Hydrological Modelling of Water Level near "Hahoe Village" Based on Multi-Layer Perceptron

Sang-Hoon Oh

Division of Information Communication Engineering
Mokwon University, Daejeon, 302-729, Korea

Hiroshi Wakuya

Graduate School of Science and Engineering
Saga University, Saga, 840-8502, Japan

ABSTRACT

"Hahoe Village" in Andong region is an UNESCO World Heritage Site. It should be protected against various disasters such as fire, flooding, earthquake, etc. Among these disasters, flooding has drastic impact on the lives and properties in a wide area. Since "Hahoe Village" is adjacent to Nakdong River, it is important to monitor the water level near the village. In this paper, we developed a hydrological modelling using multi-layer perceptron (MLP) to predict the water level of Nakdong River near "Hahoe Village". To develop the prediction model, error back-propagation (EBP) algorithm was used to train the MLP with water level data near the village and rainfall data at the upper reaches of the village. After training with data in 2012 and 2013, we verified the prediction performance of MLP with untrained data in 2014.

Key words: *Flooding, Water Level Prediction, Hahoe Village, Error Back-Propagation, Multi-Layer Perceptron.*

1. INTRODUCTION

DPD (Disaster Prevention Design) concept has been proposed in order to realize securable society from the catastrophic disasters such as earthquake, firing, landslide, storm, and tsunami etc [1]. Especially, DPD emphasizes an alarm system for preemptive protection rather than recovery strategy of the damage occurred. It is estimated that of the total economic loss caused by all kinds of disasters, 40% are due to flooding [2]. Although flooding has been focused because of the drastic impact, however, the relationship between rainfall and flood discharge is very complex and flood prediction is still unsolved problem [2].

Based on the mathematical proofs that multi-layer perceptron (MLP) neural networks can approximate any function with enough number of hidden nodes [3]-[5], MLPs have been widely applied in various fields such as pattern recognition, speech recognition, time series prediction, hydrology etc. Furthermore, deep learning enlarges the application area to image understanding and language processing [6]. Especially, it is not necessary to elucidate complex mechanisms of phenomena to be modelled and this property expands hydrological modelling using MLPs [7]-[12].

UNESCO concluded the "Convention Concerning the Protection of the World Cultural and Natural Heritage" in 1972 for national and international protection activities of world heritages. Among many UNESCO world heritage sites in Korea, "Hahoe Village" in Andong region is adjacent to Nakdong River and, therefore, the water level near the village should be carefully monitored for protection from flooding.

In this paper, we develop a hydrological modelling using MLP to predict the water level of Nakdong River near "Hahoe Village" with rainfalls at upper reaches of the village. In section 2, we briefly introduce the architecture of MLP and its training algorithm. In section 3, the hydrological modelling of rainfalls and water level in Andong region is described and verified through simulations with real data. Finally, section 4 concludes this paper

2. MULTI-LAYER PERCEPTRON AND ERROR BACK-PROPAGATION ALGORIHTM

Consider an MLP consisting of N inputs, H hidden nodes, and M output nodes, as shown in Fig. 1. When a sample $\mathbf{x}^{(p)} = [x_1^{(p)}, x_2^{(p)}, \ldots, x_N^{(p)}]$ $(p = 1, 2, \ldots, P)$ is presented to

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* *Corresponding author, Email: shoh@mokwon.ac.kr*

the input layer of MLP, by the forward propagation, the j-th hidden node is given by

$$h_j^{(p)} = h_j(\mathbf{x}^{(p)})$$
$$= \tanh((w_{j0} + \sum_{i=1}^{N} w_{ji} x_i^{(p)})/2), \ j = 1,2,\ldots,H. \quad (1)$$

Here, w_{ji} denotes the weight connecting x_i to h_j, w_{j0} is a bias, and tanh(.) is the sigmoidal activation function of hidden node. The k-th output node with the sigmoidal activation function is given by
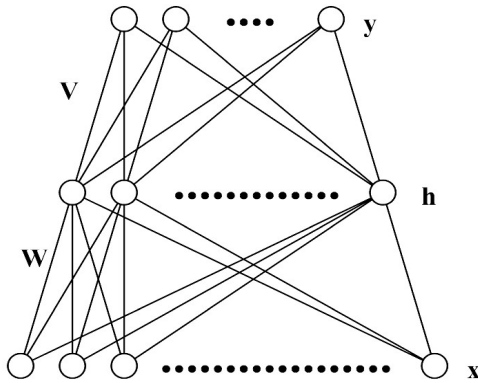

Fig. 1. The architecture of a multilayer perceptron.

$$y_k^{(p)} = y_k(\mathbf{x}^{(p)}) = \tanh(\hat{y}_k^{(p)}/2), \ k = 1,2,\ldots,M, \quad (2)$$

where

$$\hat{y}_k^{(p)} = v_{k0} + \sum_{j=1}^{H} v_{kj} h_j^{(p)} . \quad (3)$$

Also, v_{k0} is a bias and v_{kj} denotes the weight connecting h_j to y_k.

Let the desired output vector corresponding to a training sample $\mathbf{x}^{(p)}$ be $\mathbf{t}^{(p)} = [t_1^{(p)}, t_2^{(p)}, \ldots, t_M^{(p)}]$. As a distance measure between the actual and desired outputs, we usually use the mean-squared error (MSE) function for P training samples defined by

$$E = \frac{1}{2} \sum_{p=1}^{P} \sum_{k=1}^{M} \left(t_k^{(p)} - y_k^{(p)} \right)^2 . \quad (4)$$

To minimize E, according to the negative gradient of MSE, output weights v_{kj}'s are iteratively updated by

$$\Delta v_{kj} = -\eta \frac{\partial E}{\partial v_{kj}} = \eta \delta_k^{(p)} h_j^{(p)}, \quad (5)$$

where

$$\delta_k^{(p)} = -\frac{\partial E}{\partial \hat{y}_k^{(p)}} = \left(t_k^{(p)} - y_k^{(p)} \right) \frac{\left(1 - y_k^{(p)} \right)\left(1 + y_k^{(p)} \right)}{2} \quad (6)$$

is the error signal of output node and η is the learning rate. Also, by the backward propagation of the error signal, hidden

weights w_{ji}'s are updated by

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} = \eta x_i^{(p)} \frac{(1 - h_j^{(p)})(1 + h_j^{(p)})}{2} \sum_{k=1}^{M} v_{kj} \delta_k^{(p)} . \quad (7)$$

In Eq. (7), the error signal of output node is back-propagated through output weights v_{kj}. The above weight-updating procedure for training of MLPs is the EBP (error back-propagation) algorithm [13].

We usually adopt the sigmoidal activation function of output node for classification problems, in which desired values of output nodes are in two extremely saturated regions of the sigmoid function [14]. If we want to generate "warning-no warning signal" for flood forecasting, it belongs to classification problems [2]. However, our goal is to predict the water level near "Hahoe Village", which is a real number above zero, and we adopt a linear function as an activation function of output node. Consequently, $y_k^{(p)} = \hat{y}_k^{(p)}$ in Eq. (2) and Eq. (6) becomes

$$\delta_k^{(p)} = -\frac{\partial E}{\partial \hat{y}_k^{(p)}} = \left(t_k^{(p)} - y_k^{(p)} \right). \quad (8)$$

3. HYDROLOGICAL MODELLING IN ANDONG REGION

Based on an MLP with a linear output node, we develop a hydrological modelling in Andong region, that is, the relationship between water level near "Hahoe Village" and rainfalls at upper reaches of the village. Fig. 2 is a map of Andong region, in which Nakdong River flows from Andong Dam located east of Andong to "Hahoe Village". Red circles in Fig. 2 indicate the locations of water level gauge at "Gudam" and three rainfall gauges at "Pungsan", "Iljik", and "Andong". Since there is not a water level gauge at "Hahoe Village" and the gauge at "Gudam" is the nearest one, we select the gauge at "Gudam" to monitor the water level near "Hahoe Village". Also, the rainfalls at "Pungsan" and "Iljik" should be considered for the hydrological modelling, since there are tributary rivers from the two locations to Nakdong River.

Fig. 2. The map of Andong region. Red circles indicate the locations of water level gauge at "Gudam" and rainfall gauges at "Pungsan", "Iljik", and "Andong"

Avoiding the winter season of icing and snowing, the data at each gauge is collected from March 1st to November 30th in the year of 2012, 2013, and 2014 with the interval of one hour. So, there are 6,600 records in each year. The total data was provided by "Nakdong River Flood Control Office" and "Korea Water Resource Corp." We use the data in 2012 and 2013 to train MLPs for the hydrological modelling and the other to test the performance of water level prediction.

In order to predict the water level at "Gudam" after D hours, we construct an MLP whose input layer consists of the water level at "Gudam" and the rainfalls at "Pungsan", "Iljik", and "Andong" from current (denoted by "n") to previous n-L hours. When determining the number of parameters in MLPs, we usually adopt the method of trial and error since there is not a concrete theoretical guidance. Accordingly, we determine that L is two and the number of hidden nodes is forty through many trials and errors. Also, we adopt a single output node with linear activation function to predict the water level at "Gudam" after D hours. Therefore, the MLP architecture is 12 inputs, 40 hidden nodes with tanh(.) activation function, and one linear output node. After initializing the MLP with random weights uniformly distributed on $\left[-1\times10^{-4}, 1\times10^{-4}\right]$, EBP algorithm with learning rate of 0.01 updates the weights v_{kj}'s and w_{ji}'s to minimize MSE for training samples. We also estimate MSE for test samples during 10,000 iterations of MLP learning.
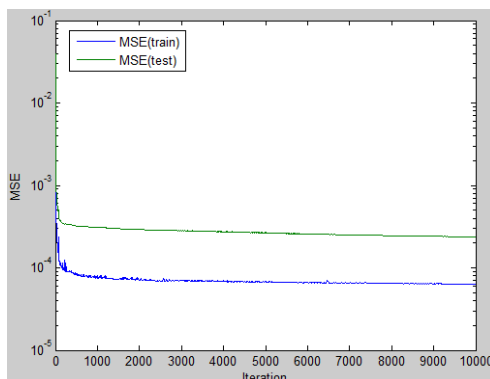

Fig. 3. MSEs(Mean-Squared Errors) for training and test samples during training of MLP to predict the water level at "Gudam" after one hour (D=1)

Firstly, we train the MLP with D=1 and plot the MSEs for training and test samples during learning in Fig. 3. After rapid reduction of MSEs in the initial stage of learning, MSEs decrease very slowly. There is a gap between MSE for training samples and that for test samples, since we never use test samples to train MLPs.

In order to verify the prediction performance of MLP after finish of learning, we plot the water level at "Gudam" in 2014 for whole period and its predicted value in Fig. 4(a). The horizontal axis has 6600 data points which corresponds to the whole period of 2014 from March 1st to November 30th. For easy readability of the horizontal axis, we include the index "month/day" just above the data index of horizontal axis in Fig. 4(a). Also, we plot detail curves of the real and predicted ones in the periods of March 21st to 25th and August 16th to 20th -

periods with very high peaks- in Fig. 4(b) and (c), respectively. Considering that the data in 2014 is not used for training, the prediction for whole period is successful.

We can estimate the statistical relationship between real data denoted by **t** and its predicted one **y** with the correlation coefficient defined by

$$Corr[\mathbf{t},\mathbf{y}] = \frac{E[\mathbf{ty}] - E[\mathbf{t}]E[\mathbf{y}]}{\sigma_\mathbf{t}\sigma_\mathbf{y}} \qquad (9)$$

where E[.] is the expectation operator and $\sigma_\mathbf{t}$ and $\sigma_\mathbf{y}$ are standard deviations of **t** and **y**, respectively. If the correlation coefficient is one, we can say that **t** and **y** have perfectly same tendency. Estimation of the correlation coefficient between the water level at "Gudam" and its prediction in Fig. 4(a) is 0.99692, which is a very high value.
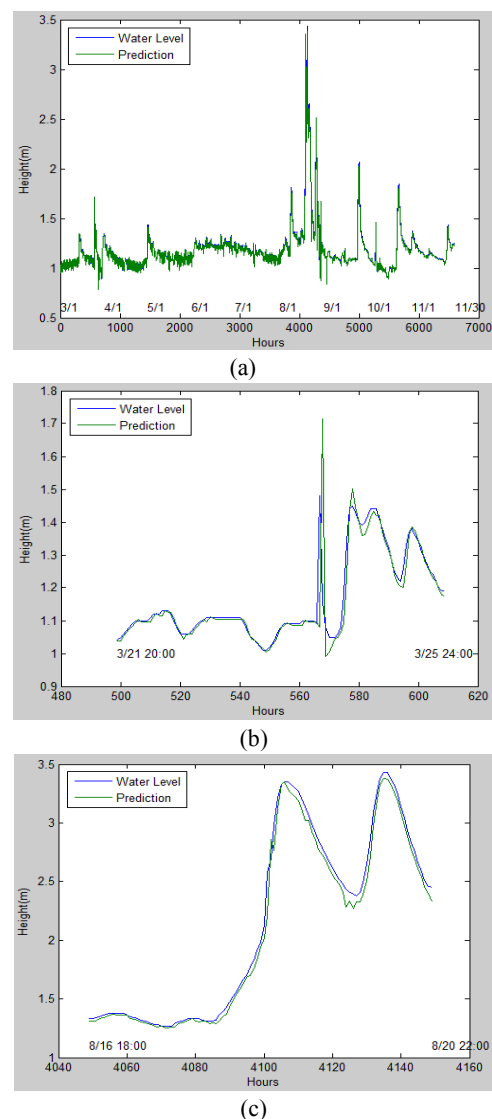

(a)

(b)

(c)

Fig. 4. The water level at "Gudam" in 2014 and its predicted value by the MLP after 10,000 iteration of learning with D=1. (a) March 1st ~ November 30th, (b) March 21st 20:00~25th 24:00, (c) August 16th 18:00 ~ 20th 22:00

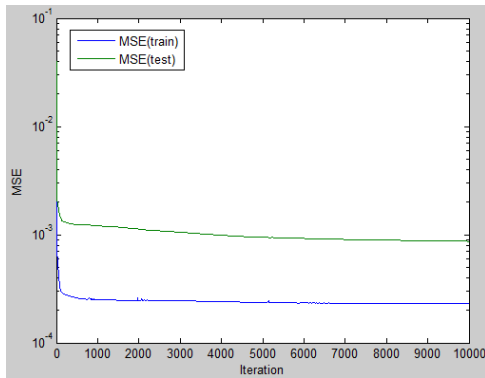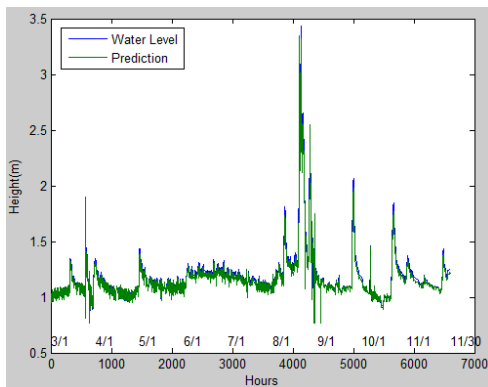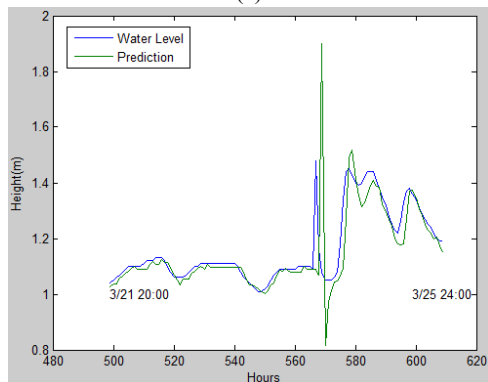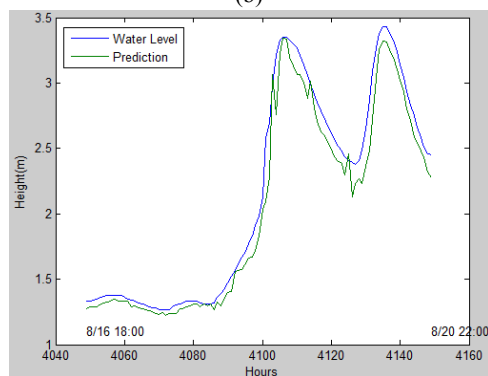Fig. 5. MSEs during training of MLP with *D*=2

(a)

(b)

(c)

Fig. 6. The water level at "Gudam" in 2014 and its predicted value by the MLP after 10,000 iteration of learning with *D*=2. (a) March 1st ~ November 30th, (b) March 21st 20:00 ~ 25th 24:00, (c) August 16th 18:00 ~ 20th 22:00

Secondly, we train the MLP with *D*=2 to verify the prediction performance after two hours. Fig. 5 shows the MSEs of two-hour prediction learning, which is inferior to those in Fig. 3. Fig. 6 shows the water level at "Gudam" and its two-hour prediction value. The general prediction curve for whole period is in Fig. 6(a). And the results for detail periods of March 21st to 25th and August 16th to 20th are in Fig. 6(b) and (c), respectively. Fig. 6 shows that the predicted values are near to real values, although they are inferior to the results for *D*=1 in Fig. 4. Also, the correlation coefficient after 10,000 iteration training of MLP with *D*=2 is 0.99116, which is slightly less than 0.99692 for *D*=1. This is because the two-hour prediction problem is more difficult than the one-hour prediction problem. However, the prediction in the period of the highest water level (Fig. 6(c)) is near to the real water level values.

We also conducted the *D*-hour prediction simulations for *D*=3,4,5,6 and the correlation coefficient between the water level at "Gudam" in 2014 and its predicted value is plotted in Fig. 7. The correlation coefficient degrades rapidly when increasing *D*. Therefore, the proposed hydrological modelling shows good prediction of the water level near "Hahoe Village" within two hours and the prediction over three hours should be improved.

In this paper, we model the relationship between the water level near "Hahoe Village" and rainfalls at upper reaches of the village. So, we can predict the water level after *D* hours with given rainfalls from current to previous *L* hours. If there is a forecast of heavy rainfalls in Andong region, it is possible to predict the water level and whether there is flooding or not. Furthermore, the water level during heavy rainy season will be an important information for the height of bank near the village.
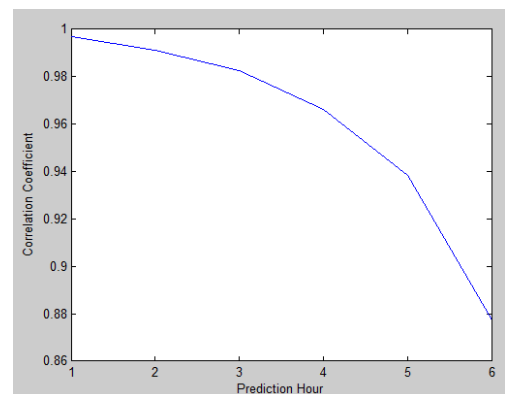

Fig. 7. The correlation coefficient vs. prediction hour after 10,000 iteration training of MLPs with *D*=1,2,3,4,5,6

4. CONCLUSIONS

Among many UNESCO world heritages in Korea, "Hahoe Village" in Andong region is adjacent to Nakdong River and it is important to monitor the water level near the village for protection from flooding.

In this paper, we developed a hydrological modelling in Andong region using MLP, which predicted the water level near "Hahoe Village" with rainfalls at the three upper reaches of the village-"Pungsan", "Iljik", and "Andong". MLP

consisted of twelve inputs, forty hidden nodes, and one linear output node. The twelve inputs corresponded to three rainfalls and the water level near "Hahoe Village" from current time *n* to previous *n-2* hours. Also, the linear output node corresponded to the water level prediction after *D* hours. We simulated the hydrological modelling with *D*=1,2,3,4,5,6. For performance verification of the water level prediction, we estimated the correlation coefficient between the water level near "Hahoe Village" and its prediction. Also, we plotted the real and predicted water levels for comparison. For *D*=1 and 2, the hydrological modelling was successful. However, when *D* was greater than two, the prediction performance degraded very much.

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Sang-Hoon Oh
He received his B.S. and M.S degrees in Electronics Engineering from Pusan National University in 1986 and 1988, respectively. He received his Ph.D. degree in Electrical Engineering from Korea Advanced Institute of Science and Technology in 1999. From 1988 to 1989, he worked for LG semiconductor, Ltd., Korea. From 1990 to 1998, he was a senior research staff in Electronics and Telecommunication Research Institute (ETRI), Korea. From 1999 to 2000, he was with Brain Science Research Center, KAIST. In 2000, he was with Brain Science Institute, RIKEN, Japan, as a research scientist. In 2001, he was an R&D manager of Extell Technology Corporation, Korea. Since 2002, he has been with the Department of Information Communication Engineering, Mokwon University, Daejon, Korea, and is now an associate professor. Also, he was with the Division of Computational Science and Engineering, Georgia Institute of Technology, Atlanta, USA, as a visiting scholar from August 2008 to August 2009. His research interests are machine learning, speech signal processing, pattern recognition, and bioinformatics.

Hiroshi Wakuya
He received the B.E. degree in electronic engineering from Kyushu Institute of Technology, Kitakyushu, Japan, in 1989, and the M.E. and Ph.D. degrees in electrical and communication engineering from Tohoku University, Sendai, Japan, in 1991 and 1994, respectively. In 1994, he joined the staff of Saga University as a Research Associate. In 1995, he became a Lecturer. From 1999 to 2000, he was a Visiting Scientist in University of Louisville, Louisville, Kentucky, USA. Since 2004, he has been an Associate Professor. His research interests include neural networks, intelligent instrumentation, and biological engineering.