Improving applicability of neuro-genetic algorithm to predict short-term water level: a case study

Gooyong Lee, Sangeun Lee and Heekyung Park

ABSTRACT

This paper proposes a practical approach of a neuro-genetic algorithm to enhance its capability of predicting water levels of rivers. Its practicality has three attributes: (1) to easily develop a model with a neuro-genetic algorithm; (2) to verify the model at various predicting points with different conditions; and (3) to provide information for making urgent decisions on the operation of river infrastructure. The authors build an artificial neural network model coupled with the genetic algorithm (often called a hybrid neuro-genetic algorithm), and then apply the model to predict water levels at 15 points of four major rivers in Korea. This case study demonstrates that the approach can be highly compatible with the real river situations, such as hydrological disturbances and water infrastructure under emergencies. Therefore, proper adoption of this approach into a river management system certainly improves the adaptive capacity of the system.

Key words | four-river remediation project, genetic algorithm, hybrid neuro-genetic, neural network, practical approach, water level prediction

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INTRODUCTION

Background

For sustainable water resources management, many countries often initiate and develop huge river remediation projects, e.g., the 'Tennessee Valley Authority Act (1993–2012)' in the USA, and the 'Isar River Remediation Project (2000–2011)' in Germany. Korea has four major rivers. Their slopes are relatively steep, and stream flows differ vastly from month to month. Thus, people living near the rivers have repeatedly suffered from chronic problems such as flood, drought, stream depletion, and low water quality. In addition, many experts (e.g., NIMR 2009; MLTM 2009, 2010; Lee & Park 2011) argue that Korean river management in the future will be much more vulnerable to climate change than in the present, projecting the increase of heavy rainfalls in the wet season and the duration of drought in the dry season. To solve these problems and to provide full amenities for the inhabitants, the Ministry of Land, Transport and Maritime Affairs (MLTM) launched a nationwide, large-scale project named the Four River Remediation Project (FRRP) in 2009. With total expenses approximately amounting to a tenth of the annual national budget, the MLTM constructed a variety of water infrastructures such as reservoirs, weirs, dikes, wetlands, and eco-parks up to 2011.

However, successful river management cannot be ensured by these structural measures. Considering 'non-stationarity' (Milly *et al.* 2008) and 'no basis for probabilities' (Foley 2010; Cha *et al.* 2012), it is necessary to supplement adaptive capacity with nonstructural measures from a perspective featuring both economics and reliability. As mentioned by Lee *et al.* (2012), when the capacity of water infrastructure exceeds a certain level, priorities should be given to better predicting and monitoring hydrological changes, arranging emergency options sufficient to cover a wide range of extreme events, and making timely and adequate decisions. In these regards, this study was initiated to more accurately predict the water levels at various measurement points of the rivers in FRRP. The authors also took into account that adaptive capacity can be further enhanced if the prediction models reveal information about how to

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operate water infrastructure constructed by the FRRP in order to maintain the water levels within desirable ranges.

When Korean river managers make plans for the operation of a reservoir or a weir, the preferred way to forecast the water level at a point is to select one or combine hydrological simulation models, e.g., SWAT (Soil and Water Assessment Tool developed by the US Department of Agriculture), WEAP (Water Evaluation and Planning System developed by the Stockholm Environment Institute), PRMS (Precipitation-Runoff Modeling System developed by the US Geological Survey), and HEC-RAS (Hydrologic Engineering Centers River Analysis System developed by the US Army). These simulation models are structured with governing equations and parameters and have been regarded as most adequate to describe physical processes related to the rain–runoff relation, especially within the hydrologic communities. The authors also agree that the simulation models are the best in achieving long-term prediction (for more detail, see Leavesley (1994) and Solomatine (2002)). However, when river managers are interested in real-time or short-term prediction, there are two serious limitations. One is the demand of the long period and numerous kinds of data to calibrate the model parameters, and the other is excessive consumption of time and endeavor to build and run the models (Grayson *et al.* 1992; Chang *et al.* 2007). These limitations definitely discourage river managers from using simulation results in making decisions upon the operation of water infrastructures.

Objectives of the study

This study is based on the viewpoint that the conventional numerical models to predict the water level are not adequate to draw out the full potential of newly constructed water infrastructures because they entail a number of assumptions and demand numerous kinds of data (Chau 2006; Chang *et al.* 2007). Hence, as an alternative method, the authors intended to examine the systemic approach of using an artificial neural network (ANN). Indeed, the ANN has become the most popular in various system engineering communities (Joo *et al.* 2000; Choi & Park 2001; Robert 2003) when models need good performance and fast calculation in short-term or real-time prediction. In studies on water resource management, many experts (Karunanithi *et al.* 1994; Imrie *et al.* 2000; Toth *et al.* 2000; Cameron *et al.* 2002; Gavin *et al.* 2003; Kisi & Asce 2004; Zhengfu & Fernando 2007) found several merits of the ANN.

1. Fast prediction speed: the ANN conducts prediction through the direct relations between inputs and outputs, without necessitating the treatment of data in the geographical information system.
2. Low data requirements: many fewer input variables are needed than when simulation models are used. Those variables can be selected in a flexible manner according to previous literature, modelers' experiences, new insights, and trial-and-error.
3. Better consideration of site characteristics: to explain highly complicated hydrological phenomena (or dynamic nature of the phenomenon at stake) of a certain site, a simulation model is usually calibrated to adjust its parameters. The ANN model's parameters and structure can be adjusted to be more site-specific. This is a great advantage in modeling non-linear and unique site characteristics of the watershed of concern.

Despite such merits, it does not seem that ANN models are widely used in practice. The authors think that the models should be improved at the perspective of the real river management system to improve applicability. For example, according to the Korean River Management Guideline (K-water 2011), river managers set up the allowable range of water levels at each point and should maintain the water levels above the lower limits during dry seasons and below the upper limits during wet seasons. The managers are obliged to periodically make decisions on the amount flowing out from upstream weirs or reservoirs and then to request approval from the River Flow Control Office under MLTM. The authors suggest improving the ANN model as follows.

1. It should be easy and systematic to optimize the model: when the ANN model is used to predict the water level at a point, the modeler should consider many of the hydrological characteristics of the watershed basin. They are also required to know where the flow gauging stations and the weather stations are located in the upper stream, and how the locations of stations influence the ANN model. Therefore, it is usually difficult to determine the structure of the model. In many previous studies

using the ANN model, this determination was done by using informal trial-and-error methods, referring to the literature, or relying on personal experiences. Even if useful, these 'subjective' methods cannot be expressed explicitly; a significant barrier for engineers and managers in the field who require at least well-coded algorithms.

2. The information regarding water levels a couple of days later should be provided: the previous studies focused on hourly predictions (see Filho & Santos 2006; Alvisi *et al*. 2006; Napolitano *et al*. 2010) is not helpful when considering the real practices articulated in the Korean River Management Guideline (K-water 2011). It usually takes 1 or 2 days to perform the management practices based on the prediction of water level to implement control action. Therefore, the ANN model must be able to know the water level after this time lag of a couple of days.
3. The model must help determine discharges of the upstream weirs or reservoirs: the climate in Korea is characterized by frequent localized torrential rainfall and high coefficient of river regime. Under such climate, maintaining the water level between the upper and lower limits during both dry and wet seasons is critical to prevent natural disasters under extreme events. In this sense, it is important to examine whether the ANN model can clearly explain the relations of the upstream discharges and the downstream water level. If possible, the modeler will be able to conduct 'what-if …' tests, and then determine emergency actions more systematically.

To test the three hypotheses, this study examines the use of the ANN model at 15 points near the locations where weirs or reservoirs were constructed by the FRRP. This article is designed as follows. Following an introduction, the authors explain the methods including study areas, data collection, the ANN model and optimization algorithms, and the way to validate the model. Then, the authors present the results of case studies, which are used to verify the established hypotheses. This study summarizes that the investigated approach using the ANN model can successfully manage river systems, cope with emergencies, and raise the adaptive capacity of the river management system.

METHODS

Study areas

From previous studies, it is seen that a modeler optimizes the performances of the ANN model at a few points in a river, and strives to improve accuracy (Maier *et al*. 2010). This observation does not appear impressive to a river manager since the results were derived only from the several specific points. To gain a river manager's confidence, it would be better to let them decide whether the existing models should really be replaced; it would be very important to ascertain that the ANN model provides good performances at multiple points in various rivers at a time. This study thus attempts to examine the applicability of the model at 15 points near the locations where weirs or reservoirs were newly constructed by the FRRP. The 15 points fall into four groups according to the rivers. The rivers have geographical and hydrological characteristics, as follows (see also Figure 1 and Table 1).

1. Han River: it flows through the northern part of Korea from the Gangwon province to Gyeonggi province via Seoul metropolitan city. The FRRP newly constructed three weirs in a section, from the Chungju dam to the Paldang Lake, of the main stream. The authors selected two water level measurement points within this section, as shown in Figure 1(a). It seems very likely that the water level at point 1 will be significantly affected by the discharges of the Chungju dam while the water level at point 2 is greatly determined by the operation of the weirs. Point 2 is of national concern because the point is at the starting point of Paldang Lake which supplies raw water for approximately 20 million inhabitants living in Seoul metropolitan city and Gyeonggi province.
2. Geum River: it is located at the center of Korea and originates from the Jeollabuk province, and then flows out into the West Sea through the Chungcheongnam province and Chungcheongbuk province. The river is characterized by rising from many tributaries, i.e., 20 streams. The FRRP constructed three weirs at the section, 99 km in length, between the Daecheong dam and Geum River estuary dam. Within the section, four points on the main stream are used to predict the water levels, as shown in Figure 1(b).

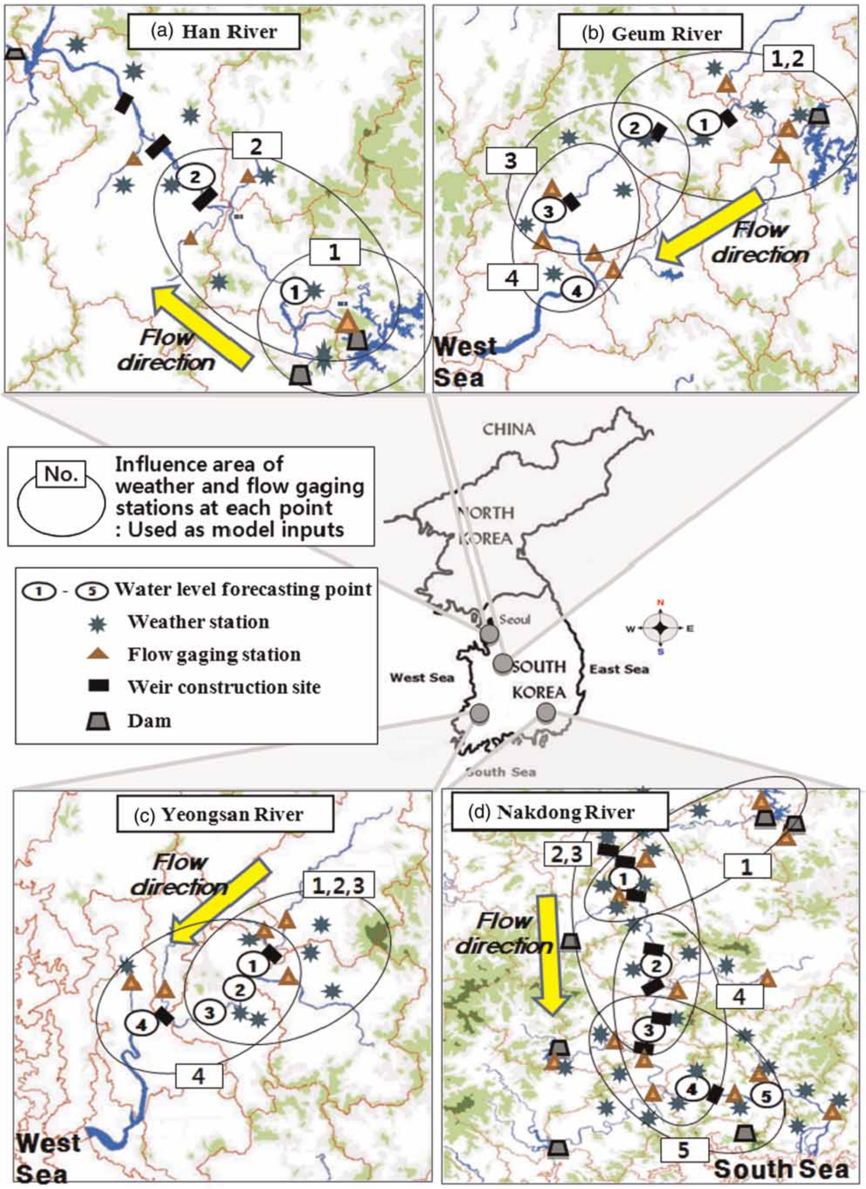

Figure 1 | Locations of the study areas.

Although point 1 is largely affected by the discharges of the Daecheon dam, it is very challenging for river managers to predict and control the water level because the influx of the Miho stream and the Gapcheon tributary at the front fills about half of the total flow in the main stream. For other points, which are placed behind point 1, the FRRP is likely to improve the ability to manage water quantity. Water levels at points 2, 3, and 4 are dominated by operation of weirs in the upper streams.

3. Yeongsan River: it passes through the Jeollanam province in the south-western part of Korea, and flows out to the West Sea. The distinctive characteristic of this river is that the regime coefficient of the watershed basin is extremely high (1:682). This implies that flow rate differs vastly from season to season so that damage due to floods and droughts frequently occurs. In the section, 98 km long, where two weirs were installed by the project, there are four points available to estimate the

Table 1 | Geographical and hydrological characteristics

Study area	Catchment area (km^2)	River length (km)	Annual mean temperature (°C)	Annual mean rainfall (mm)	Coefficient of river regime[a]
Han River	26,018	481.7	10–11	1,200–1,300	1:393
Geum River	9,912	394.8	11–12	1,100–1,300	1:299
Yeongsan River	3,371	115.5	13	1,100–1,500	1:682
Nakdong River	23,384	506.2	12–14	900–1,400	1:372

[a]The coefficient usually implies the ratio between the maximum and minimum of daily flow over an average year.

water levels, as in Figure 1(c). Among them, water levels at points 1 and 3 are affected by the operation of Seungchon and Juksan weirs, respectively. Point 2 is placed behind the confluence of the Jiseok stream having abundant flow, and thus the water level is influenced by the flow variation of Jiseok stream. Besides, point 4 is used to monitor the flow escaping into the West Sea.

4. Nakdong River: it originates from the Gangwon province and flows vertically through the Gyeongsangbuk province, Gyeongsangnam province, and Busan metropolitan city into the Southern Sea. It is the longest river in Korea. Accordingly, spatial variations in rainfall and flow are relatively large, and many inhabitants near the lower stream have suffered from floods and droughts almost every year even though five reservoirs for flood control were installed a long time ago. As a result, while planning the FRRP, the MLTM took note of these problems and constructed eight large-scale weirs. The construction projects were mainly implemented within the section, 277 km long, between Andong city and Busan metropolitan city. Although many points are available to estimate the water levels in this section, five points where flooding regularly occurs were selected as points of interest.

Model construction and calibration

An artificial neural network is a computational model mimicking the human brain that is constructed by huge networks connecting neurons, neural cells, and synapses. The ANN is not required to establish model structure with the full understanding of natural phenomena. The model rather relies on empirical training as humans normally do (Haykin 1998; Maier *et al.* 2010). Figure 2(a) exemplifies the general structure of an ANN model. A neuron corresponds to a node where Z_n is an output from nth layer, Z_{n+1} is an output from $(n+1)$th layer, w_n is a weight between nodes, u_{n+1} is the sum of multiplying Z_n by w_n, and $f_i(u_{n+1})$ is an activation function transferring the sum of node inputs into a node output. The activation function can have a logistic, hyperbolic-tangent, or linear form (Figure 2(b)). Several nodes form a layer, and several layers form the whole ANN structure again. Among a variety of ANN structures, the most popular one is the MLP (multi-layer perceptrons) and a feed-forward network with several layers (Haykin 1998; Dibike & Solomatine 2001). In several previous studies (Sahoo *et al.* 2006; Wang *et al.* 2006; Pulido-Calvo & Portela 2007), ANN with double hidden layers showed competent results. Therefore, in this study, both ANNs having a single hidden layer and double hidden layers are tested, and one is selected for the optimal ANN design at each study site.

In many ANN studies, the model structure has been selected through a trial-and-error method (Hsu *et al.* 1995; Zealand *et al.* 1999; Chiang *et al.* 2004). However, the results of optimizing the model largely depend on how appropriately the hidden layers and nodes are designed and how well the functions are defined. Thus, much effort should be given to the selection of model structure. Since the mid-1990s, there have been numerous attempts in water resource management communities to employ the genetic algorithm (GA) (see Savic *et al.* 1999; Giustolisi & Laucelli 2005; Giustolisi & Simeone 2006; Shamseldin *et al.* 2007). GA is a technique inspired by the principles of natural evolution and selection (see details in Holland (1975) and Goldberg (1989)). In previous studies, the GA has be mainly used in the neural network, as follows: (1) selection of input variables; (2) adjustment of weights; (3) number of hidden layers in the MLP; (4) number of nodes in each layer; and (5) type of activation function in each node.

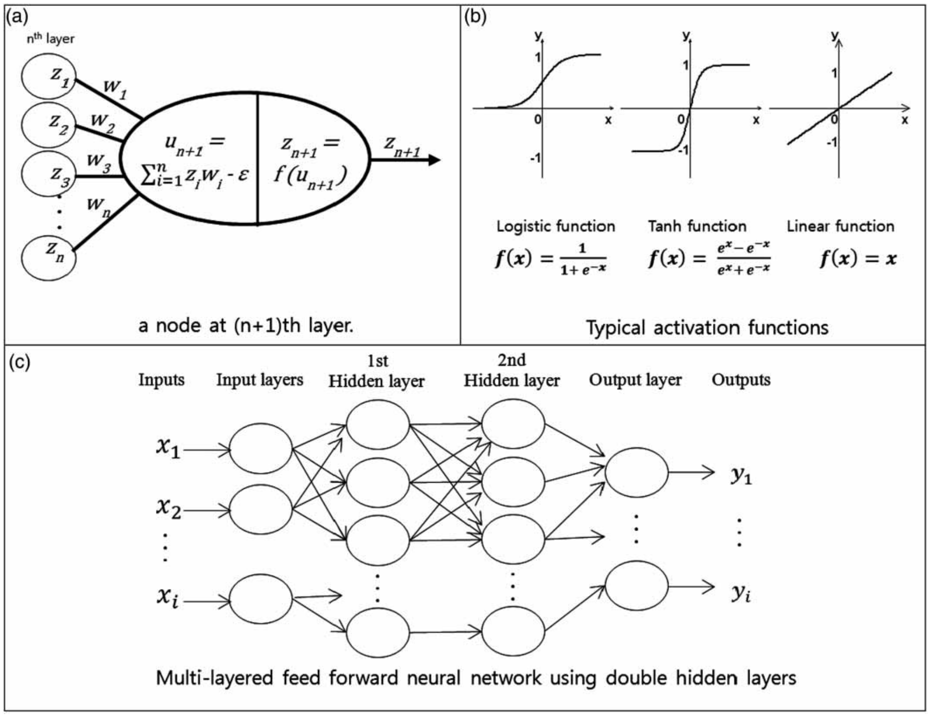

Figure 2 | General structure of the ANN model (MLP): (a) a node at $(n+1)$th layer; (b) typical activation functions; (c) multi-layered feed forward neural network using double hidden layers.

Based on literature reviews (See & Openshaw 2000; Alvisi *et al.* 2006; Maier *et al.* 2010) and Korean river condition (K-water 2011), rainfall and upstream flow are used as input variables, and rainfall/flow gaging stations are selected through preliminary statistical test (i.e., significance test) considering the travel time (maximum 4 days at study sites (K-water 2011)). The number of nodes at input layer is different at each prediction point because the Korean rivers have a different number of branches and lag-time (see Figure 1). Due to Korean climate characteristics (frequent localized torrential rainfall and high coefficient of river regime), it is difficult to construct a model using only input data for a certain period (e.g., dry and wet season). Therefore, the model is constructed by selecting representative points of annual precipitation and flow variations. To take into account the number of branches and the time window (t_0, t_{0-1}, t_{0-2}), a maximum of 16 inputs are necessary. For example, prediction point #1 in Geum River (see Figure 1) is affected by eight points (four weather gaging stations, three flow gaging stations, and one dam). Lag-time between the dam and the furthermost flow gaging station is 1–2 days depending on flow speed. To take the lag-time into account, two types of time window (t_0, t_{0-1}) at the two points should be considered as model inputs for 1-day ahead prediction. As a result, the prediction point #1 in the Geum River has 10 model inputs. To avoid 'curse of dimensionality and over-fitting in ANN' (Haykin 1998; Giustolisi & Laucelli 2005), GA is coded to select minimum nodes at hidden layers. The number of nodes at a hidden layer is limited to a maximum of 32 following 'a general principle that the node numbers of the hidden layers should be greater than the input layer nodes' (Zeng & Wang 2010). Finally, 14 average nodes are used in this study (it is similar to the number of input nodes). Weights are also anticipated to be well trained by the back propagation algorithm (BPA) solely as done by other ANN studies (Rumelhart *et al.* 1986; Rumelhart & McClelland 1987; Abebe & Price 2003; Robert 2003; Kisi & Asce 2004; Chau 2006; Chang *et al.* 2007; Napolitano *et al.* 2010; Mohanty *et al.* 2010). To take into account the high coefficient of river regime, the weights are adjusted to minimize error value for high variations of water level. Three criteria (Table 2) are used for validation.

Finally, the authors decided using the GA to select: (1) the number of hidden layers; (2) the number of nodes in

Table 2 | Criteria for testing validity of the model

Criteria	Purpose	Estimation
Coefficient of determination (R^2)	To evaluate the goodness-of-fit of models	$R^2 = \frac{\sum_{i=1}^{n}(P_i - \bar{O})^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$
Mean square error (MSE)	To quantify the error of model	$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2$
Mean absolute percent error (MAPE)	To compare the error between populations	$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\lvert P_i - O_i\rvert}{O_i}$

each hidden layer; and (3) the type of activation function in each node. Overall model construction procedure is summarized in Figure 3. In the first part, input data are decided through three steps, 'selection of water level forecasting point', 'selection of input point', and 'data collection'. In the second part, ANN is constructed using GA. The initial ANN structure consists of double hidden layers with the same number of nodes as in the input layer, and each node contains a random activation function. Then, the ANN model is constructed through iteration of three steps, selection, crossover, and mutation, and the probability of each step is 20, 60 and 20%, respectively. Before a new iteration starts, weights are adjusted by BPA. Finally, 1st-rank ANN model of one generation is created and saved for selection of optimal ANN structures. The ANN structure with the lowest coefficient of determination is selected as the optimal model. The number of generations is 50, and each generation contains 500 candidate models (population size).

At the model calibration step, all the weights, w_n, need to be trained to minimize the sum of square errors between observed data and model outputs. As a result, dozens of training algorithms have been suggested so far although none of them ensure that the solution reaches a global minimum (for details, see Coulibaly et al. (1999) and Mohanty et al. (2010)). Among those algorithms, the authors used the back propagation algorithm, first suggested by Rumelhart & McClelland (1987). The algorithm is widely known as an adequate method to train the MLP and, in particular, it is less sensitive to the noises or errors inherent in input data (Maier & Dandy 2000).

Selection of data, input variables, and validation criteria

There were some limitations in availability of data when the constructed model is trained and validated. First, the length of data is a bit short compared to that in other studies. In a large portion of water level measurement points, the data obtained prior to the year 2004 turned out to be inconsistent. Second, the FRRP perturbed the quality of data temporally. From 2009 to 2011, large-scale weirs were constructed, and dredging works were conducted in the study sites, which led to a slight change in the location of several measurement points and an increase in measurement errors. Therefore,

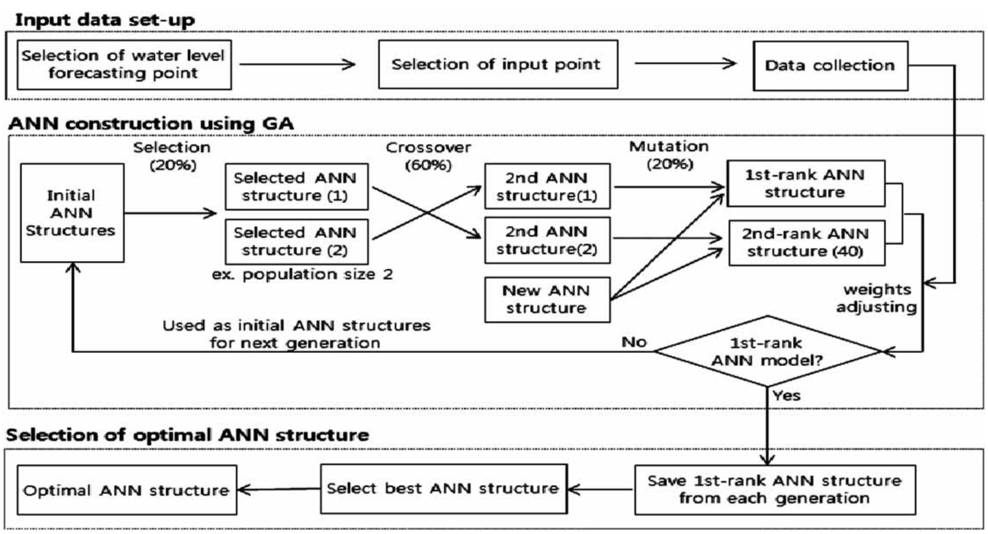

Figure 3 | Overall model construction procedure in this study.

daily data were restricted to a 5-year period from 1 January 2004 to 31 December 2008. The total period is subdivided into 3 and 2 years to distinguish model training/validation from testing periods, respectively. The 3-year training/validation period (2004–2006) is divided into training and validation parts: if the data period starts from t_0, even numbers (t_0, t_{0+2}, t_{0+4} …) are used as training data and odd numbers (t_{0+1}, t_{0+3}, t_{0+5} …) are used as validation data. This study satisfied the minimum data quantity for ANN construction suggested by Lawrence & Peterson (1993). All the input data are adjusted on a scale ranging from 0 to 1.

Table 2 represents the criteria for validating the ability of the model to predict the water level, in which Pi is the values predicted by the ANN model, and O is the observed values, and $\bar{O}$ is the average of observed values, and n is the number of samples. The three criteria, R^2, MSE, and MAPE, are widely used statistics, which refer to high validity in the constructed model as the statistics are closer to 1, 0, and 0, respectively.

RESULTS AND DISCUSSION

Selection of the model structure

Tables 3 and 4 show the results of building the ANN models, each listing the numbers of layers and nodes, and types of activation functions optimized by the GA. The results can be interpreted as follows.

1. Among the hidden layers included in all models, double layers amount to more than a third (37%). This gives an insight that there is high nonlinearity between input variables and water level, and among input variables (Haykin 1998).
2. In the first hidden layers, the number of nodes ranges from 6 to 32 (15 on average), and in the second hidden layers, this ranges from 2 to 17 (6 on average).
3. Hyperbolic tangent functions and logistic curves were dominantly selected as activation functions in hidden layers rather than linear functions. This agrees with Daliakopoulos *et al.* (2005), who stated that sigmoid-type functions ensure better performances on the ANN model.
4. In contrast, linear functions were selected for almost half of activation functions in the output layers, which corresponds to other experts' experiences (cf. Abebe & Price 2003; Chang *et al.* 2007; Pulido-Calvo & Portela 2007).

Testing of the ANN models

To test the trained model for the period 1 January 2006 to 31 December 2008, the authors applied data for input

Table 3 | Results of optimizing the model structure (1-day ahead water level)

	Site	Number of inputs	Number of hidden layers	AFs at 1st hidden layer[a]	AFs at 2nd hidden layer[a]	AF at output layer
Han River	# 1	9	2	8Lo, 10T, 5Li	1Lo, 1T, 2Li	T
	# 2	14	2	2Lo, 1T, 1Li	2Lo, 1T	T
Geum River	# 1	10	1	3T, 12Li	–	Li
	# 2	6	2	11Lo, 20T, 1Li	3Lo, 2T, 1Li	Li
	# 3	11	1	2Lo, 5T	–	Li
	# 4	9	1	1Lo, 2T	–	Li
Yeongsan River	# 1	9	1	2Lo, 1T, 1Li	–	Lo
	# 2	11	2	16Lo, 8T, 3Li	10Lo, 6T	T
	# 3	6	2	14T, 14Li	2Lo, 2T	T
	# 4	9	1	1Lo, 20T, 4Li	–	Li
Nakdong River	# 1	14	2	5Lo, 9T, 1Li	2Lo, 2T, 2Li	T
	# 2	13	2	5Lo, 4T, 5Li	1Lo, 1T	T
	# 3	14	1	2T, 1Li	–	T
	# 4	14	1	1Lo, 1T	–	T
	# 5	14	1	4Lo, 6T, 7Li	–	Li

[a]The expression 'aLo, bT, cLi' means that 'a, b, c' is the number of each function and 'Lo, T, Li' stand for logistic function, hyperbolic tangent function, and linear function in order. The sum of 'a, b, and c' is the total number of nodes at each layer.

Table 4 | Results of optimizing the model structure (2-day ahead water level)

	Site	Number of inputs	Number of hidden layers	AFs at 1st hidden layer[a]	AFs at 2nd hidden layer[a]	AF at output layer
Han River	# 1	9	1	3Lo, 6T	–	1Lo
	# 2	14	2	15Lo, 6T, 5Li	1T, 1Li	1Li
Geum River	# 1	10	1	1Lo, 1Li	–	Li
	# 2	6	1	1Lo, 1Li	–	Lo
	# 3	11	1	2Lo, 2T, 1Li	–	Li
	# 4	9	1	10Lo, 9T, 5Li	–	Li
Yeongsan River	# 1	7	1	1Lo, 2T	–	Li
	# 2	11	2	10Lo, 9T, 1Li	12Lo, 4T	T
	# 3	8	2	1Lo, 12T	2Lo, 2T	T
	# 4	9	1	6Lo, 4T, 7Li	–	Li
Nakdong River	# 1	14	1	15Lo, 9T, 4Li	–	Lo
	# 2	13	2	15Lo, 5T, 10Li	1Lo, 1T	T
	# 3	14	1	7T, 4Li	–	Li
	# 4	14	1	11T, 12Li	–	T
	# 5	14	1	3Lo, 2T, 1Li	–	Lo

[a]The expression 'aLo, bT, cLi' means that 'a, b, c' is the number of each function and 'Lo, T, Li' stand for logistic function, hyperbolic tangent function, and linear function in order. The sum of 'a, b, and c' is the total number of nodes at each layer.

variables, and then compared the results with recorded water levels. Results of the 1-day ahead prediction are as below. For all measurement points, the models could explain changes of water levels very satisfactorily considering that R^2 spans from 0.84 to 0.94 (see Table 5 and Figure 4).

1. Han River: R^2 of the four points is lower (0.84) than those in any other study site while MSE is the average and MAPE is relatively low. The first criterion reveals that there are difficulties in fitting the model as random variations of water levels are rather significant. However, the latter criteria show that errors of the models are insignificant. Overall, prediction ability is quite good even in the seasons when floods or droughts occur.
2. Geum River: R^2 is the largest (0.94) among all the study sites. Water levels in this river were once expected to be very difficult to predict as the main stream is influenced by the flows of many tributaries. However, validation testing showed that the ANN models anticipate and solve the complication these tributaries cause with excellent accuracy.
3. Yeongsan River: R^2 (0.83) is similar to that of the points in the Han River. It should be also noted that MSE is low (0.04) and simultaneously MAPE is relatively high (13.12%). MAPE is more sensitive to overestimation arising when the absolute values of observed data are smaller. Therefore, the values of MSE and MAPE are interpreted as the constructed models having a little tendency of overestimating low water levels, especially in the dry season.
4. Nakdong River: the models have excellent consistency ($R^2 = 0.91$), but the other criteria are relatively unsatisfactory. Based on these results, it is expected that random variation of the water level data are not significant, but the models do not respond in a very sensitive manner when water levels are suddenly changed.

Table 5 | Testing results of the ANN models (R^2)

	R^2: 1-day ahead	R^2: 2-day ahead
Han River	0.84	0.72
Geum River	0.94	0.87
Yeongsan River	0.83	0.82
Nakdong River	0.91	0.87

For the 2-day ahead prediction models, it is natural that validation criteria get worse. However, Figure 5 states that the models are still acceptable: $0.72 < R^2 < 0.87$, and sufficiently small MSE and MAPE. Also, the statistical properties, differing from study sites in cases of the

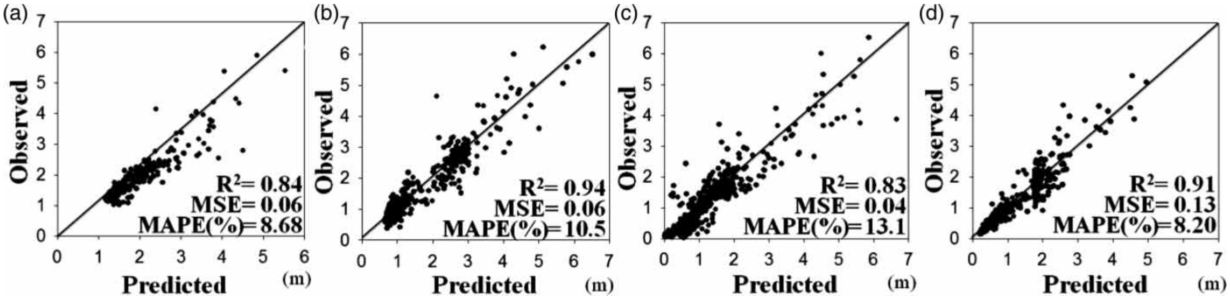

Figure 4 | Results of testing the trained model (1-day ahead water level): (a) Han River; (b) Geumgang River; (c) Youngsan River; (d) Nakdong River.

1-day prediction models, remain valid when the overall perspective of the criteria is considered. The models are most consistent with the points in the Geum River, but they are not perfectly fitted with the points in the Han River basin. In addition, the model fits with Nakdong River, but a small error results from insensitivities of the models.

In general, the ANN models are acceptable in predicting water levels at all points even when there is uncertainty in tomorrow or the day after tomorrow's weather conditions.

Discussion

At the beginning of this study, the authors form three hypotheses to examine the practicality of the ANN models. Each hypothesis is then discussed with the models constructed above. The discussion underpins the opinion that the ANN models, especially optimized with the genetic algorithm, can achieve many requirements necessary to replace the existing models and eventually enhance the adaptability of the river management system.

Is it easy and systematic to find the optimum structure of the model?

The model is optimized by using the genetic algorithm (selecting model structure) and the back propagation algorithm (adjusting weights). Although some professional efforts for programming were required (in practice, this could be easily settled by developing the GUI, interacting with the GA and back propagation (BP) codes, and a manual), these algorithms greatly reduced the labor in repeating trials and errors. Simultaneously, with the assistance of linking the ANN model with the GA, the authors could have great confidence in determining hidden layers, nodes, and activation functions, which might otherwise have been arbitrary.

Is this model advantageous to forecast 1- or 2-day ahead water levels?

As the authors mentioned previously, the Korean river management system needs 1 or 2 days to decide the operation of upstream infrastructure to maintain the downstream water levels. Practically, it is important to have the prediction

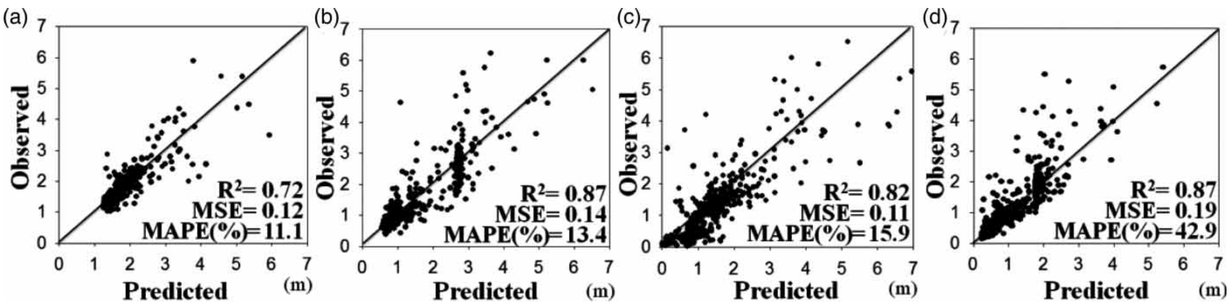

Figure 5 | Results of testing the trained model (2-day ahead water level): (a) Han River; (b) Geumgang River; (c) Youngsan River; (d) Nakdong River.

methods and models that are highly advantageous to predict the 1- or 2-day ahead water levels. The ANN models coupled with the GA showed satisfactory validity (e.g., $0.84 < R^2 < 0.94$ for 1-day ahead water level, and $0.72 < R^2 < 0.88$ for 2-day ahead water level) and more consistent results than the hourly models (for instance, Filho & Santos (2006), Alvisi *et al.* (2006), and Napolitano *et al.* (2010)) that tried to build the prediction models for 1-, 12-, and 18-hours ahead water levels. The coefficient of determination, which was estimated from their models, ranged from 0.4 to 0.95. In addition, even at the points of the Geum River which are complicated due to the influence of many tributaries, the 2-day ahead water level can be predicted with the accuracy of $R^2 = 0.87$. For a further study, comparing the neuro-genetic algorithm and other conventional neural networks will be meaningful for additional verification of the developed model.

Will the models be helpful for deciding the operation of the upstream weirs or reservoirs?

The ANN models are implicit in explaining a quantitative relation between the upstream flow and the downstream water level. Hence, these models facilitate further decision-making in face of the anticipation that the water level at a point of concern would be risky under un-intervened conditions. The modeler can carry out 'what-if…' tests while thinking about the different operation (or different discharge) of weirs and reservoirs constructed in the upper stream. Again, these tests let the modeler determine the acceptable range of the discharge amount of the upstream in order to satisfy the management level at the point. For illustration, see Figure 6(a); we are interested in the water level at point 1 of the Geum River, and the management level is hypothetically set at 3.80 m. Let us also assume that now is day 61 (at this moment, the water level is 3.50 m, and the discharge amount from the upper reservoir is 810 m^3/s). This is the time when we get the model prediction that tomorrow's water level (3.84 m) would go beyond the management level. It is thus natural to investigate what would result from the intentionally reduced discharges. By using the ANN model with other assumptions on the upper discharges, it would be possible to get the prediction that the discharge amount should be immediately dropped to less than 789 m^3/s to maintain tomorrow's water level below 3.8 m, as in Figure 6(b). Indeed, the Korean River Management Guideline (K-water 2011) mentions that for cases where meeting the management level is threatened, the river manager is exceptionally allowed to 'act first, report later'.

CONCLUSION

Recently, the Korean government implemented the FRRP with a great deal of ambition. However, it is hard to think that the constructed weirs, dams, and reservoirs will solve all the chronic problems that riparian areas have long faced, and climate change is likely to aggravate. For adaptive

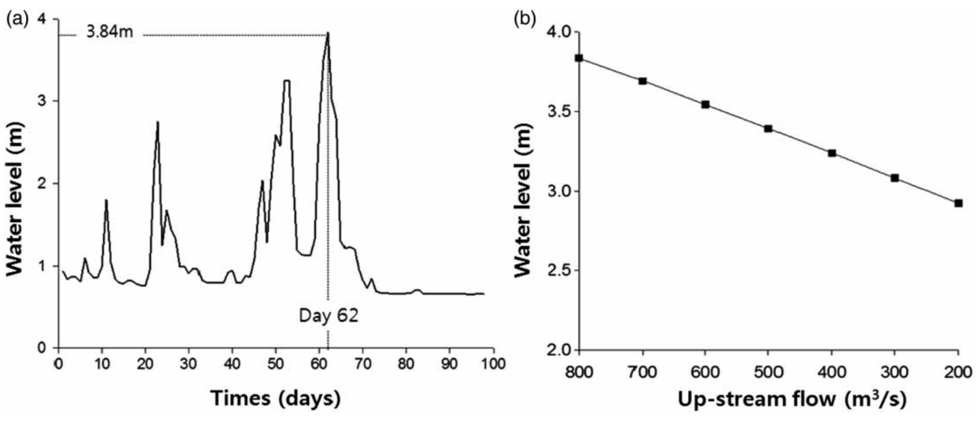

Figure 6 | Example illustrating the decision operation of the upstream water infrastructure at point 1 of the Geum River: (a) prediction of the 1-day ahead water level; (b) estimated relation between upstream flow (day 61) and downstream water level (day 62).

capacity of the river management system, this study had a special interest in raising the capability of predicting water levels at various points of the rivers. Such intelligent forecasting capabilities can be heightened by carefully monitoring weather conditions and upstream water flow data, adequately utilizing the data in predicting 1- or 2-day ahead water level, and building the models properly to satisfy practical requirements. In this context, the authors tested the use of a hybrid neuro-genetic algorithm in predicting water levels at 15 points of four rivers. The results are summarized as follows.

1. By using the genetic algorithm, it was possible to greatly reduce the trials and errors which were necessary to find out the optimum structure of the ANN model. The developed ANN model demonstrates the great advantage that hidden layers, nodes, and activation functions can be selected in a more formulated manner.
2. The ANN models showed satisfactory validity over the 15 water level measurement points. Especially, the coefficient of determination ranged from 0.84 to 0.94 for 1-day ahead water levels, and from 0.72 to 0.88 for 2-day ahead water levels. Based on these statistics, it was found that the built models have greater prediction abilities than those presented in previous studies.
3. The ANN models could clearly explain the relation between the upstream flow and the downstream water level. This advantage can be of significant merit when the river manager anticipates the water levels within the acceptance level. The models can encourage the river manager to investigate the consequences of differently operating water infrastructures located in the upstream. Therefore, they are considerably helpful in making urgent decisions regarding how water infrastructure should be properly operated and maintained.

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