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Long-Term Prediction of Discharges in Manwan Reservoir using Artificial Neural Network Models

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Abstract. Several artificial neural network (ANN) models with a feed-forward, back-propagation network structure and various training algorithms, are developed to forecast daily and monthly river flow discharges in Manwan Reservoir. In order to test the applicability of these models, they are compared with a conventional time series flow prediction model. Results indicate that the ANN models provide better accuracy in forecasting river flow than does the auto-regression time series model. In particular, the scaled conjugate gradient algorithm furnishes the highest correlation coefficient and the smallest root mean square error. This ANN model is finally employed in the advanced water resource project of Yunnan Power Group.

1 Introduction

Mathematical models are often employed to forecast the future trend of flow discharges in reservoirs. The long-term prediction results can be widely used in areas such as environmental protection, flood prevention, drought protection, reservoir control, and water resource distribution. This may have significant economic value in decision control of reservoirs and hydropower stations. Conventionally, factor analysis and hydrological analysis methods such as historical evolution method, time series analysis, multiple linear regression method and so forth, are used to forecast the long-term discharges. Nowadays, time series analysis and multiple linear regression method are the two most commonly used methods. The time series analysis is based on the decomposition of various factors into trend and cycle. After 1970s, autoregressive moving-average models proposed by Box et al. [1] are also widely used. Since 1990s, artificial neural network (ANN), based on the understanding of the brain and nervous systems, is gradually used in hydrological prediction. A comprehensive review of the application of ANN to hydrology can be found in ASCE Task Committee [2,3]. In this paper, the current development on the application of ANN in long-term prediction of flow is presented. Its prediction effectiveness is evaluated for the prototype case study in Manwan hydropower station.

2 Three Layer Feed-Forward back-Propagation Network Model

Figure 1 shows a typical three layer feed-forward back-propagation ANN. Among others, although the steepest descent method is the simplest, it has the drawbacks of slowest convergence and lack of effectiveness. In real ANN applications, the steepest descent method is seldom used. Haykin [4] discussed several data-driven optimization training algorithms such as Levenberg-Marquardt (LM) algorithm and scaled conjugate gradient (SCG) algorithm. In this paper, the SCG algorithm [5,6] is employed and the procedure is as follows [7]:

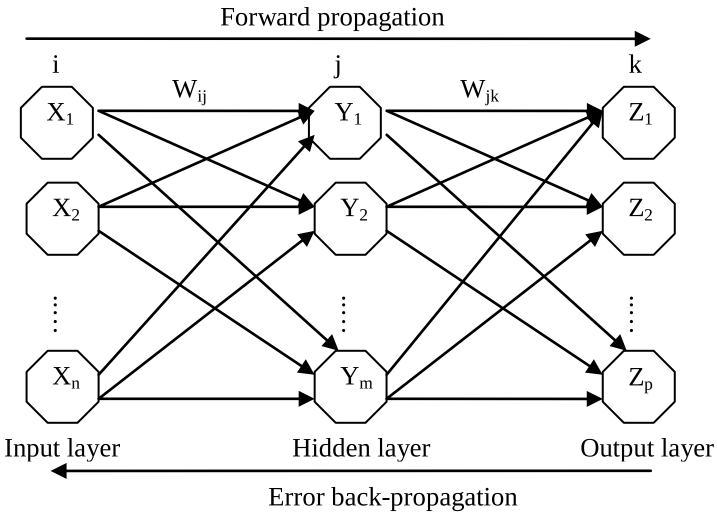

Fig. 1. Three layer feed-forward back-propagation neural network

1. The weight matrix w is initialized, with range from -0.5 to 0.5.

$$\vec{d}_0 = -\vec{g}_0 \tag{1}$$

where g_0 is the gradient of error function and d_0 is an initialized searching direction.

2. At the start of the generation number k, the learning rate α_k is determined from linear search via function $f(\vec{w} + \alpha_k \vec{d}_k)$ where $\vec{d}_k$ is the searching direction at the generation k. The weight matrix is adjusted through the following equation:

$$w_{k+1} = w_k + \alpha_k \vec{d}_k \tag{2}$$

3. If the error is smaller than the threshold value or the preset training generation is reached at the generation number k+1, the training process is terminated.

4. Otherwise, the new searching direction $\vec{d}_{k+1}$ is computed. If (k+1) is an integer multiple of dimension number of weight matrix w, then

$$\vec{d}_{k+1} = -\vec{g}_{k+1} \tag{3}$$

Otherwise,

$$\vec{d}_{k+1} = -\vec{g}_{k+1} + \beta_k \vec{d}_k \tag{4}$$

$$\beta_k = \frac{(g_k g_k^T)}{(g_0 g_0^T)} \tag{5}$$

5. Go back to step 2.

3 Application of ANN to Flow Prediction in Manwan

A three layer feed-forward back-propagation ANN model is employed for flow prediction in Manwan. It has four input neurons (Q_t, Q_{t-1}, Q_{t-2} and Q_{t-3}), four hidden neurons, and one output neuron (Q_{t+1}). Huang and Foo [8] found that, among different training algorithms, the SCG algorithm converges faster and attains a higher accuracy. The real daily flow data from 2001 to 2003 and monthly flow data from 1953 to 2003 are studied. All data are normalized to range between -1 and 1 first.

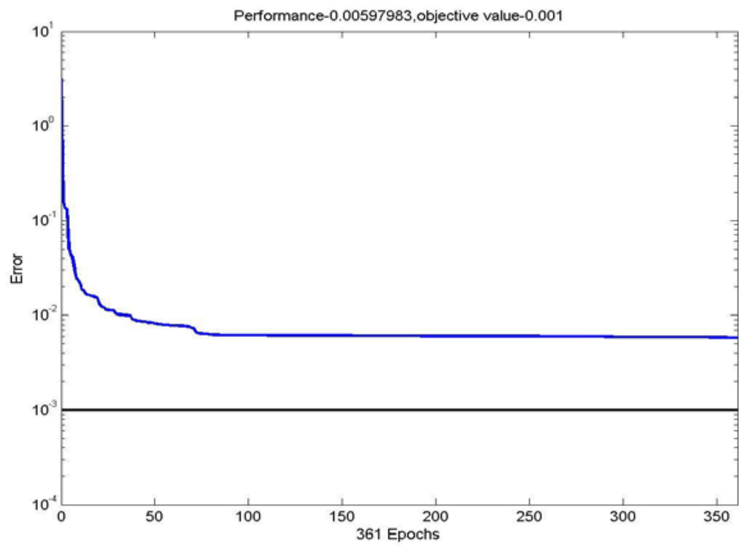

Fig. 2. Training results of daily flow data by ANN

3.1 Prediction of Daily Flow and Monthly Flow

Daily data for the entire year 2001 and those from 2002 to 2003 are used to train and verify the ANN model, respectively. Figure 2 shows that, after training for 361 sample points, the minimum error is only 0.00598. Figure 3 shows the verification results which give a correlation coefficient of 0.97 between the predicted and actual values and a root mean square error (RMSE) of 0.0087. It is demonstrated that the prediction of daily flow results is highly satisfactory. Similarly, monthly data from 1953 to 1993 and those from 1994 to 2003 are used to train and verify the ANN model, respectively. The prediction of monthly flow results is also satisfactory.

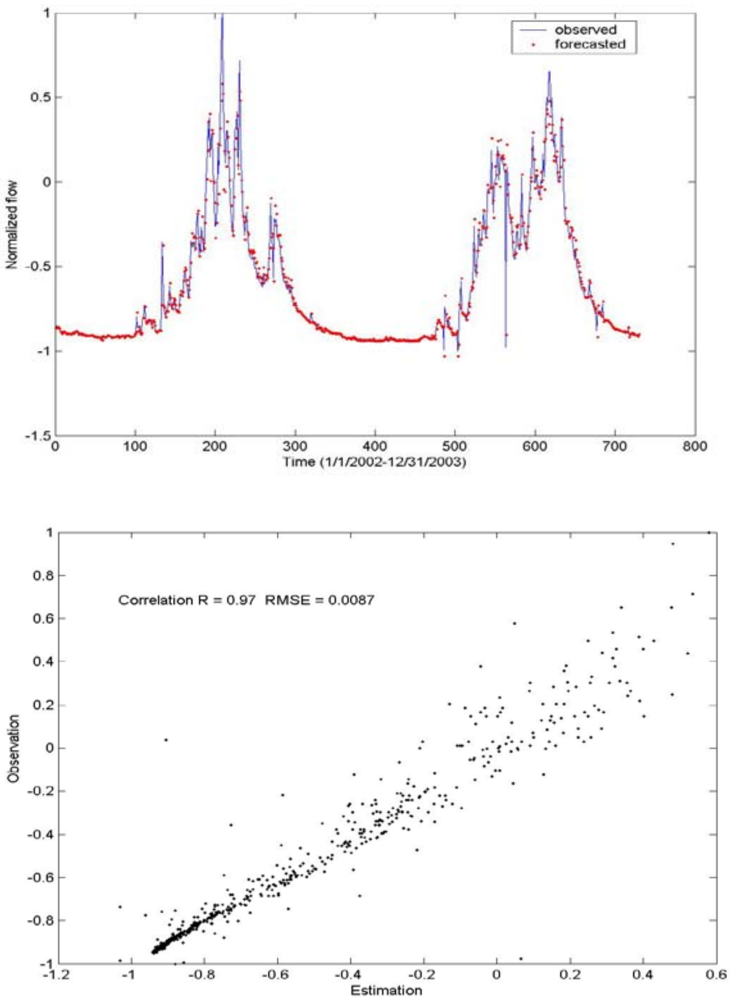

Fig. 3. Verification results of daily flow data by ANN

3.2 Sensitivity Analysis of Various Training Algorithms

Although many algorithms are available in training ANN, each one has its own advantages and limitations. Here, the gradient descent, LM and SCG algorithms are compared. All three algorithms undergo the training of ANN under the same conditions. Table 1 shows the simulation results, which show that the gradient descent algorithm has the slowest convergence, smallest correlation coefficient and the largest RMSE. On the other hand, the SCG algorithm has the highest accuracy and the LM algorithm converges most quickly.

4 Result Comparison with Time Series Model

Auto-regression time series model is a conventional time series prediction model. Owing to the simplicity of both the model and its data requirements, it has been widely applied in flow prediction [9]. Hence, it is used as the yardstick to gauge the performance of the ANN model in this case. In order to have the same basis of comparison, the same training and verification sets are used for both models. It is demonstrated that, when employed for flow prediction in Manwan, ANN exhibits distinct advantages over conventional time series model. Table 2 shows the performance comparison between ANN model and time series model for prediction of monthly flow. The correlation coefficient of ANN model is 0.89, which is larger than its counterparts of time series model (0.84). Moreover, the RMSE of ANN model is 0.03, which is much smaller than that of time series model (0.108).

Table 1. Sensitivity analysis of various algorithms for monthly flow prediction in Manwan

Training algorithm	Correlation coefficient	Normalized RMSE	Number of sampling points
Gradient descent	0.799	0.057	1000
LM	0.878	0.036	71
SCG	0.890	0.03	415

Table 2. Performance comarison between ANN model and time series model for prediction of monthly flow

Correlation coefficient		Normalized RMSE	
ANN model	Time series model	ANN model	Time series model
0.89	0.84	0.03	0.108

5 Conclusions

In this paper, an ANN model is used to predict long-term flow discharges in Manwan based on historical records. Data from 2001 to 2003 and from 1953 to 2003 are used for daily and monthly flow predictions, respectively. The results indicate the ANN model can give good prediction performance. The correlation coefficients between the prediction values and the observational values are 0.97 and 0.89 for daily and monthly flow analysis, respectively. The sensitivity analysis of the training algorithms show that the SCG algorithm can enhance the accuracy of model prediction results effectively. It is found, through result comparison with a conventional time series model, that the ANN model is able to give more accurate prediction. This demonstrates its distinct capability and advantages in identifying hydrological time series comprising non-linear characteristics.

6 Acknowledgement

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