American Journal of Environmental Sciences 1 (1): 86-89, 2005
ISSN 1553-345X

Application of Rainfall-runoff Models to Zard River Catchment's

[1]M.B. Rahnama and [2]G. A. Barani
[1]Department of Irrigation, Shahid Bahonar University, Kerman, Iran
[2]Department of Civil Engineering, Shahid Bahonar University, Kerman, Iran

Abstract: Rainfall-runoff models are nonlinear processes according to the sequential and spatial distribution of the rainfall. So, it is difficult to explain the response of catchments systems with the simple models. In the present work simulation of the rainfall-runoff processes have been carried out by the Artificial Neural Networks (ANN) and the HEC-HMS models. The ANN models of Multi Layer Perceptron (MLP) with two hidden layers and Radial Basis Function (RBF), were used to simulate this process. It has been applied to the Zard river basin in Khuzestan province using daily rainfall and runoff data, during the period of 1991 to 2000. During this period, 14 flood events were selected to simulate rainfall-runoff processes by the HEC-HMS model. Results of two models were compared with the observed data of Zard river basin. It is shown that RBF model is much better than, MLP and HEC-HMS models for simulating of the rainfall-runoff process in Zard river basin.

Key words: Artificial Neural Network, HEC-HMS model, Rainfall-runoff Process, Zard River Catchment's

INTRODUCTION

Simulation of rainfall-runoff process is very important in water resources management, river engineering, flood control and utilization of surface and groundwater. Due to existence of various basin hydrologic factors, response to the rainfall-runoff phenomena are very complex. Runoff depends on the basin geomorphologic properties (such as geometry, vegetations covering and soil type) and climate characteristics such as rainfall, temperature, etc. The effects of these factors are not uniform in runoff prediction. Up to now many models, such as HEC-HMS model, have been suggested to simulate this process. These models have required a lot of catchments and climate information, such as rainfall, evapotranspiration, soil infiltration, initial losses, time of concentration, etc. Recent development of technology causes, many world scientific communities become interested to use different branches of artificial intelligence, such as neural networks. With the same logic, hydrologists also were interested to use these techniques to simulate the hydrologic processes [1]. Artificial neural networks (ANN) are simple models of human's brain. These models are nonlinear mathematical structures that have ability to show the nonlinearity process for communicating between inputs and outputs of any system [2]. The network of these models can be trained with an exciting of a system and then it can be used for future date prediction of that system. Generally, each ANN model is formed with a number of layers each built-up with some neurons. Neurons are the smallest unit of an ANN model constructor and are comparable to human brain cells. Each network has been formed with input, output and one or more hidden layers. Neurons of each layer are connected to next layer by weights. During the network training process, weights and values which called bias are frequently changed until the objective functions are satisfied. For transferring outputs of each layer to the others, activation functions are used. The technique is adopted for access of weights and biases to ideal values called "Learning Rule", which is almost a complex mathematical algorithm [3]. Each ANN model needs two data sets, one for create an acceptable train set and the other for test set. Usually about 80% of data are used for train set and the remainder for test set. During the training process, network learning rate is regularly measured by objective functions and finally a network will be acceptable which has less value of error and maximal correlation coefficient. The objective functions such as, Root Mean Squared Error (RMSE), the Sum Squared Error (SSE) and the correlation coefficient (R^2) which can be calculated by the equations 1 to 3, (as follows), are used [4].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2} \tag{1}$$

$$SSE = \sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2 \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2}{\sum_{i=1}^{n}(Q_i - \overline{Q}_i)^2} \tag{3}$$

Where, Q_i is the observed data, $\hat{Q}_i$ is the forecasting data and $\overline{Q_i}$ is the average of observed data.

Multi Layer Perceptron (MLP) Neural Network: The MLP neural network structure is shown on Fig. 1. In this network, each input-layer has been entrance to next hidden-layer neurons and it is continued to import the network's output. Training algorithms of MLP neural network are based on Back Propagation algorithm (BP) [5].

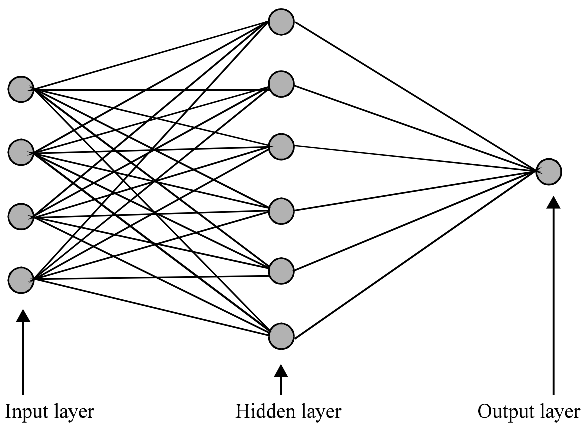

Fig. 1: Multi Layer Perceptron (MLP) Neural Network

Learning process in MLP neural networks can be carried in three steps, forward, backward and computation iterance passes. The input value to the each neuron is given by:

$$net_i^n = \sum W_{ji}^n . o_j^{n-1} \qquad (4)$$

Where, net_i^n is the input value of ith neuron in nth layer, W_{ji}^n is the connection weights between ith neuron in nth layer and jth neuron in the (n-1)th layer; o_j^{n-1} is the output of jth neuron in the (n-1)th layer and n is the number of neurons in the (n-1)th layer.

The output of each neuron will be obtained after applying the activation function. The common activation function used in back propagation algorithm is a Sigmoid function. The output value of each neuron can be calculated by:

$$Sig(net_j^n) = \frac{1}{1+\exp(-net_j^n)} \qquad (5)$$

Radial Basis Function (RBF) Neural Network: The RBF network structure is shown on Fig. 2. The main differences between this network and MLP network are as follows [6]:

* The RBF network activation functions of neurons are Gussian function with particular center and spread for each hidden layer.
* There are not weights between input layer and hidden layer and the distance between each pattern and center vector of each neuron in hidden layer is used as an input of Gussian activation function.
* In this network, activation functions of output neurons are simple linear functions and because of this reason we can use linear optimum algorithms. They have been caused to improve the processing rate and prevent to fall in local minimums that deal with there at learning process in MLP network.

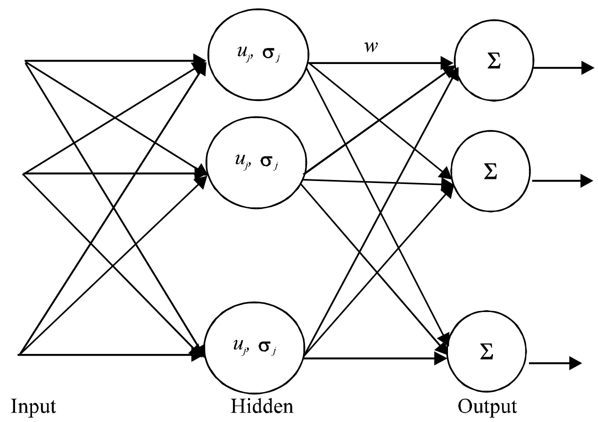

Fig. 2: Radial Basis Function Neural Network

Output of jth hidden neuron given by:

$$h_j = \exp\left\{\frac{-\left\|X^i - U_j\right\|}{2\sigma_j^2}\right\} \qquad (6)$$

Where, U_j and σ_j are the center and the spread of Gaussian function respectively and X^i is the ith input vector.

HEC-HMS Program: The HEC-HMS program was developed at the Hydrologic Engineering Center (HEC) of the US Army corps of engineers. This program advantages is ability to parameters optimization. It is used for simulation of rainfall-runoff process by losses, direct runoff and base flow that each of those calculated by different methods. In this research the SCS curve number to losses calculation, SCS unit hydrograph to runoff and exponential recession model for the calculation of base flow were used [4].

Case Study (Zard River Basin): The Zard river basin is located in the Khuzestan province in southwest of Iran. This basin with 875 square kilometers area and 70 kilometers length of main channel has an average slope of about 3%. In this basin there are six precipitation gages and one hydrometric station, as shown in Fig. 3. Rainfall and runoff data of this basin from years 1990 to 2000 were used to the above models.

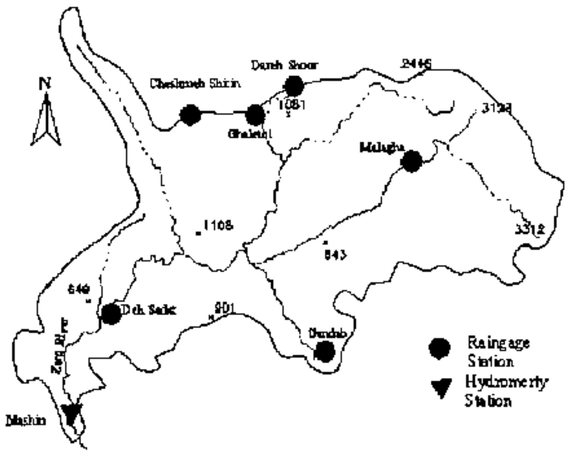

Fig. 3: Zard River Basin

RESULTS AND DISCUSSION

The target of this research was estimation of river discharge in a number of events. For training of MLP and RBF models part of Zard river basin rainfall data were used as an input and stream flow data as output. Also, the MLP model was used in two different structures, with one and two hidden layer. To simulate the above mentioned models, the MATLAB software was used. Results are shown in Fig. 4-6. Also the amounts of RMSE were calculated using the test data series for MLP one and two hidden layers and RBF models. As it shown in the Fig. 4-6 and Table 1, it can be conclude that the RBF model has a better ability than the MLP model to predict stream flow data.

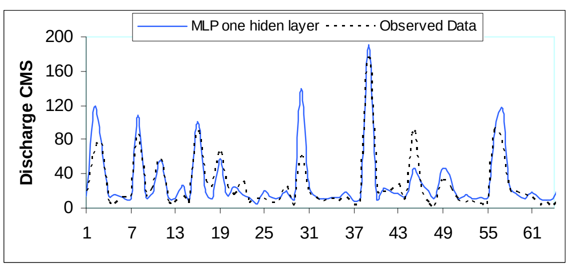

Fig. 4: Comparison between Observed and MLP-one Hidden Layer Model Data

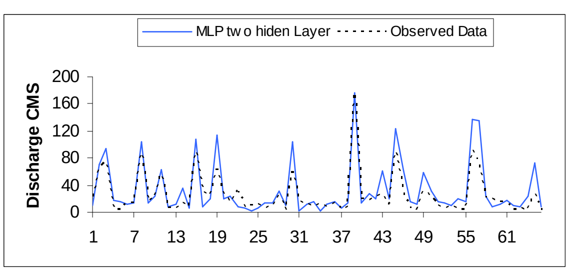

Fig. 5: Comparison between Observed and MLP-two Hidden Layer Model Data

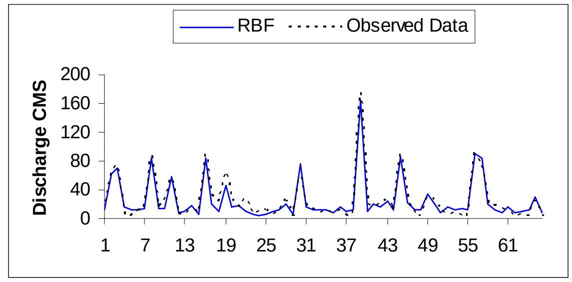

Fig. 6: Comparison Between Observed and RBF Model Data

Table 1: The Amount of RMSE Calculated Using the Test Sires for MLP & RBF Models

Flow ranges CMS	MLP one hidden layer	MLP two hidden layers	RBF
0-20	7.06	8.52	5.45
20-40	11.15	21.74	9.78
40-60	1.64	4.20	0.08
60-80	47.80	41.98	12.38
>80	23.37	27.55	7.02

The 14 flood events were simulated and required parameters were optimized with use of HEC-HMS program. To compare the MLP and RBF models with HEC-HMS model one of the flood events that weren't used in previous simulations are calculated using these models, results are shown in Fig. 7.

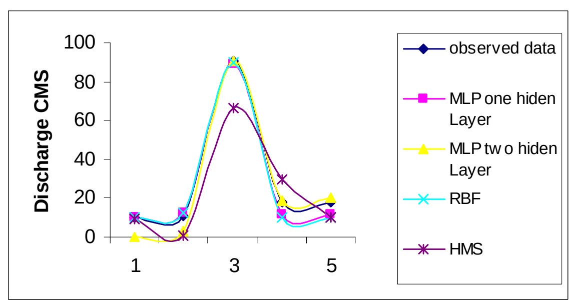

Fig. 7: Comparison between MLP, RBF and HEC-HMS Model

From the results that are plotted on Fig. 7, it can be concluded that RBF and MLP model are stronger than HEC-HMS model to predict stream flow data.

CONCLUSION

In general ANN is a technique, which solves the nonlinear and complex nature of a catchments system. It is required an accurate and long series of input data. And if non-adequate data is given, the inaccurate output data will be obtained. Both ANN and HEC-HMS models have their own advantages. The HEC-HMS model if calibrated for a basin then can be used to estimate the stream flow in ungaged catchments. The advantage of ANN model is that the data prediction is based on the in previous time interval data.

REFERENCES

1. Dawson, C.W. and R.L. Wilby, 2001. Hydrological modeling using artificial neural networks. Progress in Physical Geography, 25: 80-108.
2. Hsu, K., H.V. Gupta and S. Sorooshian, 1995. Artificial neural network modeling of the rainfall-runoff process. Water Resources Research, 10: 2517-2530.
3. Sajikumar, N. and B.S. Thandaveswara, 1999. A nonlinear rainfall- runoff model using neural network. J. Hydrol., 216: 32-55.
4. Shamseldin, A.Y., K.M. Conner and G.C. Laing, 1997. Methods for combining the outputs of different rainfall-runoff models. J. Hydrol., 197: 203-229.
5. Imrie, C.E., S. Durucan and A. Korre, 2000. River flow prediction using artificial neural networks: generalization beyond the calibration range. J. Hydrol., 233: 138-153.
6. Jayawardena, A.W., D. Achela and K. Fernando, 1998. Use of radial basis function type artificial neural networks for runoff simulation. Computer-Aided Civil and Infrastructure Engineering, 13: 91-99.