International Journal of Artificial Intelligence and Neural Networks – IJAINN
Volume 4 : Issue 3 [ISSN 2250 – 3749]
Publication Date : 30 September, 2014

A Methodology for Water Level Predictions using Artificial Neural Network

Jiho Lee, Moojong Park, Hwandon Jun

Abstract— **We suggest the methodology of possible water level predictions on a short time period for the mid and small river flood warning system which is excluded the results of rainfall-runoff model. Technique is proposed that it can predict water level within 30 minutes based on upstream water level by using ANN (Artificial Neural Network). Accuracy of water level forecasting was verified by applying to Nam river dam upstream of the Nakdong river basin.**

Keywords*— *mid and small rivers, flood warning, Artificial Neural Network, water level prediction, lead time

I. Introduction

For flood forecasting and warning in rivers, it may be a better way to use observed water levels between upstream and downstream[1, 2, 3], instead of using the rainfall-runoff models such as the storage function method, to minimize the error involved in flood forecasting [4]. In addition, the advanced time should be acquired to prepare the disaster mitigation action to minimize flood damages. For this purpose, in this study, we suggest a flood forecasting and warning methodology which is able to predict downstream water levels at the point of flood forecasting in short time period, based on the currently observed upstream water levels. Applying the ANN(Artificial Neural Network) to the currently observed upstream water levels, we can predict water levels at a flood forecasting region which may occur within 30 minutes. After the suggested method is applied to the upstream Nam-gang watershed in the Nakdong-River basin, it is concluded that the method can predict downstream water levels in certain accuracy and will be used as a flood forecasting and warning system in the region.

Jiho LEE
Department of Civil Engineering, Seoul National University of Science and Technology
Korea

Moojong Park
Department of Civil Engineering, Hanseo University
Korea

Hwandon Jun
Department of Civil Engineering, Seoul National University of Science and Technology
Korea

II. The theoretical background of the ANN

ANN is computational models inspired by animals' central nervous systems (in particular the brain) that are capable of machine learning and pattern recognition. They are usually presented as systems of interconnected "neurons" that can compute values from inputs by feeding information through the network. The structure of the neural network was proposed by McCulloch and Pitts (1943) [5] and the delta rule, perceptron learning rules have been developed. Backpropagation algorithm proposed by Rumelhart et al. (1986) [6] is suitable for the non-linear characteristics model based on a multi-layered perceptron learning and it is one of the learning rule which is the most commonly used today. Figure 1 shows the schematic of multi-layered perceptron learning

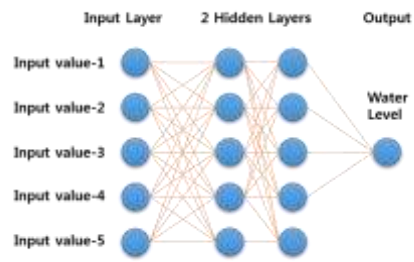


Figure 1. Schematic of multi-layered perceptron learning

III. Application of Namgang Dam basin

A. *Study basin*

In this study, the downstream water level is predicted by using ANN to Namgang dam basin which is located in downstream of Nakdong dam basin. Area of Namgang dam basin is 2,285 km ², the stream length is 111 km and the stream slope is approximately 0.0041. 10 rainfall gage stations and 21 water level stations is located in the study basin [7].

B. *Water Level Station Coupling for water level Prediction*

It is necessary to select upstream water level station which can be represented well downstream water level characteristics for predicting downstream water level. This is because the efficient water level prediction is possible when the selected station is operated by coupling with the flood danger area in downstream. Possible coupling cases in the study area are # C1 (Macheon - Imcheon), # C2 (Teasu - Changchon) and # C3 (Samga - Sinan). It means the water level data of Macheon, Teasu and Samga station are available to predict the water level of Imcheon, Changchon and Sinan station. The following figure 3 shows the water level stations location depending on coupling cases and table 1 is summarized the topographic characteristics depending on coupling cases.

Figure 2. Water level station coupling for water level prediction

TABLE I. COUPLED WATER LEVEL STATIONS AND TOPOGRAPHIC CHARACTERISTIC

# Coupling		Area (km²)	Stream Length (km)	Stream Slope	Form Factor
# C1	Macheon	315.4	31.3	0.00937	0.322
	Imcheon	459.0	47.2	0.00936	0.206
# C2	Teasu	243.2	28.3	0.03724	0.304
	Changchon	328.3	40.0	0.01882	0.205
# C3	Samga	101.0	13.3	0.00681	0.571
	Sinan	397.26	36.37	0.00213	0.300

C. *Input data Format*

ANN model needs at least three date to training and prediction. That means that 3 hours prior water level data needs for hour interval prediction and 30 minutes prior water level date needs in case of 10 minutes interval prediction. 10 minutes interval data is more suitable for small and medium rivers in considering of a short concentration time of small rivers and 10 minutes interval water level is applied in this study. First, to predict 10 minute after downstream water level, it is predicted by using the three data of upstream current water level, 10 minute ago upstream water level date and 20 minute ago upstream water level. Next, to predict after 20 minute downstream water level, it is predicted by using the three data of 10 minute ago water level data, upstream current water level, and predicted 10 minute later upstream water level data. Fig. 3 shows the prediction process.

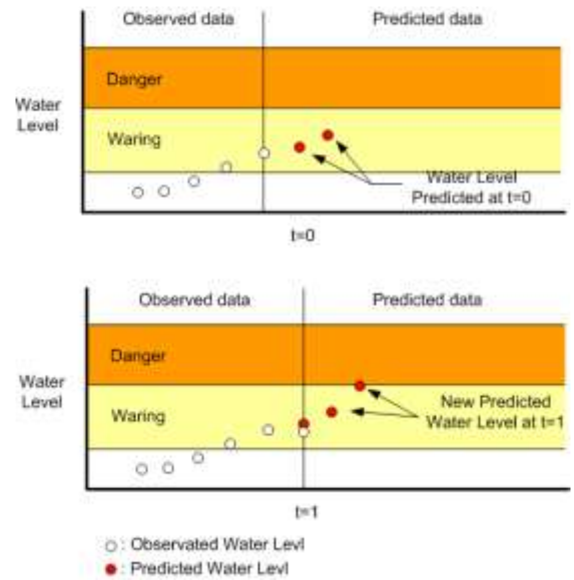
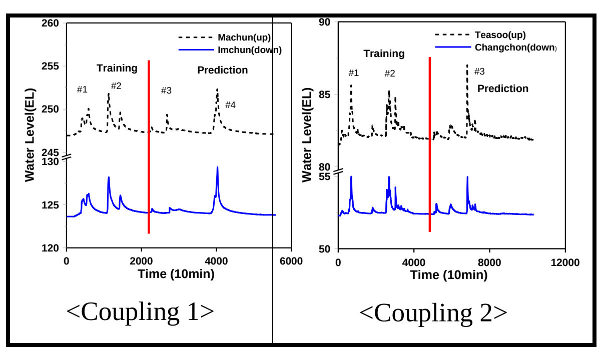


Figure 3. Water levels prediction methodology by input data type

D. *Result of Water Level Prediction using ANN*

Downstream water level of the Imcheon, Changchon, Sinan is predicted using ANN model based on the coupling result between the water level stations. Training methodologies of ANN model are RP (Resilient propagation), BP (Back propagation) and LM (Levenberg Marquardt) and so on. Among the variety of training methods, BP training methodology is applied due to the fast computing speed. 30 and 60 minute after water level is predicted by using BP training methodology.



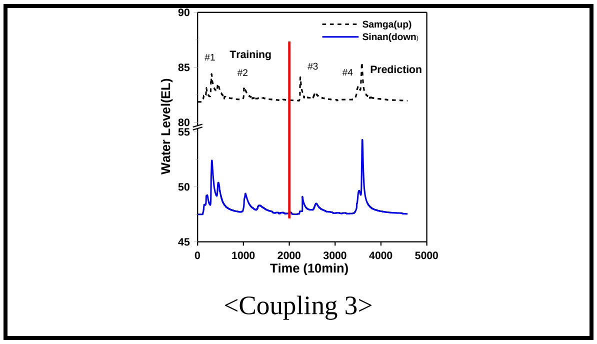


Figure 4. Applied water level events for downstream water level forecasting

Table 2 is summarized the characteristics of the extracted water level events from Fig. 4. In case of the coupling 1, the time difference of peak water level occurrence between upstream and downstream is about 30 ~ 50min, in case of the coupling 2 and coupling 3, about 50 ~ 70min, 60 ~ 90min, respectively. It means that the lead time can be secured as much as peak time difference. If the concentration time at the mid and small river is considered within 1~2 hour, the coupling between the water level stations reflects the characteristics of mid and small river well.

TABLE II. CHARACTERISTIC OF APPLIED WATER LEVEL EVENTS

# Cou pling	# Water Level Event		Peak Discharge Occurrence Time		Time Difference Of Peak Water Level Occurrence (min)
			Upstream	Dowmstream	
1	Training	#1	8/24 15:50	8/24 16:40	50
		#2	8/28 09:30	8/28 10:00	30
	Prediction	#3	9/08 04:40	9/08 16:20	-
		#4	9/17 12:10	9/17 13:00	50
2	Training	#1	6/26 10:30	6/26 11:40	70
		#2	7/10 06:40	7/10 07:30	50
	Prediction	#3	8/08 00:20	8/08 01:10	50
3	Training	#1	8/23 11:50	8/23 12:50	60
		#2	8/28 10:30	8/28 14:40	-
	Prediction	#3	9/08 04:50	9/08 12:30	-
		#4	9/17 12:20	9/17 13:50	90

In case of the coupling 1and 3, the water level event 3 and 4 are predicted by the training of the water level event 1and 2. In addition, in case of the coupling 2, the water level event 3 is predicted by the training of the water level event 1and 2.(Fig 4. reference) The figure 5 compares the prediction results between the observed downstream water level and predicted downstream water level after 30 and 60 minute later. Figure 5 shows that the prediction result is quite accuracy.

# Coup ling	< After 30 min>	< After 60 min>

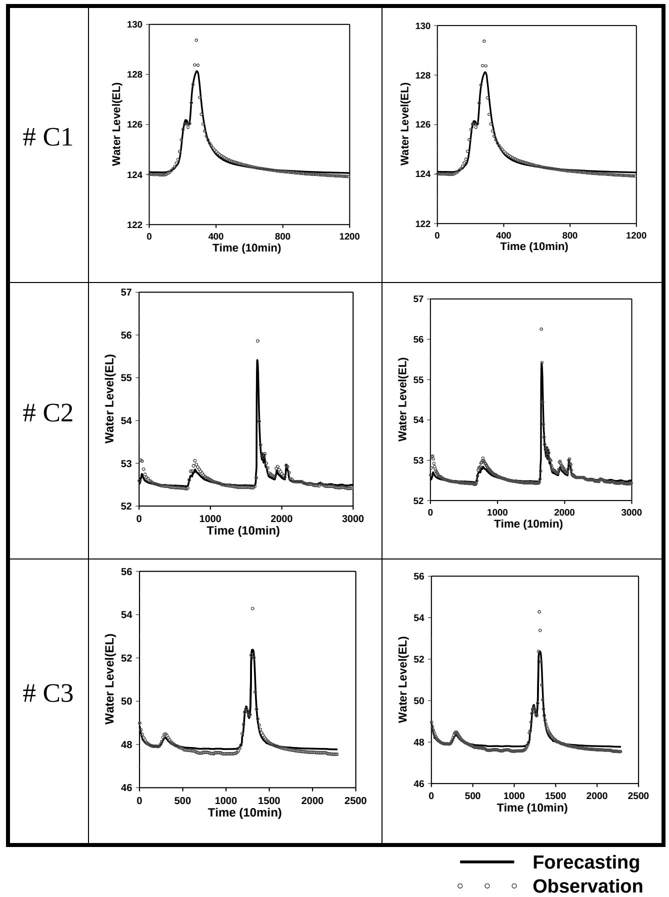
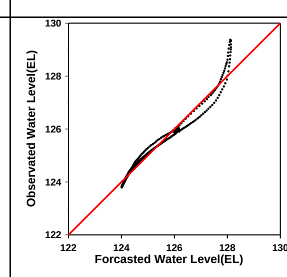
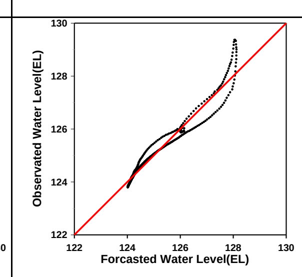


Figure 5. Water level forecasting results of coupled water level station

The prediction result is evaluated quantitatively by R^2 value. It is shown that the prediction result is a considerable accuracy above 0.9 even though R^2 value is reduced gradually as the prediction time is longer. Figure 6 compares the water level prediction results using a scatter plot and it can be reconfirmed that the error of prediction is larger as the prediction time is longer.

.

# Cou pling	< After 30 min>	< After 30 min>
# C1		

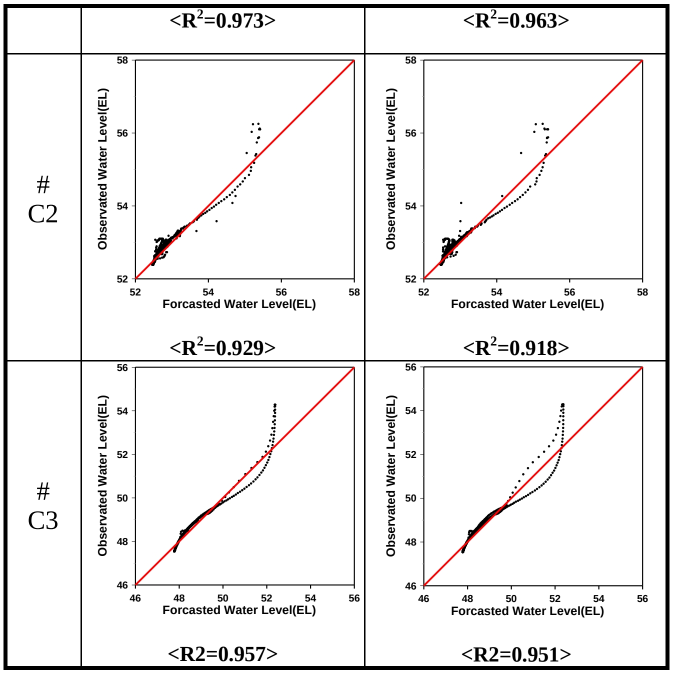


Figure 6. Comparison of water level forecasting results by scatted diagram

IV. Result

Dangerous situation occurs at mid and small rivers basin by sudden rising water levels. Therefore, flood warning system of mid and small rivers basin is difficult to be based on the rainfall- runoff model unlike big river basin. Rainfall -runoff characteristics is difficult to simulate accurately by the lack of data for small watersheds and conventional hydrology techniques. Warning system based on the observing water level can be method to reduce the forecast error not conventional storage function. In addition, the lead time is important to establish preparedness for flood damage reduction.

In this study, we suggest the methodology of possible water level predictions on a short time period for the mid and small river flood warning system which is excluded the results of rainfall- runoff model. Technique is proposed that it can predict water level within 30 minutes based on upstream water level by using ANN. Accuracy of water level forecasting was verified by applying to Nam river dam upstream of the Nakdong river basin.

Acknowledgment

This research was supported by a grant [NEMA-NH-2011-45] from the Natural Hazard Mitigation Research Group, National Emergency Management Agency of Korea.

References

[1] K.W. Chau, “Particle swarm optimization training algorithm for ANNs in stage prediction of shing mun river,” Journal of Hydrology, Vol. 329, No. 3-4, 2006, pp. 363-367.

[2] B. Bazartseren, G. Hildebrandt, and K. P. Holz, “Short-term water level prediction using neural networks and neuro-fuzzy approach,” Neurocomputing, Vol. 55, No. 3-4, 2003, pp. 439-450.

[3] G. Wilson, and M.H. Khondker, “Data selection for a flood forecasting neural network,” Proceedings of the 4th International Conference on Hydroinformatics 2000, 2000, Iowa, USA.

[4] W. K. Yeo, Y. M. Seo, S. Y. Lee, and H.K. Jee, “Study on water stage prediction using hybrid model of artificial neural network and genetic algorithm,” Journal of Korea Water Resources Association, Vol. 43, No. 8, 2010, pp. 721-731.

[5] W.S. McCulloch, and W.H. Pitts, “A logical calculus of the ideas immanent in nervous activity,” Bulletin of Mathematical Biophysics, 5, 1943, pp. 115-133.

[6] D. E. Rumelhart, G. E. Hinton, and R.J. Williams, “Learning internal representations by error propagation,” Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Vol. 1: Foundations, Cambridge, MA: MIT Press, 1986, pp. 318-362.

[7] Water Management Information System. Homepage, http://www.wamis.go.kr/.

About Author (s):

Dr. Jiho Lee is currently a research professor of civil engineering at Seoul national university of science and technology, Korea. He focuses on the flood warning and hydrologic observation network evaluation.