DAILY RESERVOIR INFLOW FORESCASTS BY AN INPUT DELAYED NEURAL NETWORK MODEL

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1. INTRODUCTION

Input delayed artificial neural networks (IDNN) are dynamic artificial neural networks capable of accounting for nonlinearities and representing temporal information of input sequences. This work employs an IDNN for forecasting daily reservoir inflows to the reservoir that supplies water to the city of Matsuyama, in Japan. Scarcity of water is a periodical problem faced by this city and therefore, accurate forecast of daily reservoir inflows are very important for a more adequate real-time operation management[1].

2. STUDY SYSTEM

The study system consists of the Ishitegawa Dam reservoir, which is responsible for half of the water supply of Matsuyama and is also used for the irrigation of an area of approximately 550 ha. Figure 1 shows the layout of the system.

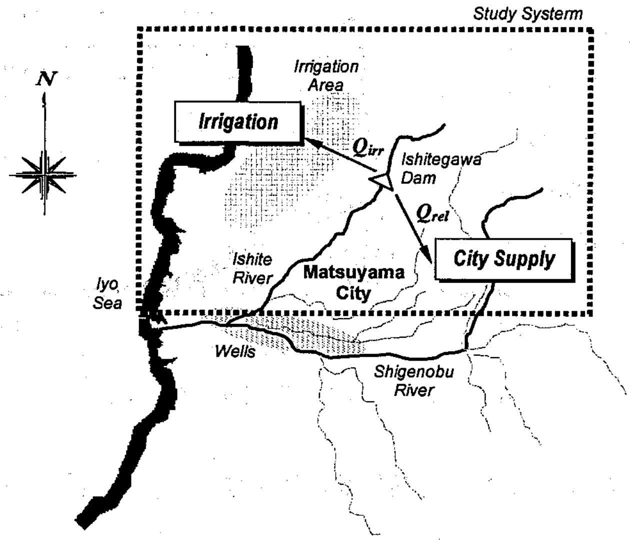

Figure 1 Study system.

3. INPUT DELAYED NEURAL NETWORK MODEL

IDNNs contain two components: a memory and an associator. The memory is responsible for holding the past information, which in this study is composed of two previous daily inflows, two previous daily rainfalls and the current-period rainfall. The associator is a multilayer perceptron network that relates the memory with the desired output, i.e., the current-period inflow. Thus, the memory component represents the temporal information and the associator accounts for the nonlinearity, making the IDNNs very suitable for time series modeling.

(1) Architecture

The architecture of the network is formed by the input layer, one hidden layer and the output layer. The input layer is composed of five neurons, which are two previous daily inflows, two previous daily rainfalls and the current-period rainfall. The number of neurons in the hidden layer is determined based on a trial-error procedure. The best training results were achieved with four neurons in the hidden layer. The current inflow is the single neuron of the output layer.

(2) Topology

For neural networks, not only the way neurons are implemented but also how their interconnections (topology) are made is important. In this study the network topology is constrained to be feed-forward, i.e., the connections are allowed from the input layer to the hidden layer and from the hidden layer to the output layer. Figure 2 illustrates the network topology of this study.

In this network, each element of the input vector is connected to each neuron in the hidden layer. The ith neuron in the hidden layer has a summation that gathers its weighted inputs and bias to form its own scalar output or induced local field. Each induced local field is submitted to an activation function so that they become the inputs of the output layer. The unique neuron in the output layer also has a summation that gathers its weighted inputs (from the hidden layer) and bias to form its induced local field. This induced local field is then submitted to the neuron activation function and becomes the final output or current inflow.

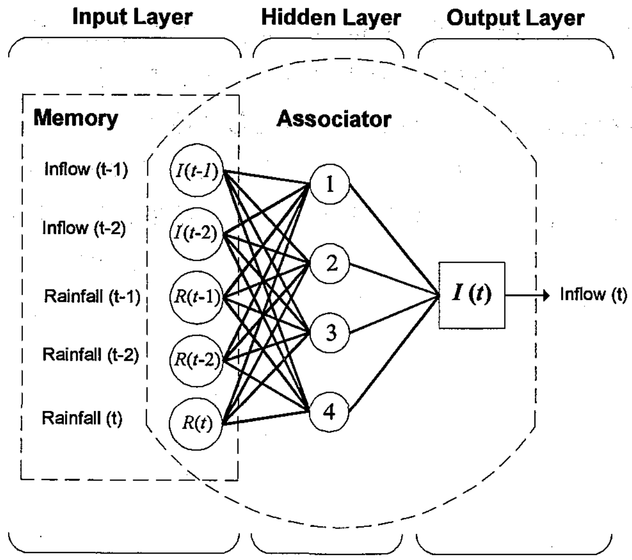

Figure 2 Topology of the IDNN.

(3) Activation functions

Continuous and differential functions are necessary for relating inputs and outputs of the artificial neural networks. According to Haykin[2] the sigmoid function is a good activation function for each neuron due to its generally accepted behavior. The tan-sigmoid function is chosen as the activation function for the hidden neurons. For the output layer neuron, a linear activation function is used.

(4) Training process

The original data (input and targets) are conveniently scaled before the IDNN training[3]. The training is performed by a back-propagation algorithm which has been successfully applied to water resources systems. In this approach, the Scaled Conjugate Gradient (SCG) method is used for the back-propagation. A detailed explanation of the SCG method is provided by Moller[4]. The network training is supervised, i.e., the series of weights between the neurons and the bias are adjusted through the iterations (epochs) in order to fit the series of inputs to another series of known outputs. The training also occurs in the batch mode. In this mode the weights and biases are updated only after the entire training set has been applied to the network.

The training process stops by means of the *Early Stopping Method*[3].

4. APPLICATION AND RESULTS

The IDNN model was applied for generating one-day-ahead inflows to Ishitegawa Dam reservoir. The historical data utilized in the procedure contain 7,305 days (1978 – 1997) of daily inflows. The IDNN was calibrated using the daily inflows of the first 7,055 days and the prediction test was carried out over the last 250 days. The model calibration used the *Early Stopping Method* and therefore, the training data set was divided in two subsets: the first was used for the IDNN model training, and the second for validation to specify when to stop the network training.

Figure 3 shows the scatter graph of IDNN-forecasted one-day-ahead inflows and training data. The correlation obtained for the model calibration revealed the very good accuracy reached by the IDNN.

The results from the prediction test are presented in Figures 4 and 5. Figure 4 shows that the IDNN-forecasted one-day-ahead inflows were very close to those from the observed data. The high correlation between observed and IDNN-forecasted inflows illustrated in Figure 5 proves that the IDNNs' capabilities of identifying nonlinear trends and representing temporal information are very appropriate for hydrologic time series modeling.

5. CONCLUSIONS

In this study, an input delayed artificial neural network model was implemented for generating one-day-ahead inflows to the reservoir that supplies water to the city of Matsuyama, Japan. The prediction test results were very reliable and hence may produce consistent data for the real-time operation of Ishitegawa Dam.

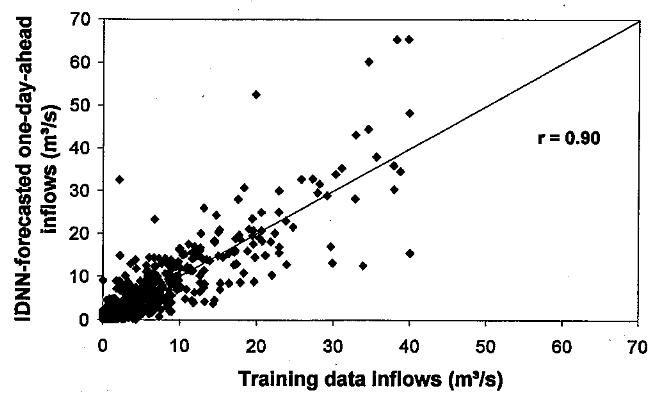

Figure 3 Scatter graph of IDNN-forecasted one-day-ahead inflows and training data inflows.

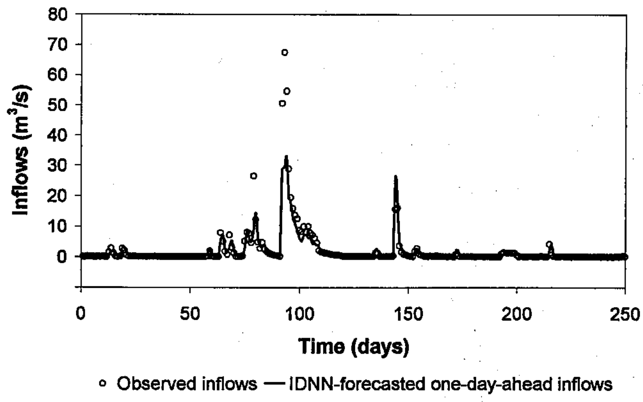

Figure 4 Prediction test results.

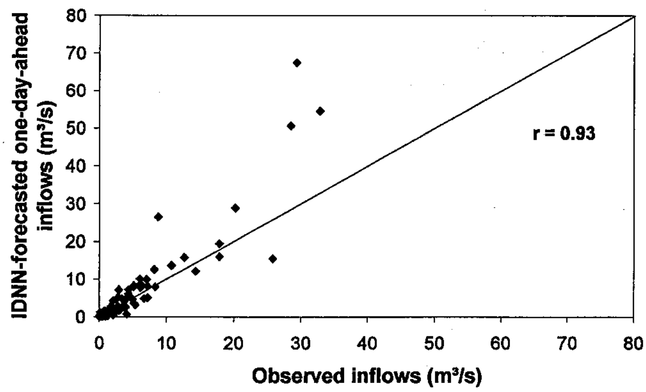

Figure 5 Scatter graph of IDNN-forecasted one-day-ahead inflows and observed inflows for the prediction test.

REFERENCES

1) Celeste, A.B., Suzuki, K., Kadota, A., Farias, C.A.S. (2004). "Stochastic generation of inflow scenarios to be used by optimal reservoir operation models." *Annual Journal of Hydraulic Engineering, JSCE*, Vol. 48, 451-456.

2) Haykin, S. (1999). "Neural Networks: A Comprehensive Foundation." *Prentice Hall, Inc.*, 2.ed, New Jersey.

3) Demuth, H., Beale, M. (2005). "Neural Network Toolbox." *MathWorks, Inc., MATLAB,* Version 4.

4) Moller, M. F. (1993). "Scaled conjugate gradient algorithm for fast supervised learning." *Neural Networks*, Vol. 6 (4), 525-533.