TELKOMNIKA, Vol. 11, No. 6, June 2013, pp. 3165 ~ 3171
e-ISSN: 2087-278X

Research on the Prediction of VNN Neural Network Traffic Flow Model Based on Chaotic Algorithm

Yin Lisheng*, He Yigang, Dong Xueping, Lu Zhaoquan
School of Electrical Engineering and Automation, Hefei University of Technology, 230009, China
Corresponding author, email: yls20000@163.com*, hyghnu@yahoo.com.cn, hfdxp@126.com, luzhquan@126.com

Abstract

This paperresearches on the prediction of traffic flow chaotic time series based on VNNTF neural network. First, the traffic flow time series chaotic feature is extracted by chaos theory. Pretreatment for traffic flow time series and the VNNTP neural networks model was build by this. Second, principles of neural network learning algorithm VNNTF is described. Based on chaotic learning algorithm, the neural network traffic Volterra learning algorithm isdesigned for fast learning algorithm. Last, a single-step prediction of traffic flow chaotic time series is researched by VNNTF network model based on chaotic algorithm. The results showed that the VNNTF network model predictive performance is better than the Volterra prediction filter and the BP neural network by the simulation results and root-mean-square value.

Keywords: *chaos theory, phase space reconstruction, time series prediction, neural networks, algorithm*

1. Introduction

Volterra series can be described as response and memory function of nonlinear behavior, and it is universality [1]. Volterra functional series become one of the main methods of nonlinear dynamic systems modeling. Traffic flow chaotic time series with the nonlinear behavior of the response and memory function, the Volterra functional series to become one of the primary means of traffic flow in nonlinear system identification. However, due to the high dimensional Volterra nonlinear system, the identification is very difficult, leading to a Volterra functional model of the application subject to considerable restrictions [2-4]. At present, most studies focus on how to simplify Volterra series and ignore the importance of an accurate model for solving practical problems.

The artificial neural network has a high degree of parallelism, fault tolerance and associative memory function [3-7], and it can be better nonlinear characteristics of the analog system. Due to the consistency of the Volterra model and the three-layer ANN model, combined with the traffic flow chaotic time series chaotic characteristics, how to make use of the Volterra accurate modeling's advantages to overcome the shortcomings of Solutions of Higher Order kernel function; and how to use the advantages of ANN neural network model for learning and training network to overcome the blindness of the ANN neural network modeling are worth exploring.

Based on the above considerations, the physical significance of the truncation order of the Volterra series model and the truncated number [8-10], thus, traffic flow chaotic time series VNNTF network model and the corresponding algorithm have been established. In the actual prediction, it has made better than the Volterra series model and the ANN neural network prediction.

2. Traffic Flow Time Series Volterra Neural Network Model (VNNTF)

2.1. Representation of Nonlinear Systems Using Artificial Neural Network

It has proven that the BP neural network with one hidden layer can approximate any continuous bounded non-linear system.Therefore, generally selected to contain a three-layer back propagation BP network with one hidden layer to approximate nonlinear systems. A single output three-layer back propagation neural network is shown in Figure 1. In the figure, the input

Received January 6, 2013; Revised April 2, 2013; Accepted April 18, 2013

vector $x_k^T = [x_{k,0}, x_{k,1}, \cdots x_{k,M}]$ at moment n can obtain by the delay of $x(k)$, where $x_{k,m} = x(k-m)$, the input of the l hidden unit($l = 1, 2, \cdots, L$) is $Z_{l,k} = S_l(u_{l,k})$; $u_{l,k} = \sum_{m=0}^{M} w_{l,m} x_{k,m}$

A single output three-layer back propagation neural network is shown in Figure 1.

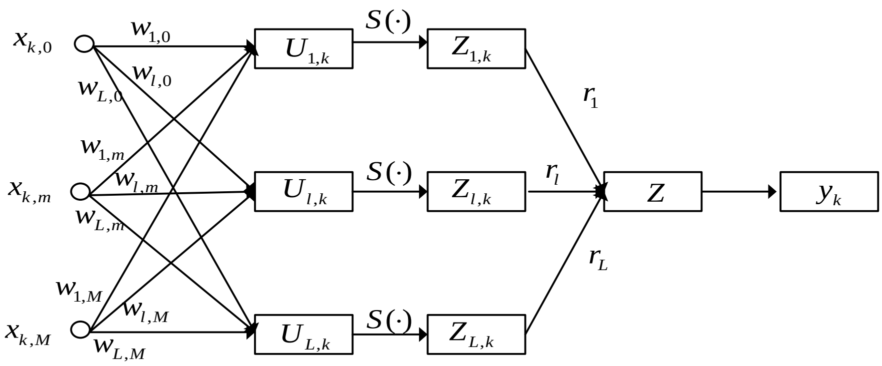

Figure 1. Three Layer Neural Networks In Response To M+1 Input and Single Output System

If the implicit function selected the sigmoid function, then $S_l(u_{l,k}) = 1 / 1 + \exp[-\lambda(u_{l,k} - \theta_l)]$, where, θ_l is the threshold of the unit n, If the output unit is linear summation unit, the output at moment n is $y_k = \sum_{l=1}^{L} r_l Z_{l,k}$. The output of each hidden unit to expand into a Taylor series at the threshold θ_l : $Z_{l,k} = \varphi_l(u_{l,k}) = \sum_{i=0}^{\infty} d_i(\theta_l) u_{l,k}^i$,where, $d_i(\theta_l)$ is the commencement of the coefficient, the value associated with θ_l, and because of $u_{l,k} = \sum_{m=0}^{M} w_{l,m} x_{k,m}$, then the output of the neural network is

$$y_k = \sum_{l=1}^{L} r_l \sum_{i=0}^{\infty} d_i(\theta_l) \cdot \sum_{m_1=0}^{M} \cdots \sum_{m_i=0}^{M} w_{l,m_1} \cdots w_{l,m_i} x_{k,m_1} \cdots x_{k,m_i} \tag{1}$$

2.2. Traffic flow Volterra neural network Model

Analysis and comparison of traffic flow Volterra series model and three-layer BP neural network, if the input vector in equation (4) in VNNTF to take the traffic flow chaotic time series, then between them in the function, structure and method for solving are inherently close contact and similarity.

From a functional point of view, the traffic flow chaotic time series, Volterra series model and ANN model can measurethe traffic flow chaotic time series and predict the traffic flow process.

From a structural point of view, the traffic flow chaotic time series Volterra model and ANN model are also isomorphic.

From a method for solving point of view, traffic flow chaotic time series Volterra model is based on orthogonal polynomials for the numerical approximation to find the approximate solution. The Meixner function systems and network weights have the same effects.

Through consistency of traffic flow chaotic time series Volterra model and ANN model, in this paper, the traffic flow chaotic time series Volterra neural network model has been proposed in Figure 2. In the figure, $X(t)=(x(t),x(t+\tau),\cdots,x(t+(m-1)\tau)^T$ ($t=1,2,\cdots$) is the traffic flow chaotic time series reconstructed phase space vector; $w_{i,j}$ ($i=1,2,\cdots;\ j=1,2,\cdots$), r_n is the traffic flow chaotic time series Volterra neural network weights parameters; g_s, ($s=1,2,\cdots,N$) is the activation function and $V_s(k)$ is the traffic flow of the convolution of the input signal $V_N(t)=\sum_{i=0}^{m} w_{Ni}x(t+(i-1)\tau)$ .Thus, the traffic flow chaotic time series Volterra neural network expression is

$$\hat{y}(t)= f(X(t))= f(\vec{x}(t))=\sum_{s=1}^{N} r_s g_s(V_N(t)) =\sum_{s=1}^{N} r_s g_s(\sum_{i=0}^{m} w_{si}x(t+(i-1)\tau)) \tag{2}$$

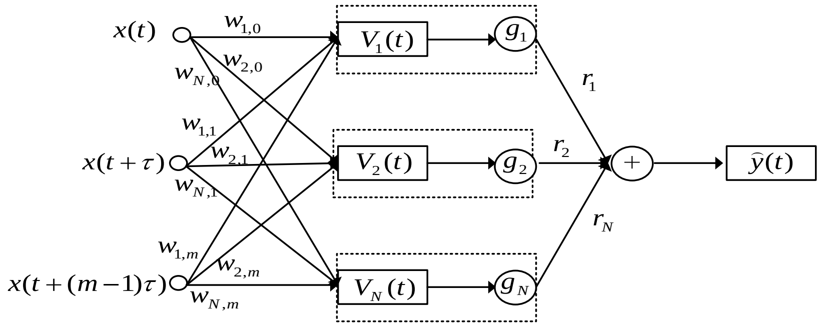

Figure 2. The chaotic time series Volterra neural network traffic flow model (VNNTF)

3. Traffic Flow Volterra Neural Network Rapid Learning Algorithm

On the establishment of traffic flow chaotic time series VNNTF, Network input the number of neurons, hidden layers and the number of neurons in the hidden layer are to be considered. The following traffic flow data used are from "Chongqing Road Traffic Management Data Sheet I and II " in 2006. There is the study of traffic volume time series of two-lane road 28 hours and 5 minutes every 5 minutes, and its sequence length $n=337$ .Then the 4-9-1 structure of traffic flow Volterra neural network was obtained, specifically shown in Figure 2. The steps of traffic flow chaotic time series Volterra Neural Network fast learning algorithm are as follows:

Algorithm VNNTF model fast learning algorithm

Step1) The 4-9-1 structure of traffic flow VNNTF neural networks was obtained. The traffic flow time series input signal is $(x(t),x(t+\tau),\cdots,x(t+(m-1)\tau)^T$, ($t=1,2,\cdots$); the output signal is $\hat{y}(t)$;the weight coefficient matrix of the hidden layer is $\boldsymbol{w}=(w_{s,l_j})_{N\times m}=(w_{s,i})_{N\times m}$, ($s=1,2,\cdots 9$, i, $j=1,2,\cdots,4$) and the parameter is r_s ($s=1,2,\cdots 9$).

Step2) The traffic flow chaotic time series Volterra Neural Network parameters $\boldsymbol{w}=(w_{s,i})_{N\times m}$ and r_s ($s=1,2,\cdots 9$, $i=1,2,\cdots 4$) are initialized, where $\boldsymbol{w}=(w_{s,i})_{N\times m}$ in each component take random function between 0 and 1; and r_s is initialized between 0 and 1 by the random function.

Step3) Based on Takens theorem, the minimum embedding dimension $m=4$, and the delay time $\tau=3$. The reconstruction phase space vector number is 327, which the top 250 vector is used as network input signals. Then, the 250 phase space vectors are to make a simple normalized.

Step4) To use the initialized network and the preprocessed traffic flow time series, the first VNNTF neural network training begin with the function $\hat{y}(t)=\sum_{s=1}^{N}\sum_{i=1}^{+\infty} r_s a_{i,s}(\sum_{i=0}^{m} w_{si}x(t+(i-1)\tau))^i$, where $a_{i,s}\in R$ are polynomial coefficients.

Step5) Calculate error function, the function formula:

$$E(\theta)=\frac{1}{2}\sum_{t=1}^{250}(y(t)-\hat{y}(t))^2 \quad (2)$$

Set the maximum error as $E_{\max}=0.035$, if $E<E_{\max}$, the storage VNNTF neural network parameter use $\boldsymbol{w}=(w_{s,i})_{N\times m}$ and r_s ($s=1,2,\cdots 9$, $i=1,2,\cdots 4$); and further $h_j(l_1,l_2,\cdots l_j)$ ($j=1,2,\cdots m$) can be calculated by combining the polynomial coefficients, otherwise, transferred to step6).

Step6) Calculate local gradient of the traffic flow Volterra neural network. Specifically, according to the formula $\delta_j(t)=(y(t)-\hat{y}_j(t))g_s{}'(V_j(t))$ (j is the output layer) and the formula

$$\delta_j(t)=-\frac{\partial E(t)}{\partial y_j(t)}g_s{}'(V_j(t)) \quad (3)$$

where, the local gradients are calculated in the hidden layer.

step7) By introducing the momentum term, to adjust the learning weights of the traffic flow chaotic time series Volterra neural network. The parameter correction calculation formula is as follows: $\Delta\boldsymbol{w}_{ji}^{l}(t+1)=-\eta\delta_j^{l+1}(t)\boldsymbol{x}_i^{l}(t)+\alpha\Delta\boldsymbol{w}_{ji}^{l}(t)$, where α is inertia factor; η is learning step.

Step8) Calculating the modified weights in the traffic flow chaotic time series Volterra neural network and transferred to step4), and train network again, then calculate the network output $\hat{y}(t)$ and the error E, repeated training until the relative error in traffic meet $E<E_{\max}=0.035$.

Step9) Output of every training storage of network parameters $\boldsymbol{w}=(w_{s,i})_{N\times m}$ and r_s ($s=1,2,\cdots 9$, $i=1,2,\cdots 4$) in the traffic flow chaotic time series Volterra neural network. The activation function $g_s(V_s(t))$ is expanded into a Taylor series at the threshold θ_s and the expansion coefficient $d_i(\theta_s)$ is obtained. If the activation function is a polynomial, then $d_i(\theta_s)=a_{i,s}$ ($s=1,2,\cdots 9$, $i=1,2,\cdots 4$).

Step10) According to the formula

$$h_j(l_1,l_2,\cdots l_j)=\sum_{s=1}^{N} r_s d_i(\theta_s)w_{s,l_1}w_{s,l_2}\cdots w_{s,l_j} \quad (4)$$

the kernel function ($s=1,2,\cdots 9$, $i=1,2,\cdots 4$) of the output system is calculated.

4. Experimental results and analysis

In order to study the prediction performance of traffic flow time series in traffic flow VNNTF network, the VNNTF network model, Volterra prediction filter and ANN are used to predict the network traffic flow chaotic time series respectively, and analyze and compare their predictions.

Here, with the remaining 77 vectors to predict the traffic flow by the trained VNNTF network model, Volterra prediction filter and ANN network, and in the graph, "+" line represents the real traffic flow, with "o" line represents the predicted traffic flow and the results were shown in Figure 3, Figure 5 and Figure 7. The horizontal axis is the network prediction number, and the vertical axis is the traffic flow in Figure 3, Figure 5, and Figure 7. Figure 4, 6 and 8, respectively, which corresponds to BP network forecast, Volterra filters network forecast, VNNTF network forecast, absolute error curve. Which, in Figure 4 the absolute error is maximum; in Figure 6 the absolute error is smaller than that in Figure 4, and in Figure 8, the absolute error is smaller than that in Figure 4 and Figure 6.

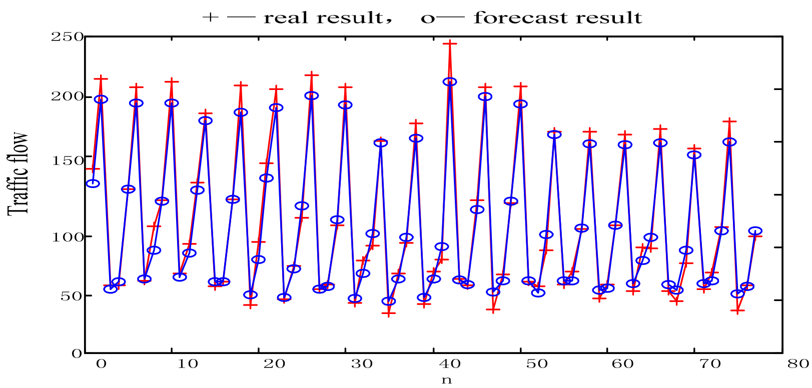

Figure 3. Comparison of the Forecast Result and Real Network Result by BP Network Forecast

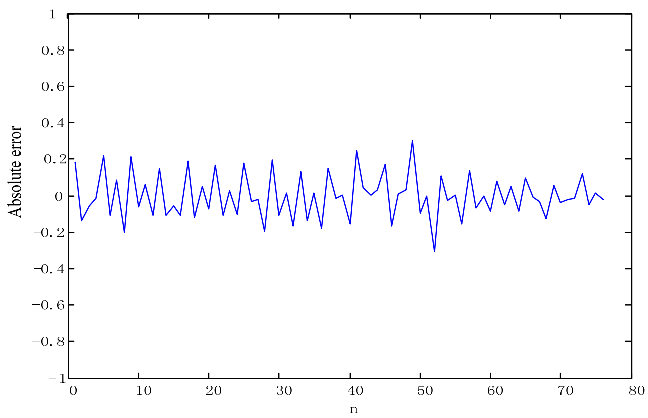

Figure 4. Absolute Error Curve of BP Forecast

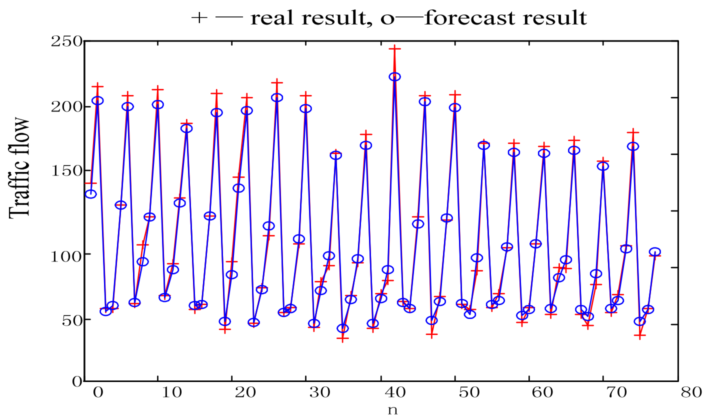

Figure 5. Comparison of the Forecast Result and Real Volterra Filters Network Result By Volterra Filters Network Forecast

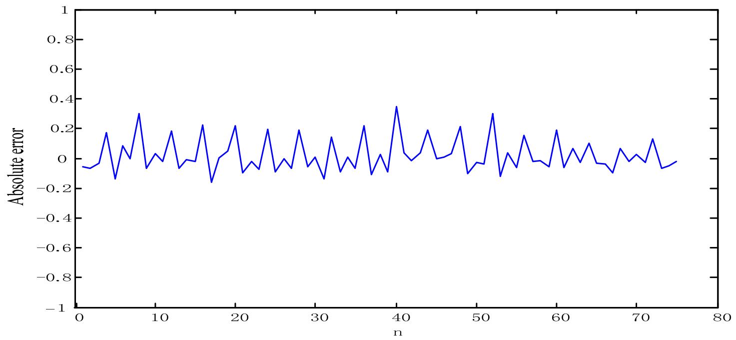

Figure 6. Absolute Error Curve of Forecas

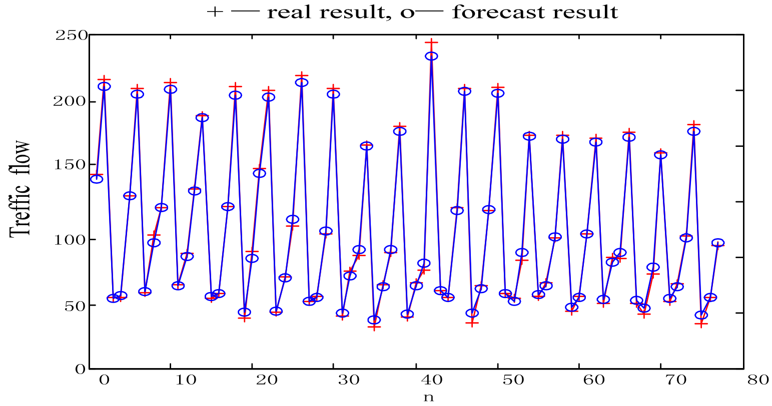

Figure 7. Comparison of the Forecast Result and Real VNNTF Network Result by VNNTF Network

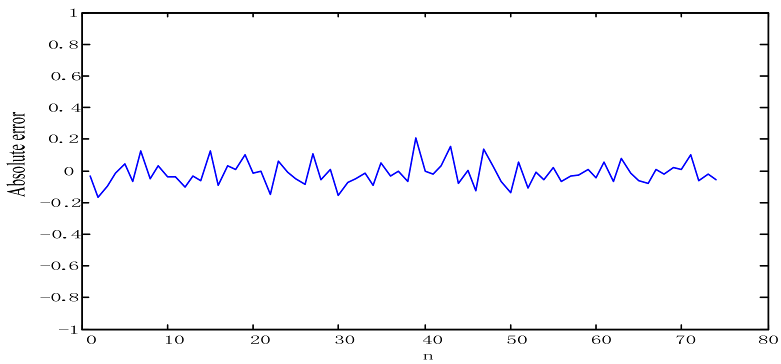

Figure 8. Absolute Error Curve of Forecast

Table 1. Normalization of RMSE Comparison

Item	BP network prediction	Volterra filters prediction	VNNTF network prediction
RMSE	0.7014	0.3567	0.1368

Figure 3, Figure 5 and Figure 7 shows that the effect of BP network prediction results is less; the effect of Volterra prediction filter prediction results is better than the BP network prediction; and the effect of VNNTF network prediction results is relatively best.

Here, the root-mean-square error (RMSE) to be compared in Figure 3, Figure 4, and Figure 5 and the compare results are shown in Table 1. From Table 1, the RMSE of traffic flow forecasts, the actual values, BP neural network , Volterra prediction filter and VNNTF network are 0.7014, 0.3567 and 0.1368, respectively. It can be seen from the data that the on traffic flow VNNTF network prediction is better than BP neural network and the effect of the Volterra filter.

To analyze the reasons, for the BP network, its modeling has blindness; for the Volterra filter, it does not fully take into account the traffic flow time series dimension. However, in the VNNTF network modeling process, fully consider the characteristics of the traffic flow chaotic time series itself, intact anastomosis with the truncation order and truncation items in Volterra series, so the VNNTF network shows better predictive effectiveness and reliability in the precise VNNTF network model.

5. Conclusions

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

Acknowledgments

This research is financially supported by the National Natural Science Funds of China for Distinguished Young Scholar under Grant(50925727), and the Fundamental Research Funds for the Central Universities, Hefei University of Technology for Professor He Yigang , the National Natural Science Foundation of China(NSFC) for Professor Xue-ping Dong (60974022) and the Universities Natural Science Foundation of Anhui Province (No. KJ2012A219) for Professor Yin Lisheng.

References

[1] Musa Asyali, Musa Alc. Obtaining Volterra Kernels from Neural Networks. *World Congress on Medical Physics and Biomedical Engineering*. 2006; (2): 11-15.

[2] M Ghasemi, M Tavassoli Kajani, E Babolian. Numerical solutions of the nonlinear Volterra–Fredholm integral equations by using homotopy perturbation method. *Applied Mathematics and Computation*. 2007; 188(1): 446-449.

[3] Bing Liu, Yujuan Zhang, Lansun Chen. Dynamic complexities in a lotka–volterra predator–prey model concerning impulsive control strategy. *International Journal of Biomathematics*. 2008; 1(1): 179-196.

[4] Fengde Chen. Permanence and global attractivity of a discrete multispecies Lotka–Volterra competition predator–prey systems. *Applied Mathematics and Computation.* 2006; 182(1): 3-12.

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

[6] Kang Ling, Wang Cheng, Jiang Tiebing. Hydrologic model of Volterra neural network and its application. *Journal of Hydroelectric Engineering*. 2006; 25(5): 22-26.

[7] Haiying Yuan, Guangju Chen. Fault Diagnosis in Nonlinear Circuit Based on Volterra Series and Recurrent Neural Network. *Lecture Notes in Computer Science.* 2006; 4234: 518-525.

[8] Wei Si, Zhe-Min Duan, Hai-Tao Wang. Novel Method Based on Projection of Vectors in Linear Space to Identify Volterra Kernels of Arbitrary Orders. *Application Research of Computers*. 2008; 25(11): 3340-3342.

[9] A Ya Yakubov. On nonlinear Volterra equations of convolution type. *Differential Equations*. 2009; 45(9): 1326-1336.

[10] 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; 8(5): 966-984.