FORECASTING WATER LEVELS OF BOCHEONG RIVER USING NEURAL NETWORK MODEL

Jitae Kim, Wonjoon Koh, and Woncheol Cho

Department of Civil Engineering, Yonsei University, Seoul, 120-749, Korea

Abstract: Predicting water levels is a difficult task because a lot of uncertainties are included. Therefore the neural network which is appropriate to such a problem, is introduced. One day ahead forecasting of river stage in the Bocheong River is carried out by using the neural network model. Historical water levels at Sangye gauging point which is located at the downstream of the Bocheong River and average rainfall of the Bocheong River basin are selected as training data sets. With these data sets, the training process has been done by using back propagation algorithm. Then water levels in 1997 and 1998 are predicted with the trained algorithm. To improve the accuracy, a filtering method is introduced as predicting scheme. It is shown that predicted results are in a good agreement with observed water levels and that a filtering method can overcome the lack of training patterns.

Key Words: prediction of water levels, neural network, back propagation, filtering method

1. Introduction

The river stage is the essential element to water resources management, planning and especially to flood control. Therefore, the accurate measurement of major rivers is an essential factor for water resources management. If the river stage can be forecasted properly, more efficient plan to control the basin's water resources can be performed. Unfortunately, however, forecasting the river stage is not a simple problem because it is affected by a lot of complex and uncertain factors.

That is, it is necessary to investigate physical processes causing the river stage variation and rainfall-runoff or routing models are widely used. Initially, runoff is predicted through a rainfall-runoff model or by routing the flow observed at an upstream gauge to the desired location. For this method, the accurate rating curve is essential. Unlike these methods Mutreja et al. (1987) used statistical correlation techniques without using rating curve.

However, it is difficult to predict water levels with a deterministic or statistical model because a variety of parameters such as rainfall, infiltration and soil characteristics influence the river stage in a highly nonlinear manner. In this study, to overcome these poorly defined problems, the neural network is introduced. The neural network is a useful tool to solve those kinds of problems because it is not required to know the whole process governing the system. It is advantageous when the specific solution does not exist or being hardly defined.

The first mathematical neural network model was developed by McCulloch and Pitts (1943), and Rosenblatt (1958) proposed single layer perceptron. In 1980's, advantages of parallel structure of computer architecture have been emphasized. Rumelhart et al. (1986) proposed multi-layer perceptron. By using the neural network model, Karunanithi et al. (1994) predicted daily flows along a river gauging station based on the same flows observed at upstream and downstream locations. Thirumalaiah and Deo (1998) used the neural network trained with stage time history recorded at the same and upstream sites.

In this study, the multi-layer perceptron neural network model is trained with both average rainfall and water levels of previous three days to predict water levels of one day ahead. The back propagation algorithm is selected as the training algorithm, and a filtering method is introduced to improve the accuracy.

2. Neural Network Model

The neural network model has been motivated from the structure of the brain. The neural network develops a solution system through a learning process and stores the acquired knowledge using interneuron connection strengths known as synaptic weights. The neural network model is made up of the interconnected set of large numbers of simple parallel processing units.

Among many techniques of learning rules, back propagation algorithm is used. Back propagation algorithm consists of forward and backward processes. In the forward process, input units are applied to the sensory nodes of the network and propagated forward through the network to produce the output values. During the forward process, the synaptic weights are fixed. In the backward process, synaptic weights are adjusted on the basis of the residual error in the predicted and observed outputs. The procedures are as follows:

Step 1. Initialize all the synaptic weights and threshold levels of the network to small random values.

Step 2. Calculate the activation levels and actual output of the network. The net input information coming into j (hidden layer, Fig. 1) is

$$H_j = \sum_i w_{ij} a_i + \theta_j \tag{1}$$

where w_{ij} is the synaptic weight between unit i (input layer) and j, a_i is the activation at unit i, and θ_j is the threshold value of unit j. H_j is transferred through a nonlinear transfer function such as sigmoid function. The activation level using sigmoid function is given by

$$a_j = \frac{1}{1+\exp(-H_j)} \tag{2}$$

where a_j is the activation at unit j. Then, the sum of squared errors is

$$E = \frac{1}{2}\sum_k (D_k - O_k)^2 \tag{3}$$

where O_k is kth element of the output and D_k is the desired output for that element.

Step 3. Compute the local gradient at the output unit for pattern p, δ_{pk} using Eq. (4).

$$\delta_{pk} = a'(H_{pk})(D_{pk} - O_{pk}) \tag{4}$$

Then using the local gradient and learning rate η, synaptic weight of output layers is modified as

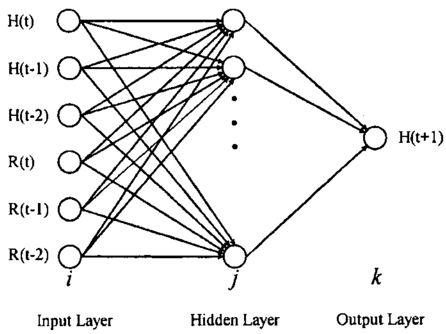

Fig. 1. Neural Network

$$\Delta_p w_{jk} = \eta \delta_{pk} a_{pk} \tag{5}$$

where $\Delta_p w_{jk}$ is a change in synaptic weight. Hence, the synaptic weights of the network are adjusted according to

$$w_{jk}(n+1) = w_{jk}(n) + \alpha \Delta w_{jk} + \eta \delta(n) a_k(n) \tag{6}$$

where α is the momentum parameter. And the learning rate by learning rate update rule is adjusted. Modified $\eta(n+1)$ at iterations n+1 can be calculated by

$$\Delta \eta(n+1) = -\gamma \frac{\partial E(n)}{\partial \eta(n)} \tag{7}$$

where γ is a control step-size parameter for the learning rate adaptation procedure. The synaptic weights of hidden layers are modified in the same manner.

Step 4. Iterate the computation until average squared error over the entire training set is within the desired limit. The momentum and the learning rate parameters are typically adjusted as the number of training iterations increases.

3. Applications

Study Area

The Bocheong River is selected for an application of the neural network based water level forecasting model. It is the one of the branch of the Keum River located in Boeun-Kun, Chungchung Buk-Do, Korea. The area of the river basin is 496 km^2 and the length of the river is 65.5 km. As shown in Fig. 2, there are 10 rainfall gauging stations in the area. Sangye gauging station which is at the downstream of the Bocheong River is used as the water level forecasting point.

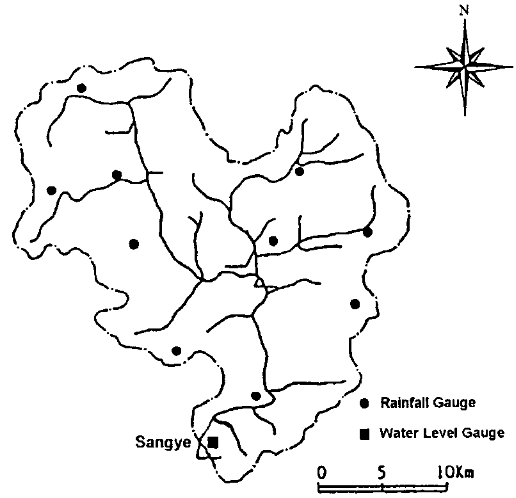

Fig. 2. Study Area

4. Procedures

To predict water levels, the neural network consists of 6 input layer nodes, 1 ouput layer node and 10 hidden layer nodes. As shown in Eq. (8) and Fig. 1, water levels and average rainfall of present and past two days are used as input layer nodes and the water level of one day ahead is used as an output value. It is assumed that the travel time affects downstream water level within 24 hours. The predicting scheme is

$$H(t+1) = (H(t), H(t-1), H(t-2); R(t), R(t-1), R(t-2)) \tag{8}$$

Table 1. Maximum average daily rainfall

Year	1994	1995	1996	1997	1998
Maximum average daily rainfall (mm)	58.3	102.3	100.7	214.4	219.0

where $H(t+1)$ is the one day ahead water level, $H(t), H(t-1), H(t-2)$ are water levels at present day, one day and two days before respectively, and $R(t), R(t-1), R(t-2)$ are average rainfall of the basin.

Thirumalaiah and Deo (1998) used only historical water level data as the input data of training algorithm, however, in this study, to consist more accurate model, average rainfall of river basin are included in input layer nodes because they have high correlation with water levels. To use the rainfall data as the input to training algorithm, average rainfall of the whole basin is made by using Thiessen method with data at 10 gauging points. The maximum average daily rainfalls are shown in Table 1.

As shown in Table 1, the maximum average daily rainfalls from 1994 to 1996 are about 100 mm or lower. However, those of 1997 and 1998 are over 200 mm. With these training data set, training process has been

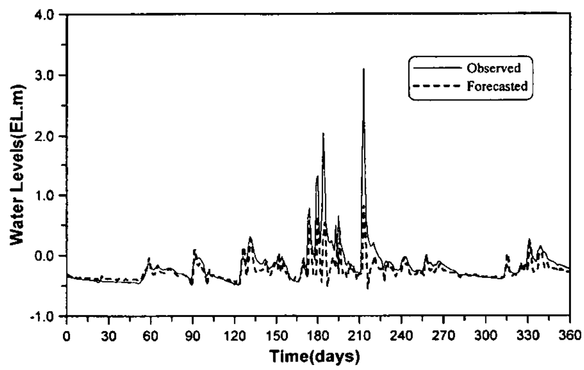

Fig. 3. 1 day ahead water levels(1997, Back Propagation)

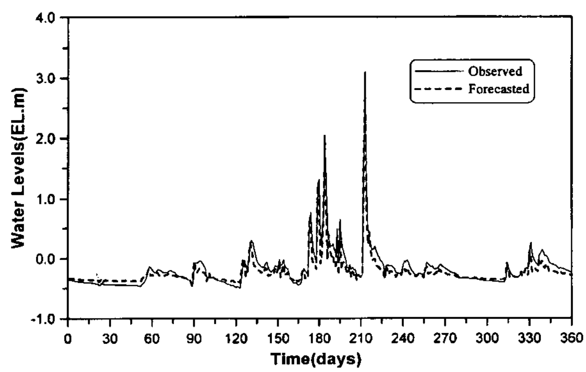

Fig. 4. 1 day ahead water levels at Bocheong River (1997, Filtered Back Propagation)

done by using back propagation algorithm.

In order to apply the trained neural network, one day ahead prediction of water levels at Sangye gauging point in 1997 and 1998 is carried out and compared with observed values. For the forecasting water levels in 1997, training data sets consist of the observed data from 1994 to 1996. After that, the observed data in 1997 are included in training data set to predict water levels in 1998.

5. Results and Analysis

The prediction results of water levels in 1997 are in a good agreement with the observed data during the low flow period. However, when water levels are high, forecasting by using the neural network are underestimated. This is due to the lack of high water level patterns in training data set, from 1994 to 1996 as shown in Table 1. The statistical results such as determination coefficient, correlation coefficient and RMSE of prediction represent poor prediction as shown in Table 2.

On the other hand, after including patterns of 1997, the prediction results of water levels in 1998 show a good agreement with the observed data as shown in Fig. 5. The feasibility of prediction for high water levels are improved. The statistical results of forecasting are better than those of 1997 as shown in Table 2.

With these results, one can find that the prediction ability of the neural network model depends on the training patterns. Therefore, it is highly recommended to use proper and accurate training data sets. However, in practical problems, it is difficult to get a lot of qualified data. To overcome these problems, a filtering method is proposed.

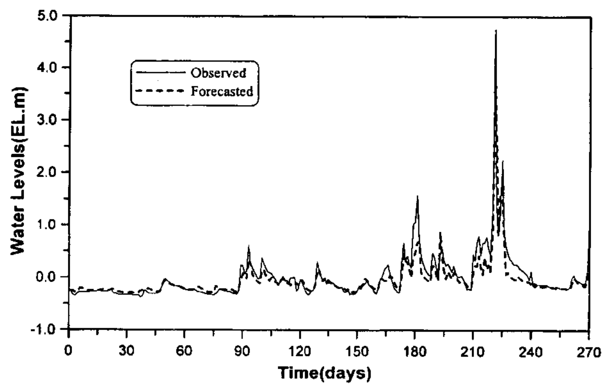

Fig. 5. 1 day ahead water levels at Bocheong River (1998, Back Propagation)

Table 2. Statistical characteristics

Year	Method	DC	CC	RMSE
1997	BP	0.3929	0.7097	0.2725
	Filtered-BP	0.5781	0.7746	0.2273
1998	BP	0.7859	0.8977	0.1888
	Filtered-BP	0.8372	0.9285	0.2169

5.1 Filtering Method

In order to improve the accuracy of the prediction, acquired parameters through the training process need to be changed considering the real values at present time. A filtering method is to change the pre-estimated water levels according to the difference between predicted and observed values at each time steps.

Generally, the neural network model calculates the connection parameters through training process and predicts the one day ahead water levels with fixed parameters. If training patterns are not good enough or new important patterns are generated, training process should be done again including those new patterns to improve the prediction ability. However, this is not efficient for the real time forecasting, so a filtering method can be applied usefully. In this study, a filtered back propagation model is proposed to improve the accuracy of real-time forecasting.

A filtered back propagation model consists of 6 input layer nodes, which are past water levels $H(t), H(t-1), H(t-2)$, average rainfall of basin $R(t), R(t-1), R(t-2)$, and 2 output layer nodes $\overline{H}(t+2), \overline{H}(t+1)$ which are one and two days ahead water levels, respectively. At the day t+1, the water level $H(t+1)$ is observed and is compared with the pre-estimated water level $\overline{H}(t+1)$. The difference between predicted and observed water levels are considered to the prediction of 2 days ahead water level, $\overline{H}(t+2)$, directly. In consequence, it is the adjusted one day ahead prediction, because $\overline{H}(t+2)$ is adjusted with comparison between the one day ahead prediction $\overline{H}(t+1)$ and the observed data of one day ahead $H(t+1)$. The adjustment is done by adding the difference $\Delta H(t+1)$ when the observed water level is higher than that of the prediction at t+1, and vice versa.

5.2 Results of Applying Filtered Back Propagation Method

Water levels for 1997 and 1998 are predicted by using a filtered back propagation method and compared with the results of back propagation method. As can be seen in Fig. 4, the forecasting results for 1997 are showing a good agreement with observed water level even during the high water level period. These results are confirmed through the statistical results. As shown in Table 2, determination coefficient (DC) is about 0.58 and correlation coefficient (CC) is about 0.78 which are better

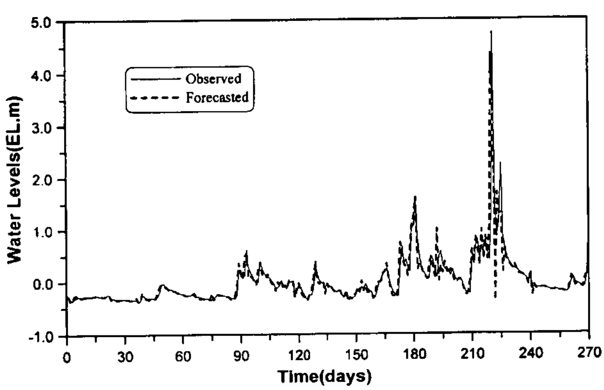

Fig. 6. 1 day ahead water levels at Bocheong River (1998, Filtered Back Propagation)

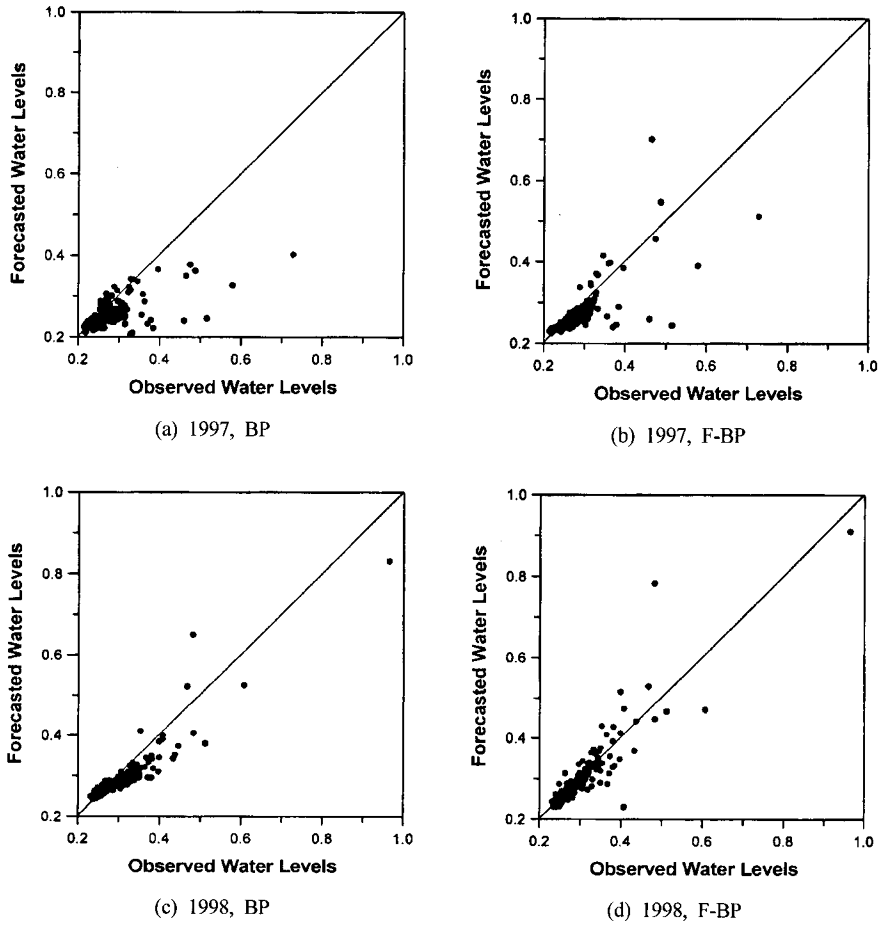

Fig. 7. 1 day ahead prediction results of normalized water levels

than those of the back propagation method. Forecasting results in 1998 proved more accurate owing to the added patterns of water levels and rainfall in 1997. Its correlation coefficient is almost 0.93 and as shown in Fig. 6 predicted water levels throughout the whole period show good agreement with observed data.

The linear variations of accuracy of prediction can be seen more easily through Fig. 7(a) to Fig. 7(d) in Fig. 7, the scatter diagrams. Fig. 7(a) shows underestimated results especially for the higher water levels and this is improved after including training patterns of 1997, as can be found in Fig. 7(c). The results by using a filtered back propagation method are shown in Fig. 7(b) and Fig. 7(d). Predicted water levels fit well with the exact fit line.

6. Conclusions

In this study, forecasting water levels by using the neural network at the Bocheong River has been done. Historical water levels and average rainfall of the basin are trained by using the back propagation algorithm. Predicting results of 1997 are in a good agreement with the observed data. However, for the higher water level period, water levels are underestimated due to the lack of training patterns of higher water levels. After including the patterns of higher water levels in 1997 to the predicting results of 1998 have shown the improved prediction ability. A filtering method, one of the adaptive prediction schemes is introduced to improve the accuracy of the prediction. Forecasting results of water levels in 1997 and 1998 compared well with the observed water levels. These results indicate that the forecasting of water levels can be done effectively by using the neural network.

References

Karunanithl, N., Greeney, W. J., Whitley, D., and Bovee, K. (1994). "Neural network for river flow prediction." *J. Computing in Civ. Engrg.*, ASCE, 8(2), pp. 201-219.

McCulloch, W. and Pitts, W. (1943). "A logical calculus of the ideas immanent in nervous activity." *Bulletin of Mathematical Biophysics* 5, pp. 115-133.

Mutreja, K. N., Yin. A., and Martino. I. (1987). "Flood forecasting model for Citandy River." *Flood Hydrology*, V. P. Singh, ed., Reidel, Dordrecht, The Netherlands, pp. 211-220.

Rosenblatt, F. (1958). "The perceptron: A theory of statistical separability in cognitive system." *Cornell Aeronautic Lab., Rep., No. VG-1196-1*, Buffalo.

Rumelhart, D. E., Hinton G. E., and Williams, R. J. (1986). *Learning internal representations by error back propagation*, Ch. 8 in Parallel Distributed Processing, D. E. Rumelhart, J. L. McCelland and PDP Research Group., MA: M.I.T. press, Cambridge.

Thirumalaiah, K. and Deo, M. C. (1998). "River stage forecasting using artificial neural networks." *Journal of hydrologic engineering*, Vol. 3, No. 1, pp. 26-32.

Jitae Kim, Wonjoon Koh, and Woncheol Cho, Department of Civil Engineering, Yonsei University, Seoul, 120-749, Korea
(e-mail : woncheol@yonsei.ac.kr)

(Received September 7, 1999 accepted March 23, 2000.)