Neural Network and Its Application to Rainfall-Runoff Forecasting

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ABSTRACT/It is a major objective for the management and operation of water resources system to forecast streamflows. The applicability of artificial neural network model to hydrologic system is analyzed and the performance is compared by statistical method with observed. Multi-layered perceptron was used to model rainfall-runoff process at Pyung Chang River Basin in Korea.

The neural network model has the function of learning the process which can be trained with the error backpropagation (EBP) algorithm in two phases; (1) learning phase permits to find the best parameters(weight matrix) between input and output.

(2) adaptive phase use the EBP algorithm in order to learn from the provided data.

The generalization results have been obtained on forecasting the daily and hourly streamflows by assuming them with the structure of ARMA model. The results show validities in applying to hydrologic forecasting system.

1. Introduction

One problem affecting the management and operation of water resources is the forecasting of streamflows in order to improve their availabilities and diminish flood damages. In the past ten years, improved computerized mathematical models have been used for the modeling and forecasting purposes. There are two different approaches tested. In the first, rainfall-runoff relation was considered as a stochastic process and the models were analyzed by relationships between the patterns of present and past data. In the stochastic approach a mathematical model based on the minimization of disturbance was established. This minimazation can be realized through the analysis of the correlation between input and output or by time series analysis. In the second approach deterministic

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model has been used which is physically formulated with the quantification of each component of runoff.

The process of rainfall–runoff has patterns as characteristics in the history and can be determined in some n–dimensional feature space from a set of relevant parameters. For the purpose of this study, daily and hourly rainfall and runoff data are used. The approach is discussed and presented based on formal neural network. The results show that it can be considered as a valid method in modeling hydrologic input and output system.

2. Conceptual bases of neural network model

Artificial neural network structure is based on understanding of biological neurons system and performs through dense interconnection of many computational elements(nodes) connected by links with variable weight. The node is characterized by an internal threshold and nonlinearity. Neural network model 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 perfomance.

A multilayer perceptron of nueral 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. The then produces its output signal by passing the summed signal through a sigmoid function.

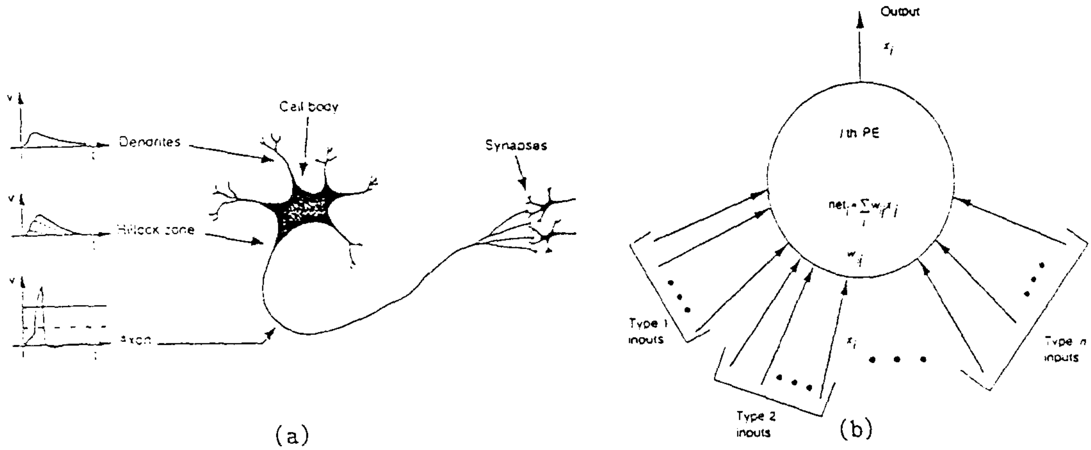


Fig.1 Biological neuron (a) and artificial neuron (b)

This method presents following advantages.

(1) It is structurally mixed method whose abilities to mimic permit to store all past data and adapt the network to last information seen.

(2) It is not necessary to keep in memory all the past data because the information is contained in the weights as parameters of the network.

(3) An explicitly built model of the studied phenomenon is not necessary.

(4) The nonlinearity of phenomenon, such as hydrologic process, can be reflected using nonlinear transfer function.

This method presents many of advantages of the nonlinear methods, adaptive methods and the statistical approaches.

3. Neural network forecasting system

One of the main features of neural network is the realization of a complex nonlinear mappings from n-dimensional input spaces to m-dimensional output spaces. The streamflows forecasting problem can be viewed as a pattern recognition. Different input patterns give rise to different output patterns. During training, the neural network would extract the relevant patterns from the input parameter and associate them with different output.

There are two points in using neural network for forecasting hydrologic process. The first point is to determine the network archtecture which is composed with the input layer, the output layer and the number and the size of the hidden layers. The second problem is to choose a forecasting algorithm. In this study, following models are assumed which is similar to time series model structure and applied using neral network architecture.

3.1 Description of model structure

The Autoregressive Moving Average model form is :

$$y_k = a_1 y_{k-1} + a_2 y_{k-2} + \cdots\cdots + a_r y_{k-r} + b_0 u_k + b_1 u_{k-1} + b_s u_{k-s}$$

where,

y_k : output(streamflow) at time k

u_k : input(rainfall) at time k

a_i : autoregressive parameters(total of r)

b_i : moving average parameters(total of s+1)

v_k : residual at time k

We applied the above method to the daily and hourly data in Pyung Chang River Basin and performed one step ahead forecasting. The system equations are expressed with ARMA model structure as follows;

Model Ⅰ $\quad y_{k+1} = f(y_k,\ u_k,\ u_{k-1})$

Model Ⅱ $\quad y_{k+1} = f(y_k,\ y_{k-1}\ u_k,\ u_{k-1})$

Model Ⅲ $\quad y_{k+1} = f(y_k,\ y_{k-1},\ y_{k-2},\ u_k,\ u_{k-1})$

Model Ⅳ $\quad y_{k+1} = f(y_k,\ y_{k-1},\ y_{k-2},\ u_{k+1},\ u_k,\ u_{k-1})$

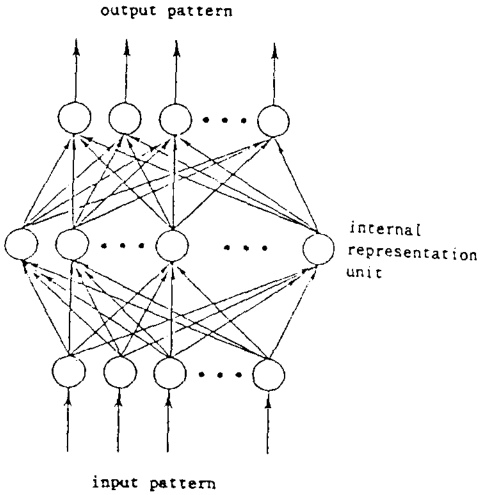


Fig. 2 Architecture of multi-layer perceptron

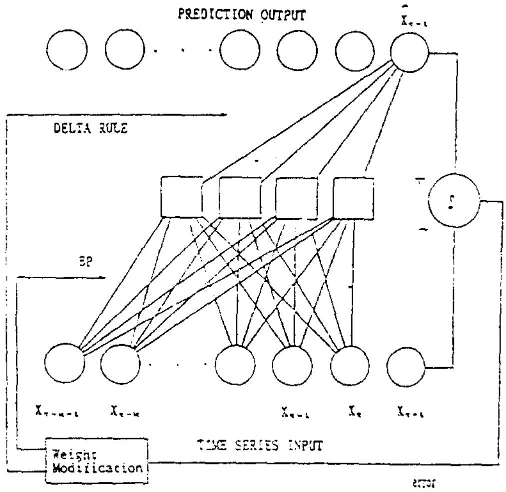


Fig. 3 Nonlinear predictor network with time series input

3.2 Training of forecasting system

In this paper, the generalized Delta rule is used to train a multilayer pceptron for forecasting. As an output, the streamflow 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 reachs 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 nodes, the state of node k is :

$$O_k = f(\Sigma_i W_{ik} O_i) \tag{1}$$

where $f(x) = 1/(1+e^{-x})$ 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

$$\frac{1}{2}(t_k - O_k)^2 \tag{2}$$

where node k is the output node.

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

$$\Delta W_{ij} \propto -\frac{\partial E}{\partial W_{ij}} = -\frac{\partial E}{\partial O_j}\frac{\partial O_j}{\partial W_{ij}} \tag{3}$$

Specially, we define the error signal as

$$\delta_j = -\frac{\partial E}{\partial O_j} \tag{4}$$

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

$$\Delta W_{ij} = \eta \delta_j O_i \tag{5}$$

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

$$\delta_i = (t - O_i)\, O_i\, (1 - O_i) \tag{6}$$

If node j is not in the output layer,

$$\delta_i = (t - O_i) O_i \Sigma_k \delta_k W_{jk} \tag{7}$$

In order to improve the convergence characteristics, we can introduce a momentum term with momentum gain to Equation (5).

$$\Delta W_{ij}(n+1) = \eta \delta_i O_i + \alpha \Delta W_{ij}(n) \tag{8}$$

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.

Table 1 Formation of network for each model

index	input unit	hidden unit	output unit	remark
Model Ⅰ	7	14	1	
Model Ⅱ	8	16	1	
Model Ⅲ	9	18	1	
Model Ⅳ	10	20	1	

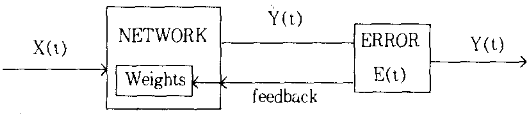
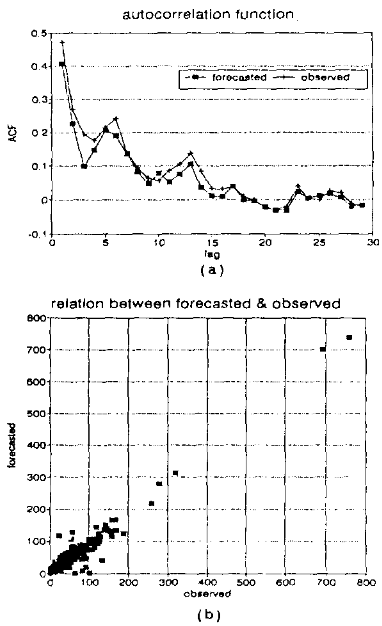


Fig. 4 Block diagram of error back propagation algorithm

4. Application results



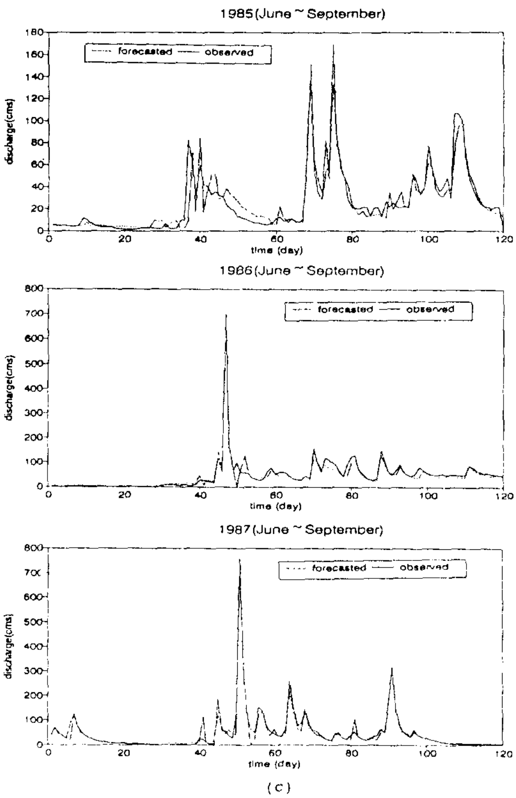
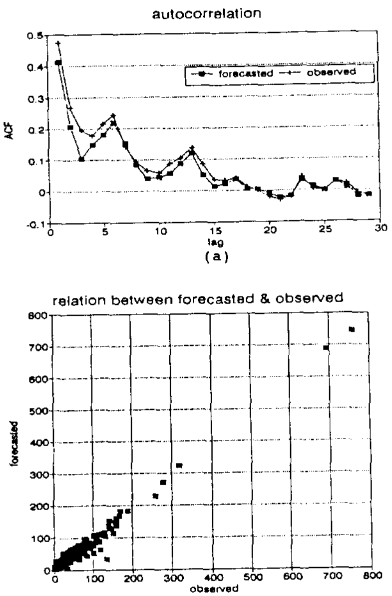


Fig. 5 Comparisons of results by Model Ⅲ
(a) autocorrelation function
(b) linear relationship between forecasted and observed data
(c) time series plotting



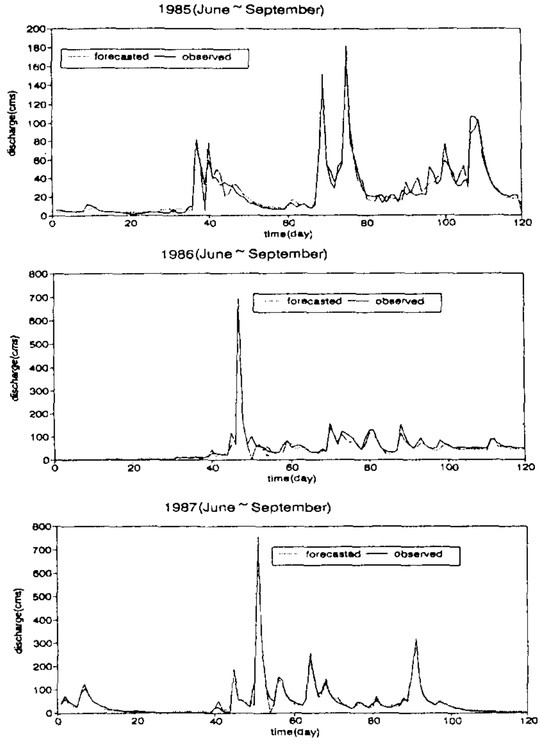


Fig. 6 Comparisons of results by Model Ⅳ
(a) autocorrelation function
(b) linear relationship between forecasted and observed data
(c) time series plotting

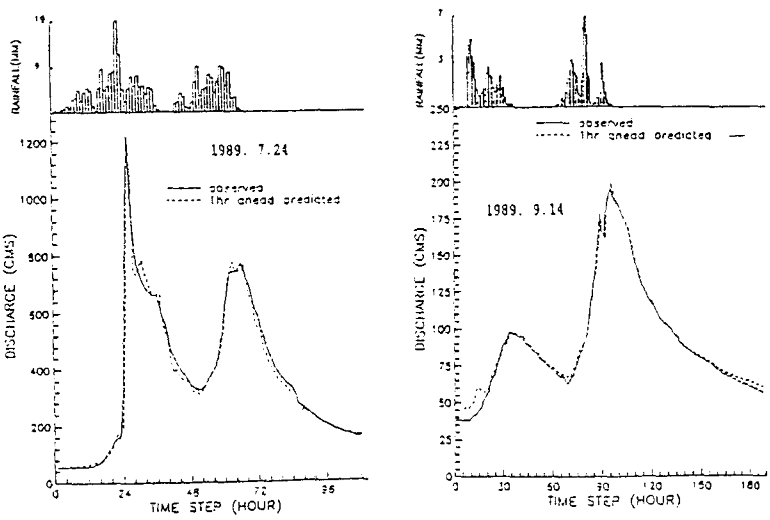


Fig. 7 Results of flood forecasting

In this section, the results of applied method are given. We use the model architecture in table 1 for forecasting of daily streamflows. In figure 5 and 6, the correlation, linear relationship and results are shown. Table 2 shows the result of frequency analysis. Their statistical properties are analyzed in table 3 for each model.

Another example is to forecast flood event using hourly data. We select 14 flood storms in the basin. The parameters are estimated by 12 storms and forecast two using obtained weight matrix.

Similar considerations are given to flood forecasting in determining model structure. The results are shown in Fig.7 and measured errors are given in table 4.

Table 2 Frequency table of the observed and forecasted daily data set

Class	Lower Limit	Upper Limit	Frequency				
			OBS.	Model I	Model II	Model III	Model IV
1	.00	29.23	194	199	201	194	195
2	29.23	58.46	106	92	105	101	94
3	58.46	87.69	35	38	30	38	36
4	87.69	116.92	12	18	12	11	15
5	116.92	146.15	6	8	7	11	10
6	146.15	175.38	3	4	4	3	7
7	175.38	204.62	2	1	1	0	1
8	204.62	233.85	1	1	0	1	0
9	233.85	263.08	0	0	0	0	1
10	263.08	292.31	1	1	1	1	1
11	292.31	321.54	1	1	1	1	1
12	321.54	350.77	0	1	0	0	0
13	350.77	380.00	0	0	0	0	0
14	380.00	409.23	0	0	0	0	0
15	409.23	438.46	0	1	0	0	0
16	438.46	467.69	0	0	0	0	0
17	467.69	496.92	0	0	0	0	0
18	496.92	526.15	0	0	0	0	0
19	526.15	555.38	0	0	0	0	0
20	555.38	584.62	0	0	0	0	0
21	584.62	613.85	0	0	0	0	0
22	613.85	643.08	0	0	0	0	0
23	643.08	672.31	0	0	0	0	0
24	672.31	701.54	1	1	1	1	1
25	701.54	730.77	0	0	0	0	0
26	730.77	760.00	1	0	1	1	1

Table 3 Comparison of statistical properties of daily models

index		Mean	Median	STD	Min.	Max.	Corr. Coeff.	Deter. Coeff.(R^2)
Model I	OBS.	40.63	25.78	66.81	0.08	757.77	0.946	0.896
	FOR.	39.95	25.66	56.23	0.12	696.86		
Model II	OBS.	40.72	25.78	66.88	0.08	757.77	0.970	0.941
	FOR.	37.50	24.10	63.66	0.08	755.25		
Model III	OBS.	40.81	25.78	66.95	0.08	757.77	0.971	0.941
	FOR.	39.56	25.14	64.09	0.13	736.79		
Model IV	OBS.	40.81	25.78	66.95	0.08	757.77	0.983	0.966
	FOR.	39.01	24.96	64.23	0.08	744.13		

Table. 4 Errors of one step ahead predicted results of flood events

No.	date of flood event	record length	S. E. F (%)	Absolute error(%)	Time series error(%)	R. M. S (%)
1	1983. 7. 2	166	10.164	1.870	0.053	4.316
2	1983. 7. 14	102	13.943	1.263	0.093	2.171
3	1984. 7. 2	139	20.330	3.088	0.446	6.149
4	1983. 8. 28	89	11.035	2.479	0.180	6.186
5	1985. 7. 10	136	0.054	2.318	0.182	5.442
6	1985. 8. 16	74	0.018	2.871	-0.072	6.387
7	1986. 7. 16	137	19.531	3.269	0.325	6.385
8	1986. 10. 10	150	0.047	0.956	0.080	2.541
9	1987. 6. 7	117	7.534	1.828	0.150	4.234
10	1987. 7. 21	113	13.049	4.128	0.346	7.742
11	1988. 7. 9	71	12.682	2.178	-0.267	3.330
12	1988. 7. 19	175	0.038	2.764	0.160	5.187
13	1989. 7. 24	108	0.196	3.938	0.511	8.767
14	1989. 9. 14	188	11.508	1.832	0.099	2.490

5. Conclusions

It is shown that hydrologic system model based on neural network provides validities in forecasting runoff series. It is possible to apply the neural network to modeling of hydrologic process due to the learning capacities of nonlinearity and the interpolation of input and output data. The learning process plays a role of mapping in the relationships between input and output data and means the estimation of optimal parameters of the system. So, the more learning continues by rule, the more accurate parameters can be estimated. Consequently, the neural network can reduce prediction error by estimated connection matrix among neurons.

By the characteristics of the network which is immune to distortion and noise, it provides the effects of filtering the hydrologic data with distortion and noise.

It is necessary to improve the procedure in modeling such as model architecture and the way to describe the number of neuron in each layer according to the dynamic behavior of hydrologic system. Further work is needed to establish more efficient approach for forecasting problems using neural network model.

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