TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.6, June 2014, pp. 4624 ~ 4630
DOI: 10.11591/telkomnika.v12i6.5444

Forecast Model of Water Quantity Based on Back Propagation Artificial Neural Network

Shihua Li
School of Business, Jinling Institute of Technology
No. 99, Hongjing Avenue, Jiangning District, Nanjing 211169
email: lishihua88@163.com

Abstract

Back Propagation (BP) *neural network, Widely adopted and utilized in automatic control, image recognition, hydrological forecasting and water quality evaluation, etc., as one of the Artificial Neural Networks, has stronger function and property of mapping, classification, functional fitting. This article takes the water flow of Lanzhou section of Yellow river in China as an example by the way of BP model to predict the water quantity. It is well proved that BP network model can reach the purposes of early warning and forecasting.*

Keywords*: the forecast model, water quantity, BP, artificial neural network, ANN*

1. Introduction

With the social and economic development, Lanzhou section of Yellow River was gradually polluted along the river. The structural characteristic of industrial pollution is explicit; the proportion of domestic pollution is increasing constantly; area-source pollution is serious. These conditions give rise to a negative impact on survival and development of Gansu Province and the whole of the Yellow River in masses. In order to decrease losses caused by the sudden water pollution accident in lower reaches of Lanzhou section of Huanghe River, it is very necessary to establish prediction model of "water amount" and "water quality" of Lanzhou reach of Huanghe River so as to respond to emergencies, ensure ecological security, water security. It is significant to built warning and forecasting system of Lanzhou section of Yellow River, to provide technical support for emergent investigation and handling of water pollution incidents.

At present, the water resources and the quality of the water environment has become one of the primary goals of the sustainable development of society and economy. Therefore, in the research project of "Unified management and scheduling, allocation of the Yellow River", it is not only absolutely necessary, but also very timing to conduct the research on "early warning and forecast based on the water quantity and water quality". Especially, there is theoretical and practical significance in the integrated water management and allocation, scheduling of Yellow River. To establish such a system model, debug and successfully operate will get huge social benefits, can greatly strengthen the unified management and protection of water resources in the Yellow River basin, and avoid direct and indirect economic loss or reduce water pollution. Meanwhile it will play an inestimable role in the social security, the people's life and property security and the rapid development of economic construction. This part only introduces the water quantity prediction.

2. The Forecast Model of Water Quantity on the Basis of BP Artificial Neural Network

2.1. Brief introduction of Artificial Neural Network—ANN

Artificial Neural Network-ANN is an emerging interdisciplinary science related to mathematics, physics, brain science, psychology, cognitive science, computer science, artificial intelligence, etc.. Study on prediction model has gradually become a very important content based on Neural Network [1]. BP network-BP, as a feed-forward network, possesses stronger function of mapping, classification and function fitting, which have been widely applied in many fields, such as automatic control, image recognition, hydrological forecasting and water quality

Received December 28, 2013; Revised February 28, 2014; Accepted March 16, 2014

evaluation[2-6]. BP neural network, through which multiple variables can be effective analyed without creating a mathematical model, is a kind of supervised multilayer feed-forward neural network composed of input layer, hidden layer and output layer in which each layer has a plurality of neurons, as shown in Figure 1 [7-9]. It is a topology structure of the three layer feed-forward neural network, where the first layer is the input nodes, the second is the hidden layer nodes, and the third layer is the output node.

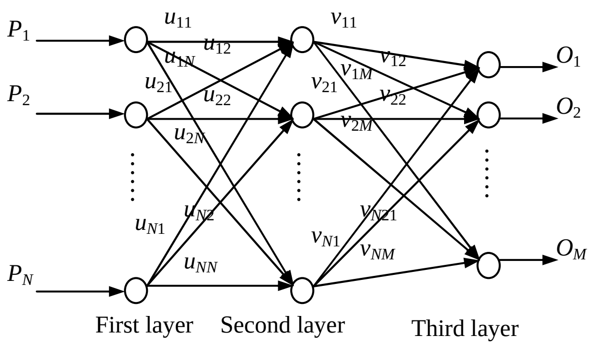

Figure 1. BP Neural Network Structural Drawing

For the input signal, it will first propagate forward to the hidden nodes, then through the action function transport the output information of the hidden node to the output node. Finally, the output results could be obtained. Action function of nodes usually select sigmoid function, called the S function (see Figure 2):

$$f(x) = \frac{1}{1+e^{-x}}, \; f'(x) = \frac{e^{-x}}{(1+e^{-x})^2} \tag{1}$$

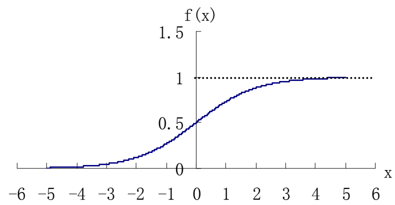

Figure 2. S Type Function Curve

2.2. BP Learning Algorithm

Assume that the neuron node of the input layer, hidden layer and output layer as N1, N2, N3, so the relationship between input and output of BP neural network is a highly non-linear mapping relationship and the network is a mapping from N1 dimensional Euclidean space to the N3 dimensional Euclidean space. Transfer function of the hidden layer and output layer neuron is S function (2):

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

Suppose that there is N pair of sample（ I_n, T_n, n=1, 2… N. Among that, $In \in R^{N1}$ is input of Nth training sample; $T_n \in R^{N3}$ is output of Nth training sample. Thus the course that input signal was transported from input layer to output layer can be indicated by equation from (3) to (7):

$$net_i = I_{pi} \tag{3}$$

$$O_{ni} = net_i = I_{pi} \tag{4}$$

$$net_j = \sum_{i=1}^{N1} W_{ji} O_{ni} - \theta_j \tag{5}$$

$$O_{nj} = f(net_j) \tag{6}$$

$$net_k = \sum_{i=1}^{N2} W_{kj} O_{ni} - \theta_k \tag{7}$$

$$O_{nk} = f(net_k) \tag{8}$$

Among above equation: $i = 1, 2, 3, ..., N1$; $j = 1, 2, 3, ..., N2$; $k = 1, 2, 3, ..., N3$. The net_i, net_j, net_k represent respectively a node i in the input layer, the node j in hidden layer and node k in the output layer; W_{ji} and W_{kj} indicates respectively connection weight between two nodes (node i, j, and k); θ_j and θ_k indicates threshold value of node j and node k; The O_{ni}, O_{nj}, O_{nk} represent the output produced by node i, j, and k when input Nth training sample.

Input vector I_n of input samples transferred by three layers of feed-forward network generates output vector O_{nk}. The sum of squares 0f the error between O_{nk} and desired output T_{nk} (k=1，2，…N3) can be expressed by:

$$E = \frac{1}{2}\sum_{n=1}^{N} E_n = \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{N3}(T_{nk} - O_{nk})^2 \tag{9}$$

As for situation that the whole network has only one output node, the N3=1, equation (9) changes to:

$$E = \frac{1}{2}\sum_{n=1}^{N} E_n = \frac{1}{2}\sum_{n=1}^{N}(T_{nk} - O_{nk})^2 \tag{10}$$

The objective of network learning is to achieve the minimum E through adjusting connection weights in the network. Optimization of the error function is an unconstrained nonlinear optimization problem by the way of putting Equation (3)～(7) into (8). By using the gradient method of optimization, as to the hidden layer and output layer exists:

$$\frac{\partial E}{\partial W_{kj}} = \sum_n \frac{\partial E}{\partial net_k} \cdot \frac{\partial net_k}{\partial W_{kj}} = -\sum_n \delta_{nk} O_{nj} \tag{11}$$

In the above formula:

$$\begin{aligned} \delta_{nk} &= -\frac{\partial E}{\partial net_k} = -\frac{\partial E}{\partial O_{nk}} \cdot \frac{\partial O_{nk}}{\partial net_k} \\ &= \left(T_{nk} - O_{nk}\right) f'\left(net_k\right) \\ &= \left(T_{pk} - O_{pk}\right) O_{nk}\left(1 - O_{nk}\right) \end{aligned} \tag{12}$$

Between the input layer and hidden layer exists:

$$\begin{aligned}\frac{\partial E}{\partial W_{ji}} &= \frac{\partial E}{\partial O_{nk}} \cdot \frac{\partial O_{nk}}{\partial net_k} \cdot \frac{\partial net_k}{\partial O_{nj}} \cdot \frac{\partial O_{nj}}{\partial net_j} \cdot \frac{\partial net_j}{\partial W_{ji}} \\ &= -\sum_n \sum_k \left(T_{pk} - O_{pk}\right) f'\left(net_k\right) W_{kj} f'\left(net_j\right) O_{nj} \\ &= -\sum_n \delta_{nj} O_{nj}\end{aligned} \tag{13}$$

In the above formula:

$$\begin{aligned}\delta_{nj} &= -\frac{\partial E_n}{\partial net_j} = \sum_k \left(T_{nk} - O_{nk}\right) f'\left(net_k\right) W_{kj} f'\left(net_j\right) \\ &= \delta_{nk} W_{kj} f'\left(net_j\right) \\ &= O_{nj}\left(1 - O_{nj}\right) \delta_{nk} W_{kj}\end{aligned} \tag{14}$$

As for the derivation of the threshold value exists:

$$\frac{\partial E}{\partial \theta_k} = \sum_n \delta_{nk} \, , \frac{\partial E}{\partial \theta_j} = \sum_n \delta_{nj} \tag{15}$$

The weights and thresholds can be obtained by the gradient descent method, the formula is:

$$W(t+1) = W(t) - \eta \cdot \frac{\partial E}{\partial W(t)} \tag{16}$$

$$\theta(t+1) = \theta(t) - \eta \cdot \frac{\partial E}{\partial \theta(t)} \tag{17}$$

Among up equation, the W and θ indicates the weight vector threshold vector; η is called learning effect (or called Learning efficiency). The put equation to (10), (12), (14), (15) into (16), (17), the formula of the weight vector and a threshold vector can be gotten:

$$W_{xy}(t+1) = W_{xy}(t) + \eta \cdot \sum_n \delta_{nx} O_{ny} \tag{18}$$

$$\theta_x(t+1) = \theta_x(t) - \eta \cdot \sum_n \delta_{nx} \tag{19}$$

Type $W_{xy}(t)$ represents the iteration value of the connection weights between x and y of any adjacent two layer of feed-forward network. The $\theta_x(t)$ indicates the t-th iteration value of x node's threshold value in hidden layer or the output layer. For a node x of output layer, there is:

$$\begin{aligned}\delta_{nx} &= (T_{nx} - O_{px}) f'(net_x) \\ &= (T_{nx} - O_{nx}) O_{nx} (1 - O_{nx})\end{aligned} \tag{20}$$

For a node X of hidden layer, we could abain:

$$\begin{aligned}\delta_{nx} &= f'(net_x)\sum_{x'} \delta_{nx'} W_{x'x} \\ &= O_{nx}(1-O_{nx})\sum_{x'} \delta_{px'} W_{x'x}\end{aligned} \tag{21}$$

What is discussed above is error back propagation algorithm of error of a multilayer feed-forward network. The learning function of BP network is materialized through the iterative process, so the above iterative algorithm is called the BP learning algorithm.

3. Forecast Model's Calculation and Prediction Results

Because there are not enough outlet flow data about the oil pipe, East big-ditch, West big-ditch between Lanzhou reach and An-ning fording. And flow is little, so neglect the influence of water quantity, utilize the properties of infinite approximation of BP algorithm to seek the relationship between flow of Lanzhou section and An-ning fording. The distance between Lanzhou sections of the Yellow River to down-stream's An-ning fording is about 170kms.

The average annual rate of flow is 1.63m/s, water flow passing from Lanzhou section to the An-ning fording will take about 29 hours. So we can apply the flow of the present period of time for predicting using the traffic flow prediction of Lanzhou section of the Yellow River down-stream's An-ning section's corresponding flow about 29 hours later.

Assume that the number of neurons is 10; learning rate (LR) is 0.05; the momentum constant (MC) is 0.9; TE (target error) is 0.001; ME (maximum number of iterations) is 5000. The samples are trained by Levenberg-marquardt method and predicted two times; the two simulation results should be optimized so as to get the final prediction. According to the "norms" of hydrological forecasting, relative error of <20% is qualified, the prediction results are shown in Table 1 and Table 2.

Table 1. The Prediction Result of An-ning Fording from Aug.24 to Sept.2.18

Time13	An-ning	First output	Relative error1 (%)	Second output	Relative error2 (%)	predict	Relative error1 (%)
Aug.23	975	965.17	-1.00821	976.11	0.113846	956.65	1.9886
Aug.24	994	845.81	-14.9085	851.46	-14.34	841.41	-14.229
Aug.25	863	857.03	-0.69177	855.83	-0.83082	857.96	2.3824
Aug.26	938	930.88	-0.75906	934.43	-0.3806	928.12	10.754
Aug.27	844	986.28	16.85782	998.14	18.26303	977.05	15.764
Aug.28	907	746.01	-17.7497	673.2	-25.7773	802.69	-12.656
Aug.29	1060	1060.3	0.028302	1056.3	-0.34906	1063.4	3.2441
Aug.30	832	869.34	4.487981	886.19	6.513221	856.22	0.73198
Aug.31	653	742.56	13.71516	677.09	3.689127	793.53	19.508
Sept.1	1360	1184.4	-12.9118	1049.7	-22.8162	1289.3	0.72402
Qualified rate		100%		90%		100%	

Table 2. The prediction result of An-ning fording from Aug.24 to Sept.2.23

Time18	An-ning	First output	Relative error1 (%)	Second output	Relative error2 (%)	predict	Relative error1 (%)
Aug.23	1260	1161	-7.85714	1193.2	-5.30159	1043	-17.224
Aug.24	1050	1117.3	6.409524	1127.3	7.361905	1080.6	2.9189
Aug.25	981	831.3	-15.2599	825.56	-15.8451	852.34	-13.115
Aug.26	969	997.83	2.975232	991.46	2.317853	1021.2	5.3847
Aug.27	988	1123.5	13.71457	1137.4	15.12146	1072.6	8.5581
Aug.28	900	1123.5	24.83333	1137.4	26.37778	1072.6	19.173
Aug.29	1070	997.83	-6.74486	991.46	-7.34019	1021.2	-4.5629
Aug.30	950	1112.8	17.13684	1123.2	18.23158	1074.7	13.124
Aug.31	719	1192.4	65.84145	1233.7	71.58554	1041	44.788
Sept.1	1370	1173.2	-14.365	1210	-11.6788	1038.3	-24.21
Qualified rate		100%		90%		100%	

The real measured value is compared with the predicted results as is shown in Figure 3 to Figure 4.

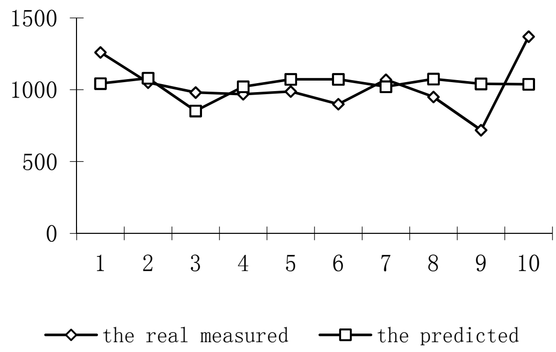

Figure 3. Comparison of An-ning's Flow between the Real Measured and Prediction from Aug. 24 to sept.2 .18

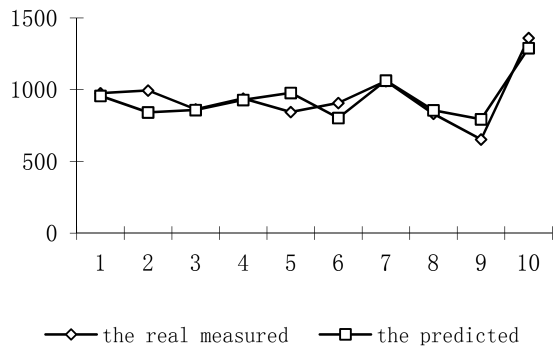

Figure 4. Comparison of An-ning's Flow between the Real Measured and Prediction from Aug. 24 to sept.2 .23

It is seen from Table 1 to Table 2 that the accuracy of the model can meet the requirements, of prediction: the qualified rate of is more than 80%. When using this model, we can predict the flow based former period of flow, and reach the purposes of early warning and forecasting.

4. Conclusion

It is seen from Table 1 to Table 2 that the accuracy of the model can meet the requirements, of prediction: the qualified rate of is more than 80%. When using this model, we can predict the flow based former period of flow, and reach the purposes of early warning and forecasting. The artificial neural network has some basic characteristics to simulate the human brain, such as self adaptation, self-organization, highly parallel intelligence, robustness and fault information processing functions, which has very important practical significance for the correct description of nonlinear problems. And it is good at association, generalization, and analogy and reasoning; can refine statistical law from a large amount of statistical data; and has been widely applied and studied in many fields. Study on prediction model (BP-back propagation model) of Lanzhou section of the Yellow River can provide technical support for water quality, water pollution incident emergency investigation. Especially, it has theoretical and practical value in the integrated water management, allocation and scheduling in the flow of Yellow River.

References

[1] Shui-jing Zhu, Xian-chen Zhu. The principle and method of predicting. Shanghai: Shanghai Jiao Tong University press. 1991:5-7.
[2] X iao-dong Tang. Image Recogn ition Ba sed on Neura l Networks in Matlab. *Computer and Digital Engineering.* 2007; 35(8).
[3] Wei-guo Xiao, Chi-bing Hu. Investigation of method for intelligent control based on neural network. *Electrical Drive Automation*. 2000; 22(3): 19-21.
[4] K En, L Xu, H Chi. Improved learning algorithms for mixture of experts in multiclass classification. *Neural Networks*. 1999; 12(9): 1229~1252.
[5] I Maqsood, MR Khan, A Abraham. An ensemble of neural networks for weather forecasting. *Neural Computer & Application*. 2004; 13: 112~122.
[6] Z Ahmad, J Zhang. Bayesian selective combination of multiple neural networks for improving long-range preddictions in nonlinear process modeling. *Neural Computer & Application*. 2005; 14: 78~87.
[7] Ji-guang Chen. The fuzzy artificial neural network analysis of Dam observation data. *Journal of Hydraulic Engineering*. 2000; (1): 19~22.
[8] Shou-ren HU. Introduction to Neural Networks. Changsha: National Defense University Press. 1993.
[9] Shun-tian Lou. System Analysis and Design Based on Matlab. Xi'an: Xi'an University of Electronic Science and Technology Press. 1998.
[10] Wen Xing. neural network application and design based on Matlab. Beijing: Science Press. 2000.