SINGLE-STEP-AHEAD MULTIVARIATE PREDICTION BY A FEEDFORWARD NEURAL NETWORK

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1. INTRODUCTION

Simulation and optimization models are commonly used in order to provide a sustainable management of the water resources[1), 2)]. However, the implementation of such models usually requires predictions of input variables such as groundwater levels and reservoir inflows. This work investigates the application of a feedforward artificial neural network (ANN) for multivariate prediction of daily reservoir inflows and groundwater levels in the water resources system of Matsuyama City, Japan.

ANNs process information analogously to the biological nervous system and are capable of extracting and detecting the most complex nonlinear trends among the variables in study[3), 4)].

2. STUDY SYSTEM

Matsuyama city water system is composed of a multipurpose reservoir and a set of 26 unconfined wells located around Shigenobu River, which is the main river of its hydrographic basin. The groundwater of Shigenobu River together with Ishitegawa Dam reservoir is used for supplying all the water needs of the city. Ishitegawa Dam is also used for irrigation and flood control in the region. Figure 1 shows the layout of the system.

3. FEEDFORWARD NEURAL NETWORK MODEL

(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 three neurons, which are the previous reservoir inflow $I(t\text{-}1)$, previous groundwater level $H(t\text{-}1)$, and current forecasted precipitation $P(t)$. The number of three neurons in the hidden layer was determined based on a trial-and-error procedure. The current reservoir inflow $I(t)$ and groundwater level $H(t)$ are the neurons 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 feedforward, 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.

(3) Activation functions

Continuous and differential functions are necessary for relating inputs and outputs of the artificial neural networks. According to Haykin[4)] 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 ANN training[5)]. The training is performed by a back-propagation algorithm which has been successfully applied to water resources systems. In this approach, the Levenberg-Marquardt (LM) method is used for the back-propagation. A detailed explanation of the LM method is provided by Hagan & Menhaj[6)]. The network

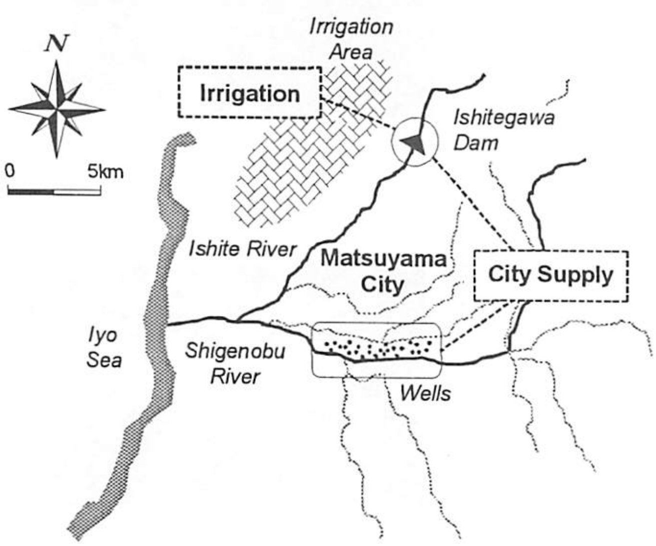

Figure 1 Study system.

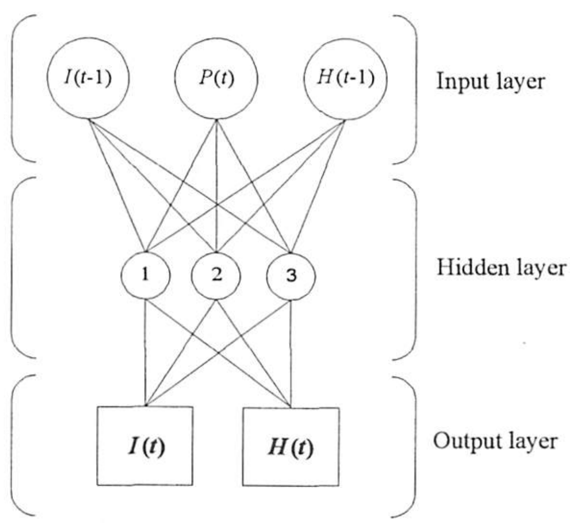

Figure 2 Topology of the feedforward ANN.

training is supervised, i.e., the series of weights between the neurons and the bias are adjusted through the iterations in order to fit the series of inputs to another series of known outputs.

The training process stops by means of the Early Stopping Method. This technique avoids a problem called overfitting that occurs during the neural network training. The network seems to be very well trained by showing very small errors from the training set data, but when new inputs are used the error is large[5].

4. APPLICATION AND RESULTS

An ANN model is employed for predicting daily reservoir inflows into Ishitegawa Dam and groundwater levels for one-step-ahead. The groundwater levels are measured at Minamitakai Observation Well, whose water table is used as a basis to operate the set of wells responsible for part of Matsuyama's water supply.

The observed data set for the ANN calibration and test was composed of 4,748 days (1991-2003). The model was calibrated using the first 3,653 days (1991-2000) and tested over the last 1,095 days (2001-2003). The ANN training used the Early Stopping Method and, therefore, the calibration data set was divided into two subsets: the first used 2,922 days (1991-1998) for the training process and the second used the other 731 days (1999-2000) for validation to specify when to stop the network training.

The correlation (r) and bias (B) statistical indexes were used as criteria for evaluating the performance of the ANN model used for generating the hedging rules. The correlation computes the variability of a number of predictions around the true value. Different from correlation, the bias is a measure of systematic error and thus calculates the degree to which the prediction is consistently below or above the actual value. High correlation alone does not mean high accuracy. For example, a significant constant bias in the predictions would provide the highest correlation (r = 1) but poor accuracy. As a result, the accuracy of predictions is better analyzed by using both bias and correlation. The perfect fit between observed and predicted values, which is unlikely to happen, would have $r = 1$ and $B = 0$. Salas[7] provides the equations to calculate these indexes.

The results from the prediction test for reservoir inflows and groundwater levels are presented in Figures 3 and 4, respectively. The high correlations and low biases observed in Figures 3 and 4 reveal that the ANN model could perform accurate predictions of reservoir inflows and groundwater levels for one-step ahead.

5. CONCLUSIONS

A feedforward artificial neural network model was implemented for generating one-day-ahead reservoir inflows and groundwater levels based on their previous daily values and the precipitation forecast. The prediction results suggest that this model may produce reliable data to be used by the optimization models being developed for the sustainable management of Matsuyama City's water resources system.

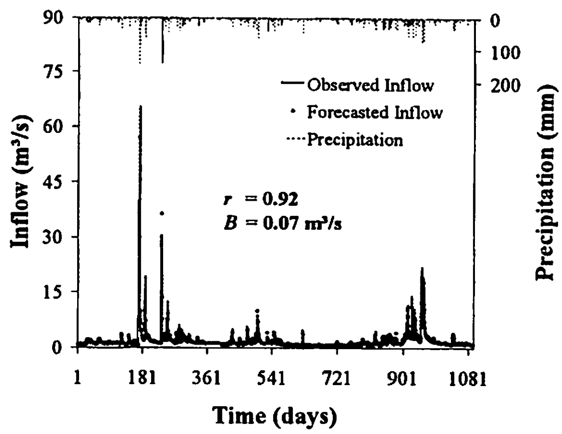

Figure 3 Comparison between observed and ANN-predicted reservoir inflows of the test data set for one day ahead.

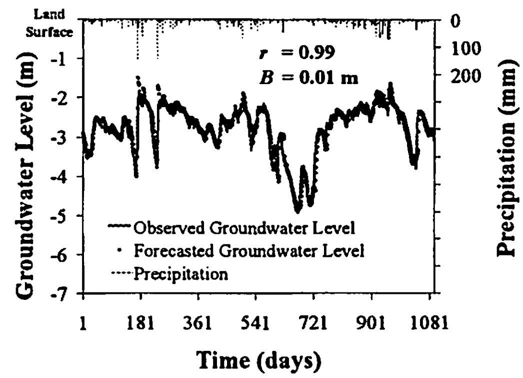

Figure 4 Comparison between observed and ANN-predicted groundwater levels of the test data set for one day ahead.

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