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Predicting Streamflows Based on Neural Networks

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Abstract

A number of approaches has been proposed in the literature for predicting and forecasting monthly streamflows. Neural networks (NN) is a fairly recent technique which has been suggested and applied for many computational problems in water resources. NN and periodic transfer function models (PTF) are compared for forecasting monthly flows of the Rio Grande Basin. Forecast biases and root mean square errors (RMSE) obtained from both models are calculated. The results show that forecast biases are about the same for both methods. On the other hand, smaller RMSE's are obtained for forecasts based on neural networks models. The differences are specially significant when forecasts are made based on independent data sets.

Introduction

Existing methods for predicting and forecasting monthly and seasonal streamflows in many western states are based on the usual multiple regression analysis. However, this method has a number of shortcomings (see for instance, Tabios and Salas, 1982). In the past two decades a number of alternative forecasting approaches based on more structured models such as ARMA, ARMAX, and transfer function models became available. It has been well documented in the literature that for many water resources problems prediction and forecasting based on these methods are better suited than the conventional regression models (Wang and Salas, 1991).

More recently neural networks (NN) has been proposed for a number of applications in water resources. There is a rapidly growing interest among water

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resources specialists in using NN for various water resources problems. Some of the recent literature on the subject include: forecasting water quality (Dandy and Meir, 1993), predicting daily water demands (Zhang et al, 1993), flow forecasting (Zhu and Fujita, 1993; Lachtermacher and Fuller, 1993), and spatial interpolation (Rizzo and Dougherty, 1994). In this paper NN is applied for forecasting monthly streamflow in the Rio Grande Basin in Southern Colorado. The method is compared with a periodic transfer function model which was developed for that basin.

Neural Networks and It's Implementation

Neural networks is a computational algorithm which was developed to simulate the function of intelligent systems. Neural networks consists of neuron-like nodes that are arranged in layers and pass information through weighted connections. Figure 1 shows a a feed-forward neural network (FFNN) topology consisting of three layers, namely, an input layer, a hidden layer, and an output layer. The neurons in the hidden layer receive a weighted sum of a number of inputs. This sum is then transformed by an activation function, such as a step function and a sigmoid function, yielding the output of the neuron. For further description on artificial neural networks, see for instance Hertz et al.(1991).

The general dynamics of a FFNN can be expressed as

$$Y = f\left[\sum_{j=1}^{J} W_j \; f\left(\sum_{i=1}^{I} V_{ij} X_i - b_j\right)\right] \tag{1}$$

where, X_i, i = 1, ... , I, is the input vector (I = the number of input nodes) , V_{ij} is a weight for connecting the i-th input node to the j-th hidden node, b_j is a threshold value for the j-th hidden node, and W_j is a weight for connecting the j-th hidden node to the output. The function f (.) is an activation function for all nodes which performs a nonlinear transformation. The sigmoid function, $f(x) = 1/(1+e^{-x})$, was used in this study. Furthermore, J represents the number of hidden nodes and Y represents the output. For setting the weights of all connections between layers and the threshold values for all hidden nodes, the back-propagation (BP) learning algorithm structured by Rumelhart et. al (1986) was used. BP algorithm uses the concept of the gradient descent method for minimizing the sum of square error of the output values as

$$E = \frac{1}{2} \sum_{t=1}^{N} (Y_t - \hat{Y}_t)^2 \tag{2}$$

where, Y_t , $t = 1, \ldots , N$, are the observed output values, $\hat{Y}_t$, $t = 1, \ldots , N$, are the output values estimated from Eq.(1), and N is the sample size of training data (input-output pairs). The foregoing FFNN and BP algorithm were implemented for forecasting monthly streamflows. Two cases were considered. Case 1, where monthly streamflows are forecasted based on monthly snow water equivalent, and Case 2, where the forecasts are based on monthly snow water equivalent and monthly temperature.

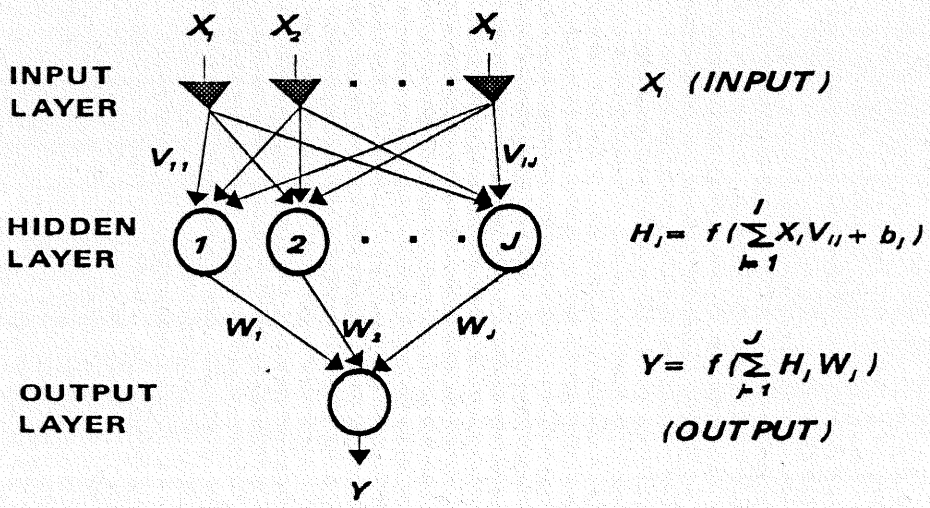

Figure 1. Schematic Diagram of Feed-Forward Neural Networks

In Case 1, Eq.(1) is applied considering four input nodes, and one hidden node

$$Z_{\nu,\tau} = f\,[\,W_1\, f(Z_{\nu,\tau-1}V_{11} + X_{\nu,\tau}V_{21} + X_{\nu,\tau-1}V_{31} + X_{\nu,\tau-2}V_{41} - b_1)] \tag{3}$$

where, $Z_{\nu,\tau}$ is standardized streamflow for month τ and year ν , $X_{\nu,\tau}$ is monthly standardized snow water equivalent, and W_1, V_{11}, V_{21}, V_{31}, and V_{41} are weights as defined previously. Since the sigmoid activation function has the range 0 to 1, the variables $Z_{\nu,\tau}$ and $X_{\nu,\tau}$ were standardized to the 0 - 1 range. In Case 2, the monthly snow water equivalent and temperature are the input variables, and the monthly streamflow is the output. In applying Eq. (1), the foregoing input variables are considered : previous month flow, the current and two previous months snow water equivalent, and the current and two previous months temperature. Thus, Eq.(1) with seven input nodes, one hidden node, and one output node takes the form

$$Z_{\nu,\tau} = f(\,W_1\, f(\mathbf{X} \cdot \mathbf{B}^T - b_1)) \tag{4}$$

where $$\mathbf{X}^T = [\,z_{\nu,\tau-1}, X_{\nu,\tau}, X_{\nu,\tau-1}, X_{\nu,\tau-2}, T_{\nu,\tau}, T_{\nu,\tau-1}, T_{\nu,\tau-2}\,]$$

and $$\mathbf{B}^T = [\,V_{11}, V_{21}, V_{31}, V_{41}, V_{51}, V_{61}, V_{71}\,]$$

in which, **X** is the vector of input variables, **B** is the vector of weights between input nodes and the hidden node, and W_1 is the weight between the hidden node and the output node. $Z_{\nu,\tau}$, $X_{\nu,\tau}$, and $T_{\nu,\tau}$ are variables representing streamflow, snow water equivalent, and temperature, respectively, for month τ and year ν, and all variables are in standardized values.

Applications

The methodology described above was applied to forecast monthly streamflows of the Rio Grande Basin in Southern Colorado. Monthly snow water equivalent, monthly temperature, and monthly flows at the Del Norte gauging station, for the period 1948-1987 were available. The data were divided into training data (1948-1977) for estimating the parameters of the models, and testing data (1978-1987) for testing the forecast results with an independent data set. The forecast based on neural networks (NN) was compared with forecasts obtained based on periodic transfer function (PTF) models reported by Wang and Salas (1991). All forecasts comparisons were made for the months of May through August.

Forecasts performances for both models are expressed in terms of forecast bias and forecast root mean square error (RMSE). All results are given in standardized flow values for both training and testing phases. Table 1 shows biases and RMSE's obtained based on PTF and NN models for Case 1, while Table 2 shows results for Case 2. Tables 1 and 2 show that the forecast biases for both models (PTF and NN) are practically negligible for the training phase. The biases for the testing phase are not negligible and although some differences are observed, overall both models appear to give quite similar biases. Note also that biases for the testing period become much smaller for Case 2, because of the addition of temperature in the forecasting functions. Tables 1 and 2 also show that for the training phase the RMSE's are slightly smaller for the NN model than for the PTF model, but the differences are somewhat more significant for the testing phase. In addition, comparing between Cases 1 and 2, the RMSE's for both models become significantly smaller for Case 2. The comparison between the RMSE's obtained by both models can be seen more clearly in Figure 2 for Case 1, and Figure 3 for Case 2.

Table 1. Comparison of Forecast Biases and RMSE's in Standardized Values Obtained Based on PTF and NN Models for Case 1. Averages are for Absolute Values.

	Month	Training		Testing	
		PTF	NN	PTF	NN
Bias	May	0.000	0.002	-0.508	-0.507
	June	0.000	0.001	0.106	0.069
	July	0.000	0.000	0.469	0.327
	August	0.000	0.007	0.023	0.068
	Average	0.000	0.002	0.276	0.243
RMSE	May	0.536	0.537	0.728	0.727
	June	0.427	0.399	0.487	0.434
	July	0.434	0.422	0.735	0.553
	August	0.427	0.431	0.629	0.656
	Average	0.456	0.447	0.645	0.592

Table 2. Comparison of Forecast Biases and RMSE's in Standardized Values Obtained Based on PTF and NN Models for Case 2. Averages are for Absolute Values.

	Month	Training		Testing	
		PTF	NN	PTF	NN
Bias	May	0.000	0.000	0.035	-0.101
	June	0.000	0.000	0.127	-0.107
	July	0.000	0.000	0.263	0.264
	August	0.000	0.011	0.008	0.055
	Average	0.000	0.003	0.108	0.132
RMSE	May	0.338	0.322	0.431	0.416
	June	0.327	0.317	0.514	0.399
	July	0.374	0.320	0.597	0.492
	August	0.426	0.427	0.623	0.656
	Average	0.366	0.346	0.541	0.491

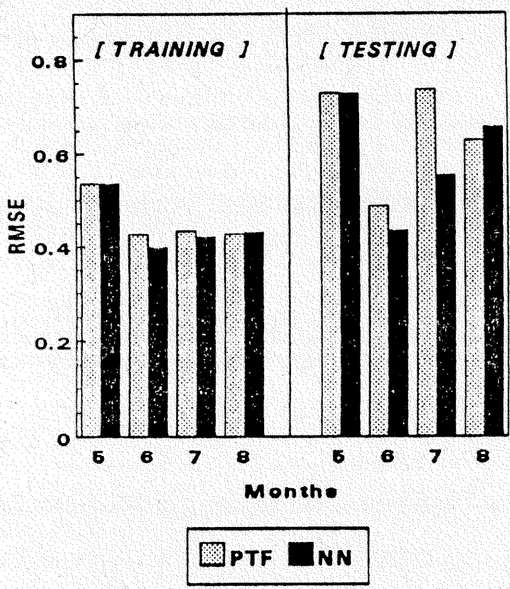

Figure 2. RMSE's for Training and Testing Based on PTF and NN Models (Case 1)

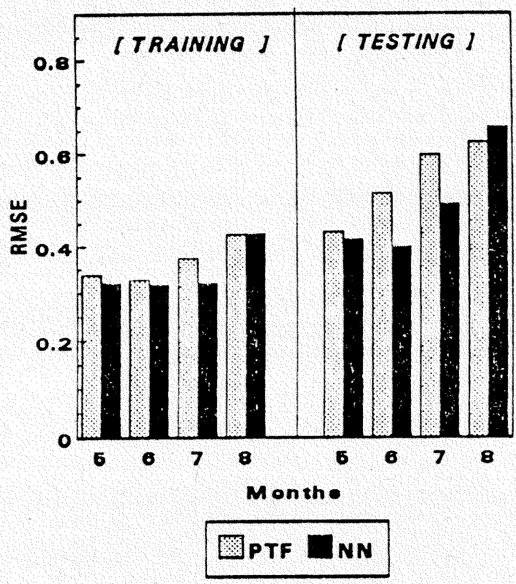

Figure 3. RMSE's for Training and Testing Based on PTF and NN Models (Case 2)

Conclusions

The main purpose of this study was to compare the neural networks method and the periodic transfer function method for forecasting monthly streamflows. The comparisons were made by using data of the Rio Grande Basin in Southern Colorado.

Forecast biases and forecast root mean square errors for both the training and the testing phases were the basis of the comparisons. The results showed that forecast biases are about the same for both methods. On the other hand, some differences between the methods are observed for the RMSE's. Generally, smaller RMSE's are obtained for both the training and the testing phases for forecasts made based on the NN method. The differences are specially significant for the testing phase which is important from the practical standpoint.

Acknowledgments

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Appendix I: References

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