DEVELOPMENT OF ARTIFICIAL NEURAL NETWORK MODELS SUPPORTING RESERVOIR OPERATION FOR THE CONTROL OF DOWNSTREAM WATER QUALITY

Se-Woong Chung[1] and Ju-Hwan Kim[2]
[1]Water Resources Operations Center, KOWACO, San 6-2, Yeonchuk-Dong, Daeduk-Gu, Daejeon, Korea
[2]Water Research Institute, KOWACO, 462-1, Jeonmin-Dong, Yusung-Gu, Daejeon, Korea

Abstract: As the natural flows in rivers dramatically decrease during drought season in Korea, a deterioration of river water quality is accelerated. Thus, consideration of downstream water quality responding to changes in reservoir release is essential for an integrated watershed management with regards to water quantity and quality. In this study, water quality models based on artificial neural networks (ANNs) method were developed using historical downstream water quality (rm NH_3 -N) data obtained from a water treatment plant in Geum river and reservoir release data from Daechung dam. A nonlinear multiple regression model was developed and compared with the ANN models. In the models, the rm NH_3 –N concentration for next time step is dependent on dam outflow, river water quality data such as pH, alkalinity, temperature, and rm NH_3 –N of previous time step. The model parameters were estimated using monthly data from Jan. 1993 to Dec. 1998, then another set of monthly data between Jan. 1999 and Dec. 2000 were used for verification. The predictive performance of the models was evaluated by comparing the statistical characteristics of predicted data with those of observed data. According to the results, the ANN models showed a better performance than the regression model in the applied cases.

Key Words: water quality, drought season, dam outflow, artificial neural network

1. INTRODUCTION

Since most of intake stations that withdraw water from rivers in Korea are located along downstream reach, river water quality management is important issue for securing public health and clean water supply in Korea. In particular, as the natural flows in rivers dramatically decrease during drought season, a water quality deterioration in the downstream reach of river is accelerated. In addition, the efficiency and cost of water treatment are quite dependent on the quality of raw water.

The major roles of multi-purpose dams are flood control, water supply, hydropower generation, and conservation of downstream water quality through supplying environmental maintenance flow. In the reservoir operation, consideration of downstream water quality responding to the changes in reservoir release is essential for an integrated watershed management with regards to water quantity and quality. Water quality models can be applied to predict downstream water quality when monthly reservoir operation plan is made to improve the efficiency of reservoir water utilization. In other words, an adequate allocation of monthly reservoir releases considering the characteristics of downstream water quality may improve the river water quality while satisfying a safe water supply.

Fig. 1 shows the trend of daily ammonia nitrogen(NH_3-N) concentrations from 1993 to 1998 at the intake site of a water treatment plant located in the lower reach of Geum River, Korea.

It revealed that the river water quality dramatically deteriorates during drought season as the water temperature drops. The most concerned period is between December and April. During this period, the NH_3 -N concentrations reach as high as 2.0~5.0 mg/L, which is quite grater than the water quality standard (0.5 mg/L) for drinking water. The plant operators have experienced a great difficulties in the treatment process in recent dry season due to the occurrences of high level NH_3 -N concentrations in the raw water. Some extent of deterioration of water quality can be attenuated by control of reservoir releases based on the predicted water quality in the downstream of the river.

The major objective of this study is to develop water quality models based on ANNs algorithm and multiple regression method for predicting the effect of dam reservoir outflow on the water quality, NH_3 -N, in downstream where a water treatment is located. The model parameters were determined using monthly data from Jan. 1993 to Dec. 1998, then another set of monthly data between Jan. 1999 and Dec. 2000 were used for verification. The predictive performance of the models was evaluated by comparing the statistical characteristics of the predicted data with those of observed data.

2. METHODOLOGY

Two different methods are used in the development of water quality models. The first

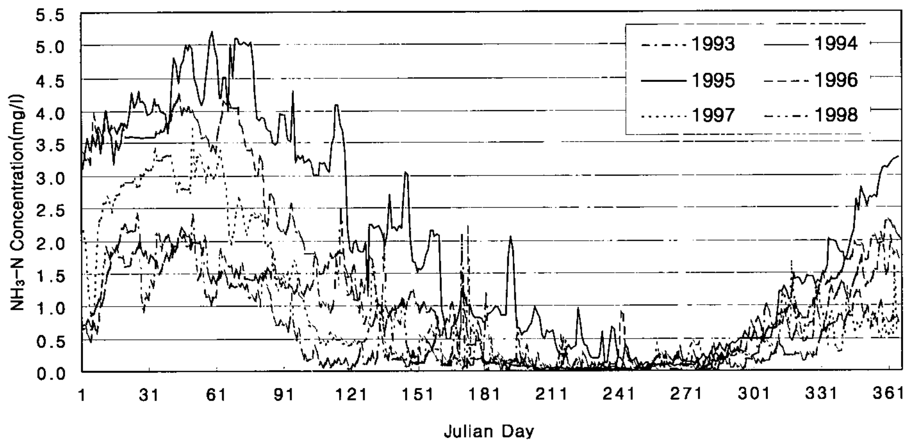

Fig. 1. Seasonal variation of daily NH_3-N concentrations in Geum River

one is a statistical method of multiple nonlinear regression. The second is the ANNs method, which simulates biological neural systems and human way of thinking and learning. There are many applications of ANNs to water resources in last decades. Theses include rainfall forecasting (French et al., 1992) and streamflows forecasting(Kim et al., 1992), multivariate modeling hydrological time series (Kim, 1993; Roman and Sunilkumar, 1995), water resources time series modeling, modeling of rainfall and runoff process (Hsu et al., 1995; Shamseldin, 1997), and river flow forecasting (Karunanithi et al., 1994; Zealand et al., 1999). These contribute to the field of water resources to get a conclusion on the usefulness and applicability of ANNs. Furthermore, many applications of ANNs have shown the improved accuracy and experienced excellence in water resources predictions by adoption of ANNs techniques.

One of the main features of neural network is the realization of a complex nonlinear mapping from n-dimensional input spaces to m-dimensional output spaces. The prediction problem of water quality can be regarded as pattern recognition problem. It can be explained that different input patterns give rise to different output patterns. During training, the ANNs would extract the relevant patterns from the input parameter and associate them with different output.

A black box type water quality model based on multiple regression and neural network methods may have practical advantages compared to a mathematical model in river and reservoir operational purposes in which various input data are difficult to obtain in time. In particular, once the black box type model is constructed based on historical records. it can be applied immediately using key variables without various initial and boundary conditions that are inevitably needed in mathematical models. Once the models are constructed by using enormous historical records, they can be used directly for prediction without various input data which is inevitably needed in mathematical models as boundary conditions.

2.1 Multiple nonlinear regression

Scatter diagrams of each of the predictor variables were individually analyzed against the response variable as water quality. A multiple nonlinear regression model that describes the relationship between the NH_3 –N and the independent variables is given as follows :

$$y = a_0 x_1^{a_1} x_2^{a_2} x_3^{as_3} \cdots x_n^{a_n} + e_t \qquad (1)$$

where y denotes dependent variable; x_1, x_2 ···, x_n denote the independent variables; $a_0, a_1, a_2, \cdots, a_n$ denote model parameters; and e_t denotes the error term.

2.2 Artificial neural network

2.2.1 Overview of ANN

The ANN is a mathematical model of theorized mind and brain activity which attempt to exploit the massively parallel local processing and distributed storage properties believed to exist in the brain. A conventional method based on the mathematical model uses algorithm-based calculation. However, the ANNs operate with highly distributed transformations through thousands of interconnected neurons and appear to store the informations as distributed correlations among connections. The primary elements characterizing the neural network are the distributed representation of information, local operations and nonlinear processing. These attributes emphasize the popular application area of neural networks.

2.2.2 Structure and learning process of ANNs

The structure of ANNs is based on understanding of biological neurons system and it performs through dense interconnection of many computational elements connected by links with variable weight. The node is characterized by an internal threshold and non-linearity. Neural network models are specified by the net topology, node characteristics and training or learning rules. These rules specify an initial set of weights and indicate how weights should be adapted during use to improve performance. The structure of neural network can be shown in Fig.2 (b) as compared with biological neurons system.

In this paper, the generalized Delta rule is used to train a multilayer perceptron for forecasting. As an output, the water quality is produced by presenting an input pattern to the network. According to the difference between the produced output and the observed, the parameters of network are adjusted to reduce the output error. The error at the output layer propagates backward to hidden layer, until it reaches the input layer. Because of feedback propagation of error, the generalized Delta rule is also called error back propagation algorithm The output from node i, O_i, is connected to the input node j through the interconnection weight W_{ij} Unless node k is one of the input

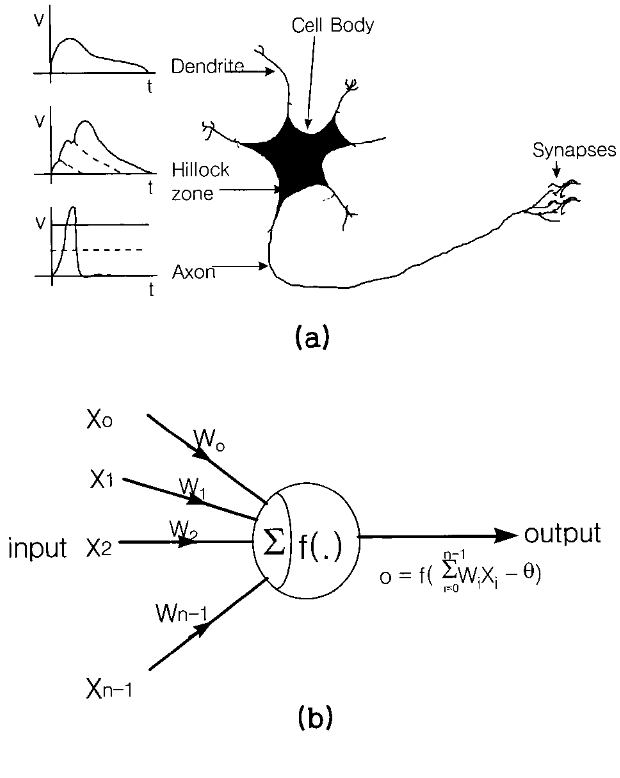

Fig. 2. A prototype of biological neuron (a) and artificial neuron (b) (Lisboa, 1992)

nodes, the state of node k is:

$$O_k = f(\sum W_{ik} O_i) \quad (2)$$

where, $f(x) = 1/(1+e^{-x})$ called transfer function, and the sum is over all nodes in the adjacent layer. Let the resulting target(output) state node be t. Thus, the error at the output node can be defined as;

$$E = \frac{1}{2}(t_k - O_k)^2 \quad (3)$$

where node k is the output node.

The gradient descent algorithm adapts the weights according to the gradient error, i.e.,

$$\Delta W_{ij} \propto \frac{E}{W_{ij}} = \frac{E}{O_j}\frac{O_j}{W_{ij}} \quad (4)$$

Specially, we define the error signal as;

$$\delta_j = \frac{E}{O_j} \quad (5)$$

With some manipulation, we can get the following generalization Delta rule;

$$\Delta W_{ij} = \eta\, \delta_j O_i \quad (6)$$

where η is an adaptation gain. δ_j is computed, based on whether node j is in the output layer or not. If node j is one of the output nodes,

$$\delta_j = (t - O_j)\ O_j(1 - O_j) \quad (7)$$

If node j is not in the output layer,

$$\delta_j = (t - O_j)\ O_j \sum k\ \delta_k\ W_{kj} \quad (8)$$

In order to improve the convergence characteristics, we can introduce a momentum term with momentum gain α to Equation (6).

$$\Delta W_{ij}(n+1) = \eta\ \delta_j O_i + \alpha \Delta W_{ij}(n) \quad (9)$$

where n represents the iteration index.

Once the neural network is trained, it produces very fast output for a given input data. It only requires a few multiplications and calculations of sigmoid function as transfer function.

3. DESCRIPTION OF MODEL STRUCTURE

3.1 Multiple nonlinear regression model

A multiple nonlinear regression model is used in this study as follows ;

$$C_t = \alpha_0 \cdot Q_t^{a_1} \cdot T_t^{a_2} \cdot (ALK_t)^{a_3} \cdot C_{t-1}^{a_4} + e_t \quad (10)$$

where, C_t is the concentration of NH_3 –N in downstream, Q_t is the dam outflow, T_t is the temperature, ALK_t means alkalinity, and C_{t-1} denotes previous monthly concentration of NH_3 –N as input variables. The model given by equation (10) will be called as Model I.

3.2 ANNs model

A multilayer perceptron of neural network consists of one input layer, one or more hidden layers and output layer. Each layer employs several nodes and each node in a layer is connected to the nodes in the adjacent layer with different weights. Signals flow into the input layer, pass through the hidden layers, and arrive at the output layer. With the exception of input layer, each node receives signals from nodes of previous layer linearly weighted by the interconnect values between nodes. Then, it produces its output signal by passing the summed signal through a sigmoid function. There are two important points in using a neural network for water quality prediction. The first point is to determine the network architecture which is composed with the input layer, the output layer, the number and size of the hidden layers. The second point is to choose a prediction algorithm. In this study, following models are assumed which is similar to time series model structure and applied using ANNs architecture. The autoregressive characteristics of NH_3 -N are analyzed for determining lag and outflow. Also, temperature and alkalinity are considered as model variables.

The ANNs equations of each model are ex-

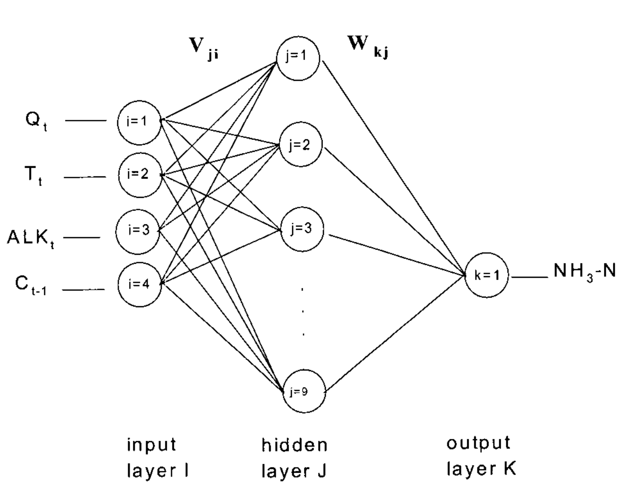

Fig. 3. The architecture of ANNs for prediction of water quality (Model II)

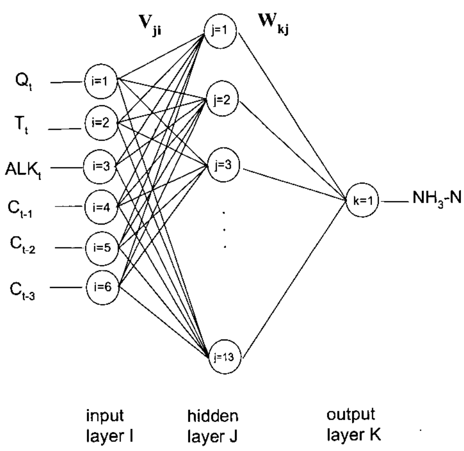

Fig. 4. The architecture of ANNs for prediction of water quality (Model III)

pressed as follows;

Model II

$$C_t = ANN(Q_t, T_t, ALK_t, C_{t-1}) + e_t \qquad (11)$$

Model III

$$C_t = ANN(Q_t, T_t, ALK_t, C_{t-1}, C_{t-2}, C_{t-3}) + e_t \qquad (12)$$

where, C_t is the concentration of NH_3 –N in downstream, Q_t is dam outflow, T_t is the temperature, ALK_T means alkalinity, C_{t-1}, C_{t-2}, C_{t-3} denotes the NH_3–N concentration of previous months, past two months and three months ago respectively. Architecture of Model II and Model III can be shown in Fig. 3 and Fig. 4.

4. APPLICATIONS AND RESULTS

The multiple nonlinear regression model and two neural network models developed in this study are applied to predict the monthly concentration of NH_3 –N in downstream of Daechung dam. The autoregressive characteristics of NH_3 –N are analyzed for determining the effective range of time lag. The amount of reservoir outflow, river water quality such as water temperature, pH, alkalinity, and NH_3 –N in previous time steps were selected as independent variables through correlation analysis with the state variable, NH_3 –N for next time step.

Three models are developed by using 72 monthly data between Jan. 1993 and Dec. 1998, and 24 months of data between Jan. 1999 and Dec. 2000 are used for verification. These data are measured and collected by Seuksung water treatment plant. The plant uses the raw water taken from pump station located in Geum river.

The model performances are evaluated by correlation coefficient between the observed and the predicted water quality. The determination coefficient values of three models are more than 0.92 as the results are shown in Ta-

Table 1. Comparison of models performance in training phase

Model	Architecture of model	Performance	
		R^2	RMSE
Model I	$C_t = f(Q_t, T_t, ALK_t, C_{t-1})$	0.92	0.38
Model II	$C_t = ANN[Q_t, T_t, ALK_t, C_{t-1}]$	0.99	0.14
Model III	$C_t = ANN[Q_t, T_t, ALK_t, C_{t-1}, C_{t-2}, C_{t-3}]$	0.99	0.14

Table 2. Comparison of models performance in training phase

Model	Architecture of model	Performance	
		R^2	RMSE
Model I	$C_t = f(Q_t, T_t, ALK_t, C_{t-1})$	0.92	0.15
Model II	$C_t = ANN[Q_t, T_t, ALK_t, C_{t-1}]$	0.90	0.23
Model III	$C_t = ANN[Q_t, T_t, ALK_t, C_{t-1}, C_{t-2}, C_{t-3}]$	0.95	0.13

ble 1. It shows the training results of each model. According to the results, it can be found that ANN models give more excellent predictive capability than multiple regression model. Time series plot of calibration results for each model (Jan. 1993 ~ Dec. 1998) can be seen in Fig. 5. Also the verification results are noted in Table 2. Time series plot of verification results for 24 months (Jan. 1999 ~ Dec. 2000) are presented in Fig. 6. Linear relationship between observed and predicted values can be seen in Fig. 7 ~ Fig. 9. As they are presented through the

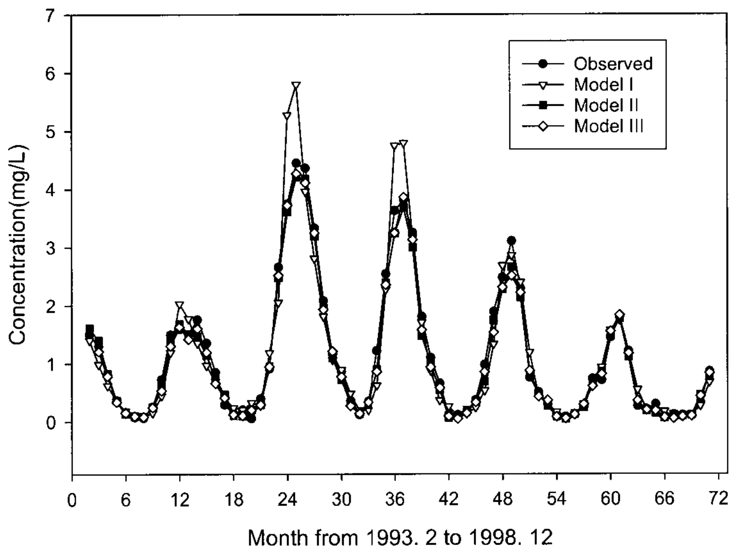

Fig. 5. Time series plot of calibration results for each model

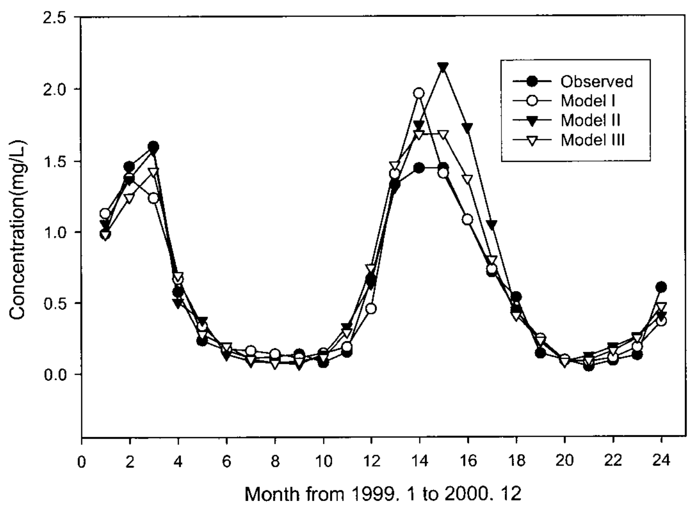

Fig. 6. Time series plot of verification results for 24 months

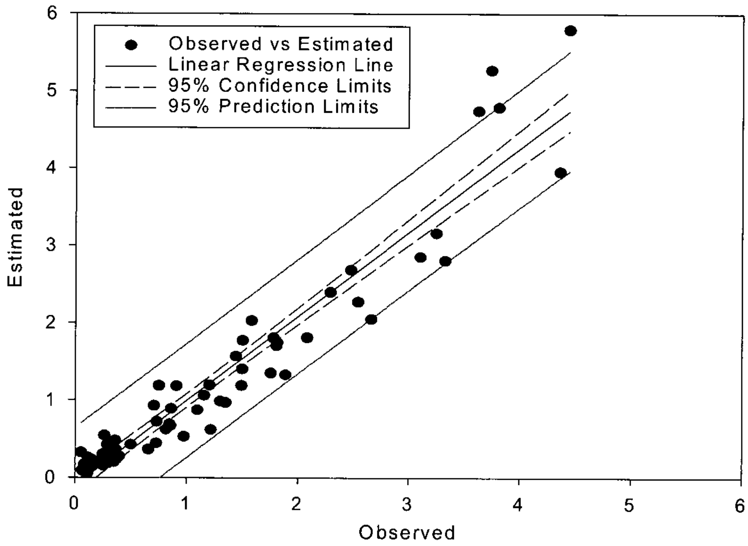

Fig. 7. Linear relationship between observed and predicted values of Model I

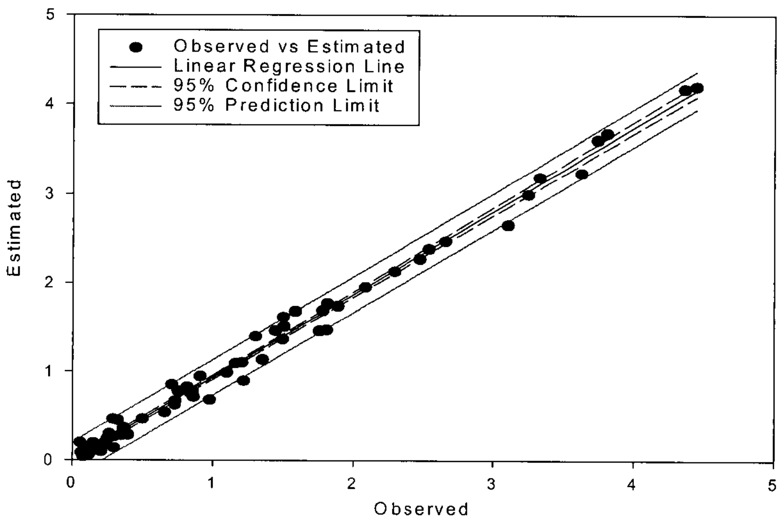

Fig. 8. Linear relationship between observed and predicted values of Model II

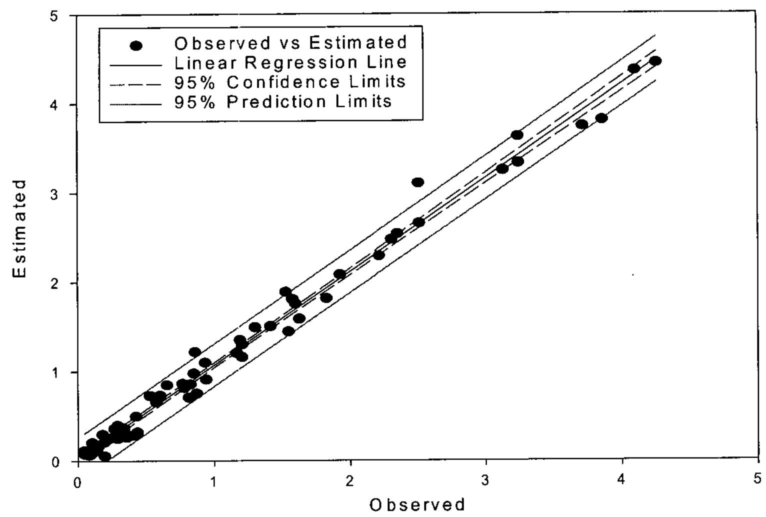

Fig. 9. Linear relationship between observed and predicted values of Model III

ranges of 95% prediction limits and confidence limits, the Model Ⅲ showed the best predicting performance among three models.

5. CONCLUSIONS

Two different types of water quality models were developed based on ANNs and a multiple nonlinear regression method to support the control of downstream water quality, ammonia nitrogen concentrations, during dry season through an approximate regulation of reservoir release. The model parameters were determined using monthly data collected in Geum River from Jan. 1993 to Dec. 1998. Then, the predictive performance of the models were tested using another set of monthly water quality and reservoir operation data. The results indicated that the performance of ANNs based model Ⅲ is best among the proposed models but model Ⅱ is not better than model Ⅰ which is based on multi- regression technique. It can be seen that not enough data series for training of ANNs can cause inaccurate prediction. In this case, it should be more careful to configure the neural network structure and determine input variables. Since the consideration of river water quality in the operation of river and reservoir systems is essential, the methodology suggested in this study can be a promising tool for the integrated water resources management. It is expected that further applications in this field is needed to improve the predictive capability.

REFERENCES

French, M.N., Krajewski, W.F., and Cuykendall, R.R. (1992). "Rainfall forecasting in space and time using a neural network." *J. of Hydrology, Amsterdam*, 137, pp. 1~31.

Hsu, K.L., Gupta, H.V., and Sorooshian, S. (1995). "Artificial neural network modeling of the rainfall-runoff process." *Water Resources Research,* 31(10), pp. 2517~2530.

Kim, J.H., Kang, K.W., and Park, C. Y. (1992). "Nonlinear forecasting of streamflows by pattern recognition method." *Korean J. of Hydroscience,* Korean Ed., Vol. 25, No. 3. pp. 105~113.

Kim, J.H. (1993). A study on hydrological forecasting of streamflows by using artificial neural network. Ph. D. Dissertation, Dept. of Civil Engrg., Inha Univ., Korea.

Lisboa, P.G.J. (1992). *Neural networks.* Chapman & hall, London, pp. 5~6.

Karunanithi, N., Grenney, W.J., Whitley, D., and Bovee, K. (1994). "Neural networks for river flow prediction." *J. Comp. in Civ. Engrg.,* ASCE, 8(2), pp. 201~220.

Roman, H. and Sunilkumar, N. (1995). "Multivariate modeling of water resources time series using artificial neural networks." *Hydrological Sci. J.,* 40(2) pp. 145~163.

Shamseldin, A.Y. (1997). "Application of a neural network technique to rainfall-runoff modeling." *J. Hydro., Amsterdam,* 199, pp. 272~294.

Zealand, C.M., Burn. D.H., and Simonovic, S.P. (1999). "Short term streamflow forecasting using artificial neural networks." *J. Hydro., Amsterdam,* 214, pp. 32~48.

Water Resources Operations Center, KOWACO, San 6-2, Yeonchuk-Dong, Daeduk-Gu, Daejeon, Korea.
(E-mail : schung@kowaco.or.kr)

Water Research Institute, KOWACO, 462-1, Jeonmin-Dong, Yusung-Gu, Daejeon, Korea.
(E-mail : juhwan@kowaco.or.kr)