otherwise, then a second training network will be required.

Step5) Adjust the adaptive learning rate If A previous training error is recorded as E_{n-1}, the current error is recorded as E_n, then Calculate the ratio of E_n to E_{n-1}, Setting constants $k = 1.04$, if $\dfrac{E_n}{E_{n-1}} > k = 1.04$, then substitute $\beta\eta$ for η to reduce learning rate; otherwise, replace η with $\gamma\eta$ to increase learning rate.

Step6) In the adaptive RBF neural network filtering for the chaotic time series prediction in Figure 1, $x(k) = x(t)$ $t = 1, 2, \cdots, N$ is the input, $\hat{y}(k) = \hat{x}(t)$ is the output.

Introduce nonlinear feedback into the weighting formal to adopt Chaos Mechanisms, due to the nonlinear feedback is vector form of weighting variables. In order

to facilitate understanding, respectively, gives the vector w and its weighting formal, as follows.

Note

$$\Delta w_{ji}^{l}(t+1) = w_{ji}^{l}(t+1) - w_{ji}^{l}(t),$$

which represents the current value of weighting variables, then

$$\Delta w_{ji}^{l}(t+1) = w_{ji}^{l}(t+1) - w_{ji}^{l}(t) = -\eta\delta_{j}^{l+1}(t)x_{i}^{l}(t)$$

In order to speed up the learning process, in the right to join a momentum term $\alpha\Delta w_{ji}^{l}(t)$, then

$$\Delta w_{ji}^{l}(t+1) = -\eta\delta_{j}^{l+1}(t)x_{i}^{l}(t) + \alpha\Delta w_{ji}^{l}(t) \qquad (10)$$

where α is inertia factor. As a constant, the weight of amendments is linear, not introduce chaos mechanism. then we Introduce a nonlinear feedback (chaos mechanism on the right):

$$\Delta w_{ji}^{l}(t+1) = -\eta\delta_{j}^{l+1}(t)x_{i}^{l}(t) + g(\Delta w_{ji}^{l}(t+1)) \qquad (11)$$

Expand this equation into scalar form as follow:

$$\begin{cases} \Delta w_{ji}^{l}(t+1) = -\eta\delta_{j}^{l+1}(t)x_{i}^{l}(t) + g(\Delta w_{ji}^{l}(t)) \\ \Delta w_{ji}^{l}(t+1+\tau) = -\eta\delta_{j}^{l+1}(t+\tau)x_{i}^{l}(t+\tau) + g(\Delta w_{ji}^{l}(t+\tau)) \\ \Delta w_{ji}^{l}(t+1+2\tau) = -\eta\delta_{j}^{l+1}(t+2)x_{i}^{l}(t+2\tau) + g(\Delta w_{ji}^{l}(t+2\tau)) \\ \cdots\cdots\cdots\cdots\cdots \\ \Delta w_{ji}^{l}(t+1+(m-1)\tau) = -\eta\delta_{j}^{l+1}(t+(m-1)\tau)x_{i}^{l}(t+(m-1)\tau) \\ \qquad\qquad + g(\Delta w_{ji}^{l}(t+(m-1)\tau)) \end{cases}$$
$$(12)$$

where, feedback can take a variety of vector functions, for example:

$$g(x) = \tanh(px)\exp(-qx^2)$$

or

$$g(x) = px\exp(-q|x|),$$

in the study, $p = 0.7$, $q = 0.1$.

Step7) Using the new learning rate in Step5) and RBF network parameters with nonlinear feedback in Step6) to calculate the new value, and train network again, then get the error and enter into Step4), repeated training until the relative error in traffic meet $E < E_{\max}$.

Step8) Output of each stored network parameters and training error curve.

V. EXAMPLE ANALYSIS AND CONCLUSIONS

A. Model and Data

In this paper, the chaotic time series is the object of study of the numerical simulation in Lorenz dynamic system. In 1963, the meteorologist Lorenz describe the evolution of the weather by three-dimensional autonomous equations; when the parameter $\sigma = 10$, $r = 28$, $b = \dfrac{8}{3}$, the long-term changes in the weather unpredictable, that is, the system presents a chaotic state, and for the first time given a strange attractor. The attractors are shown in Figure 2 (a), Figure 2 (b), Figure 2 (c) and Figure 2 (d):
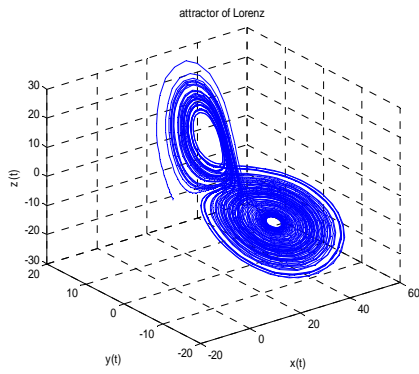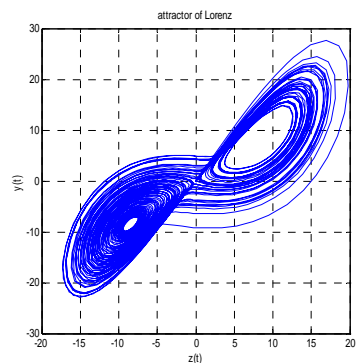
(a) three-dimensional map of Lorenz attractor
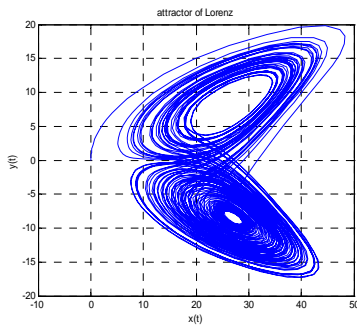
(b) two-dimensional map of Lorenz attractor in the x-y-plan
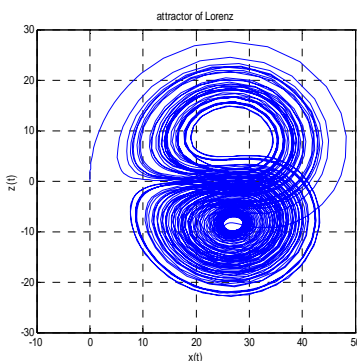
(c) two-dimensional map of Lorenz attractor in the x-z-plan

(d) two-dimensional map of Lorenz attractor in the z-y-plan

Figure 2. Lorenz attractor in the phase space reconstruction

Considering Lorenz chaotic system

Lorenz map:

$$\begin{cases} \dot{x} = \sigma(y-x) \\ \dot{y} = rx - y - xz \\ \dot{z} = -bz + xy \end{cases} \qquad (13)$$

Where $\sigma = 10$, $r = 28$, $b = \dfrac{8}{3}$ .The initial value is $x(0) = 0$, $y(0) = 5$, $z(0) = -5$; and the fixing step length of initial value is $0.05s$. Time series to the branch x with $70s$ is produced by the Runge-Kutta algorithms and the total data is 1200. The embedded dimension of the sampling chaotic time series m is 8 by the G- P algorithms. The delay time is τ=1 by the self-correlation function algorithms and the input dimension of the adaptive RBF neural network filtering is 8.The former 1200 data is trained and other 200 data is predicted by the adaptive RBF neural network filtering predictive model.

B. Evaluation of the Predictive Ability

The model's predictive ability is generally measure the following three indicators: of MAPE (mean absolute percentage error), RMSE (root mean square error) and RMSPE (root mean square percentage error), they are calculated as follows:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \times 100 \right|, \qquad (14)$$

$$RMSPE = 100 \times \sqrt{\frac{1}{n} \sum_{I=1}^{n} \left(\frac{\hat{y}_i - y_i}{y_i} \right)^2} , \qquad (15)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{I=1}^{n} \left(\hat{y}_i - y_i \right)^2} \qquad (16)$$

where, $\hat{y}_i$ is predictive value of the model; y_i is the real value; n is prediction phases, and MAPE assess the predictive capability are as follows: less than or equal to 10%, then predictive ability is excellent; 10% -20%, then the predictive ability is excellent; 20% -50%, more than 50%, then the prediction is inaccurate. For RMSPE, the prediction square vulnerable to the impact of outliers, for the larger error given greater weight, but still can be modeled on the MAPE to determine the model of the pros and cons. RMSPE values range from zero to infinity. MAPE and RMSPE are the relative indicator, RMSE is the absolute indicator. The RMSE is the smaller, the model predictive ability is the stronger.

C. The Simulation Results

That the experimental outcome of Lorenz chaotic sampling time series, the true value (real line) and the predictive value (star line) and the predictive error curve are showed in Figure 3., Figure 4. and Figure 5.
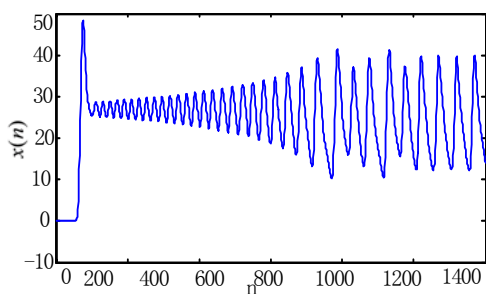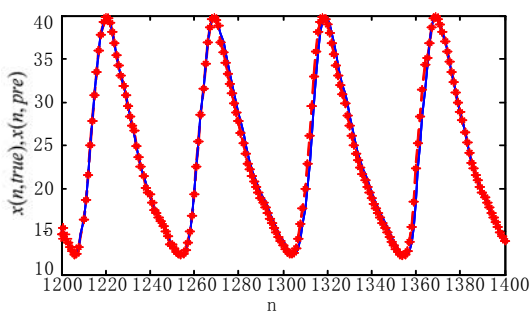
Figure 3. Lorenz chaotic sampling time series

Figure 4. True value (real line) and predictive value (star line)
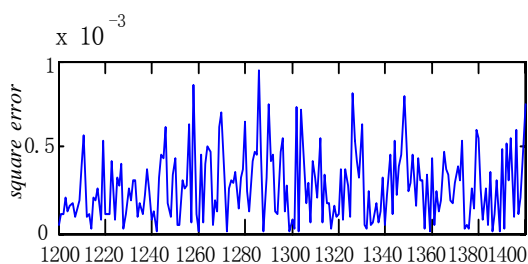

Figure 5. Predictive error curve

In Figure 3 the sampling chaotic time series number is 1200 by the Runge-Kutta algorithms.

The former 1200 datum is used to learn and train the adaptive wavelet neural networks every 8 datum. After the learned and trained stage, the true value (real line) and predictive value (star line) are shown in Figure 4.

The predictive error curve of the true value and the predictive value is very small in Figure 5.

The true value and the predictive value in the adaptive RBF neural network filtering is to find a inner law in the series itself, which can avoid the disturbance of some subjective factors and enjoys higher reliability. In this study, the fusion of chaotic theory with the adaptive RBF neural network filtering based on chaotic algorithm provides a new method for chaotic time series prediction. The experimental indicated that the network system can enhance the stabilization and associative memory of chaotic dynamics and generalization ability of predictive model even by imperfect and variation inputs during the learning and prediction process by selecting the suitable nonlinear feedback term. Simulation results for the modeling and prediction of chaotic time series show better predictive effectiveness and reliability.

TABLE 1
PREDICTIVE PERFORMANCE COMPARISON TABLE

comparative indicators	BP neural network prediction	RBF neural network prediction
MAPE	5.01%	3.71%
RMSPE	6.13%	4.55%
RMSE	62.50	46.37

From Table 1, the mean absolute percentage error of Lorenz chaotic sampling time series prediction and actual values, BP neural network based on the learning rate variable training algorithm, RBF network based on fast learning algorithm, are 5.1% and 3.71%, respectively. Similarly, for the RMSPE, the results were 6.13% and 4.55%; For RMSE, the results were 62.50 and 46.37. Can be seen from the data on Lorenz chaotic sampling time series RBF network prediction is better than BP neural network.

VI. CONCLUSIONS

In the paper the chaotic time series RBF neural network model was designed. A RBF neural network Adaptive learning algorithm based on Chaos mechanism was proposed. The method of model selection and algorithm design, are considered the chaos of Lorenz chaotic sampling time series, which is a theoretical value. Simulation results show that the method can reduce MAPE, RMSPE, RMSE, and improve the forecast accuracy, and show better predictive effectiveness and reliability.

REFERENCES

[1] Jieni XUE, Zhongke SHI, "Short-Time Traffic Flow Prediction Based on Chaos Time Series Theory", *Journal of Transportation Systems Engineering and Information Technology*, 8 (5), pp. 68-72, 2008.

[2] Ajit Kumar Gautam, A.B. Chelani, V.K. Jaina, S. Devotta, "A new scheme to predict chaotic time series of air pollutant concentrations using artificial neural network and nearest neighbor searching", *Atmospheric Environment*, 42 (18), pp.4409-4417, 2008.

[3] Roman M. Balabin, Ekaterina I. Lomakina, Ravilya Z. Safieva, "Neuralnetwork (ANN) approach to biodiesel analysis: Analysis of biodiesel density, kinematic viscosity, methanol and water contents using near infrared (NIR) spectroscopy", *Fuel*, Vol. 90, no. 5, pp. 2007-2015, May 2011.

[4] Yuanping Zhu, Jun Sun and Satoshi Naoi, "Recognizing Natural Scene Characters by Convolutional Neural Network and Bimodal Image Enhancement, "*Lecture*

Notes in Computer Science, Vol. 7139/2012, pp. 69-82, 2012.

[5] Yüksel Özbaya, Rahime Ceylanb, Bekir Karlikc, "Integration of type-2 fuzzy clustering and wavelet transform in a neuralnetwork based ECG classifier", *Expert Systems with Applications*, Vol. 38, pp.1004-1010, January 2011.

[6] Yan Fan, Niall W. Duncan, Moritz de Greck, Georg Northoff, "Is there a core neuralnetwork in empathy? An fMRI based quantitative meta-analysis", *Neuroscience & Biobehavioral Reviews*, Vol. 35, pp.903-911, January 2011.

[7] Shunsuke Kobayakawa, Hirokazu Yokoi, "Evaluation of Prediction Capability of Non-recursion Type 2nd-order Volterra Neuron Network for Electrocardiogram", *Lecture Notes in Computer Science*, vol. 5507, pp. 679-686, 2009.

[8] Li-Sheng Yin, Xi-Yue Huang, Zu-Yuan Yang, et al, "Prediction for chaotic time series based on discrete Volterra neural networks", *Lect Notes Comput SC* vol. 3972, pp. 759-764, 2006.

[9] Satoru Murakami, Pham Huu, Anh Ngoc, "On stability and robust stability of positive linear Volterra equations in Banach lattices", *Central European Journal of Mathematics*, 2010, pp.966-984.

[10] Yu. V. Bibik, "The second Hamiltonian structure for a special case of the Lotka-Volterra equations", *Mathematics and Mathematical Physics*, 2007, 47, pp.1285-1294.

[11] Zhi Xiao, Shi-Jie Ye, Bo Zhong, Cai-Xin Sun, "BP neural network with rough set for short term load forecasting", *Expert Systems with Applications*, 36 (1), pp. 276-279, 2009.

[12] Shiwei Yu, Kejun Zhu, Fengqin Diao, "A dynamic all parameters adaptive BP neural networks model and its application on oil reservoir prediction", *Applied Mathematics and Computation*, 2008, 195 (1), pp.66-75.

[13] R. Bakker, J. C. Schouten, and C. L. Giles et al., "Learning chaotic attractorsby neural networks", *Neural Computer*, 12, pp.2355-2383, 2000.",

[14] H. Leung, T. Lo, and S. Wang, "Prediction of noisy chaotic time series using an optimal radial basis function neural network", *IEEE Trans. Neural Networks*, 12, pp.1163-1172, 2001.

[15] Zhang Yun, Zhou Quan, Sun Caixin, Lei Shaolan, Liu Yuming, Song Yang, "RBF Neural Network and ANFIS-Based Short-Term Load Forecasting Approach in Real-Time Price Environment", *Power Systems*, 23 (3), pp.853-858, 2008.

[16] Zidong Wang, Yurong Liu, Xiaohui Liu, "State estimation for jumping recurrent neural networks with discrete and distributed delays", *Neural Networks*, 22 (1), pp.41-48, 2009.

[17] Talebi, H.A., Khorasani, K., Tafazoli, S., "A Recurrent Neural-Network-Based Sensor and Actuator Fault Detection and Isolation for Nonlinear Systems With Application to the Satellite's Attitude Control Subsystem", *Neural Networks*, 2009, 20 (1), pp.45-60.

[18] Min Han, Jianhui Xi, Shiguo Xu, and Fuliang Yin, "Prediction of time series based on the recurrent predictor neural network", *IEEE Transactions on signal processing*, vol.52.no.12.december 2004.

[19] Sirapart Chiewchanwattana, Chidchanok Lursinsap, Chee-Hung Chu, "Time-series datd prediction based on reconstruction of missing samples and selective ensembling of FIR neural networks", *Proceeding of the 9th international conference on neural information processing*.vol.5, 2002.

[20] Dhruba C.Panda, Shyam S.Pattnaik, Rabindra K.Mishra, "Application of FIR-neural network on finite difference time domain technique to calculate input impedance of microstrip patch antenna", *International Journal of RF and Microwave Computer-Aided Engineering*, Vol. 20, pp.158-162, 2010.

[21] Wu Jian-Da, Hsu Chuang-Chin, Wu Guozhen, "Fault gear identification and classification using discrete wavelet transform and adaptive neuro-fuzzy inference", *Expert Systems with Applications*, vol. 36, pp. 6244-6255, 2009.

[22] Lee Jong Jae, Kim Dookie, Chang Seong Kyu, "An improved application technique of the adaptive probabilistic neural network for predicting concrete strength, "*Computational Materials Science*, vol. 44, pp. 988-998, 2009.

[23] Hu xiao-jian, wang wei, sheng hui, "Urban Traffic Flow Prediction with Variable Cell Transmission Model", Journal of Transportation Systems Engineering and Information Technology, vol. 4, pp.17-22, 2010.

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