AN ELMAN NEURAL NETWORK FOR MONTHLY RESERVOIR INFLOW PREDICTION

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1. INTRODUCTION

Matsuyama City is located in Ehime Prefecture, Japan and has been suffering from periodical difficulties with the lack of water. In order to tackle the water shortage-related problems of this city, reservoir operation optimization models have been applied with the purpose of providing a more efficient management (Farias, 2006). However, for the implementation of these models it is frequently necessary to use forecasts of future reservoir inflows. This work investigates the application of an Elman Neural Network (ENN) model for predicting one-month-ahead reservoir inflows to Ishitegawa Dam, which is the reservoir that supplies water to the city of Matsuyama.

2. ELMAN NEURAL NETWORK MODEL

An ENN trained by the back-propagation algorithm is proposed for monthly reservoir inflow prediction. In this model, the network has feedback connections from the output of each hidden neuron to its input, which provide to the network a dynamic memory (Elman, 1990). These recurrent connections allow the ENN to implicitly detect and produce time-varying patterns, making them very suitable for time series modelling.

2.1. Architecture and Topology

The architecture of the network is formed by the input layer, one hidden layer, context units (elements that receive the values from the recurrent connections) and the output layer. The input layer is composed of three neurons, which are previous inflow, current-period forecasted rainfall and a dummy variable for identifying the current month. The number of neurons in the hidden layer and context units is determined based on a trial-error procedure. The best training results were achieved with four neurons in the hidden layer and therefore four context units. The current inflow is the single neuron of the output layer. Figure 1 illustrates the network topology of this study.

2.2. Activation functions

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.

2.3. Training process

The original data (input and desired outputs) are conveniently scaled before the training in order to improve the efficiency of the ENN. The scaling approach consists of normalizing the inputs and targets so that they will have mean and standard deviation equal to zero and one, respectively (Demuth & Beale, 2005).

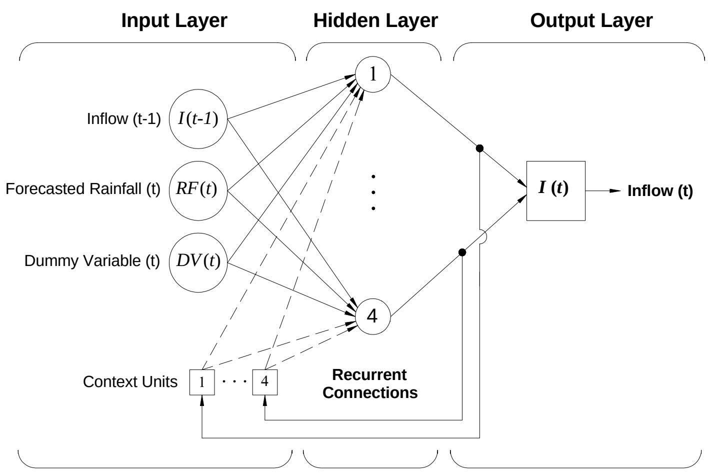

Figure 1 Topology of the ENN.

Key words: Elman Neural Network, Inflow Prediction, Reservoir Operation

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The training is performed by a back-propagation algorithm which has been successfully applied to water resources systems. In this approach, the Gradient Descend (GD) method is used for the back-propagation. A detailed explanation of the GD method is provided by Haykin (1999). 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. In order to improve generalization, the training is stopped by the Early Stopping method (Demuth & Beale, 2005).

3. APPLICATION AND RESULTS

The ENN model related the current-period forecasted rainfall and the previous reservoir inflow with the current inflow. The historical data utilized in the procedure contain 20 years of monthly inflows. The ENN was calibrated using the monthly inflows of the first 16 years and validation was carried out over the last four years. Figure 2 shows the scatter graph between historical and ENN-predicted inflows for the last four years of the data set. The relationships between the inflows from historical data and ENN are displayed in Figure 3.

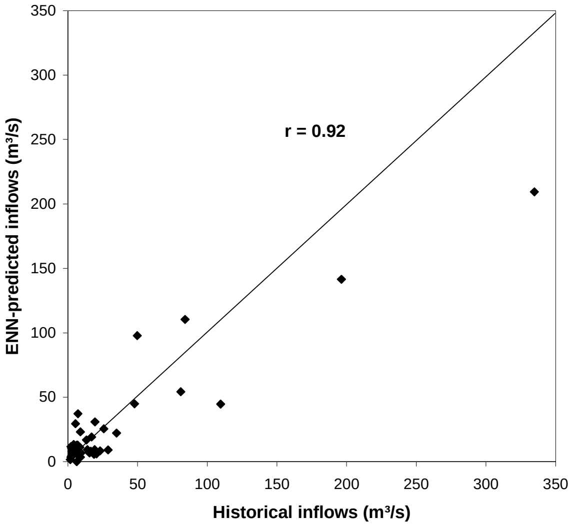

Figure 2 Scatter graph of historical and ENN-predicted inflows for the last four years of the data set.

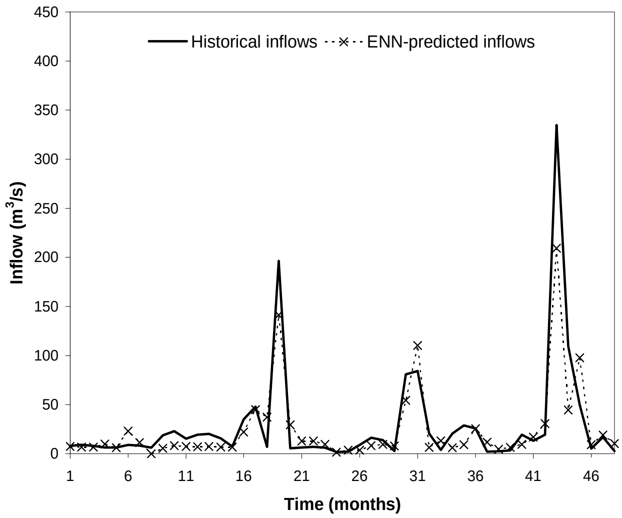

Figure 3 Comparison between historical and ENN-predicted inflows for the last four years of the data set.

The correlation between historical and ENN-predicted inflows was 92%. Observing Figures 2 and 3, the excellent accuracy obtained by the ENN suggests that they are very effective for predicting reservoir inflows.

4. CONCLUSION

An Elman Neural Network was employed for generating one-month-ahead inflows to the reservoir that supplies water to the city of Matsuyama, Japan. The ENN-based prediction results were very trustworthy and consequently may produce reliable data for the optimization models of Ishitegawa Dam.

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