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Developing of Halil River Rainfall-Runoff Model, Using Conjunction of Wavelet Transform and Artificial Neural Networks

Mohamad Bagher Rahnama and Mojtaba Noury
Department of Irrigation, Agriculture College, Shahid Bahonar University of Kerman,
22 Bahman Blv., P.O. Box 7616914111, Kerman, Iran

Abstract: In present study, stream flow forecasting performance of Halil river basin, located in Kerman South of Iran, had been investigate. Artificial Neural Networks (ANN) is a positive mathematical tool to represent complex relationships in many branches in hydrology. A multi-layer artificial neural networks and a neuro-wavelet hybrid system were used. The proposed conjunction model is based on use of wavelet transform and artificial neural networks. Daily precipitation and runoff data of Halil river basin were used to train ANN's model. Then it was used to forecast the stream flow from the rainfall information. The final result indicates that the conjunction model significantly improves the ability of neural networks to forecast the daily stream flow for Halil river basin. It can be proposed that this model capable to predict the maximum stream flow of the river, which could help to design hydraulic structure and it will be very useful for the management of the dam.

Key words: Rainfall-runoff model, artificial neural networks, wavelet transform, Halil river basin

INTRODUCTION

Hydrologic modeling is very important in many water resources planning design and management activities (Jain and Srinivasulu, 2004). Forecasting of stream flow has been one of the important problems for hydrologists, reservoirs operators and flood protection engineers. In this connection, the relationship between rainfall and runoff has been widely studied in many conceptual rainfall runoff models (Danh *et al*., 1999). The Rainfall-Runoff process is believed to be highly nonlinear time-varying, spatially distributed and not easily described by simple models. Rainfall-Runoff process consists of the movement of rainfall through different media and its transformation to the runoff in channels either natural or man-made (Phien and Danh, 1997). Two major approaches for modeling the Rainfall-Runoff process have been explored in literature: conceptual (physical) modeling and system theoretic modeling (black box). Conceptual Rainfall-Runoff (CRR) models are designed to approximate within their structures the general internal sub processes and physical mechanisms which govern the hydrologic cycle (Hsu *et al*., 1995). While such models ignore the spatially distributed, time-varying and stochastic properties of the Rainfall-Runoff process, they attempt to incorporate realistic representation of the major nonlinearities inherent in the Rainfall-Runoff relationships. Also conceptual models are of importance in the understanding of hydrologic processes; there are many practical situations such as stream flow forecasting where the main concern is with making accurate predictions at specific watershed locations. In such a situation, a hydrologist may prefer not to expend the time and effort required to develop and implement a conceptual model and instead implements a simpler system theoretic model. In the system theoretic approach, difference equation or differential equation models are used to identify a direct mapping between the input and output without detailed consideration of the internal structure of physical processes (Shamseldin, 1997).

Corresponding Author: Mohamad Bagher Rahnama, Department of Irrigation, Agriculture College, Shahid Bahonar University of Kerman, 22 Bahman Blv., P.O. Box 7616914111, Kerman, Iran
Tel: +98-9131404423 Fax: +98-3413220065

Since the early nineties, Artificial Neural Networks (ANNs) have been successfully used in hydrology related areas such as Rainfall-Runoff modeling, stream flow forecasting, groundwater modeling, water quality, water management policy, precipitation forecasting, hydrologic time series and reservoir operations (Govindaraju, 2000). ANNs have been employed as alternative tools in developing nonlinear system theoretic models of the hydrological processes. An ANN is a nonlinear mathematical structure which is capable of representation arbitrarily complex nonlinear processes that relate the input and outputs of any system. Hydrologists have been exploring ANNs for more then 10 years (Ozgur, 2004). In general the advantages of ANNs over other statistical and conceptual models are:

- The application of ANNs does not require a prior knowledge of the process because ANNs have black-box properties.
- ANNs have the inherent property of nonlinearity since neurons activate a nonlinear filter called an activation function.
- ANNs can have multiple input having different characteristics, which can make ANNs able to represent the time-space variability.
- ANNs have the adaptability to represent change of problem environments (Kim and Valdes, 2003).

However training process of ANNs requires significant amounts of data so that the patterns embedded in the system are discovered. In statistical time series forecasting, decomposition approaches seek to decompose a time series into its major sub components. Lately, Back Propagation Artificial Neural Networks (BPANNs), a particular type of neural network, have been developed and successfully used in many fields (Gorr *et al*., 1994; Lachtermacher and Fuller, 1995; Maier and Dandy, 1996).

Recently wavelet transform have become a common tool for analyzing local variation in time series (Kim and Valdes, 2003). These now classic approaches to ANN R-R modeling combine information at various frequency scales, where the hydrological process consist of a superposition of many sources and results in the limitation that the underlying system switches between these different hydrologic sources, producing different dynamics (Anctil and Tape, 2004).

The objective of this study is to explore a conjunction model performance of a neural-wavelet hybrid system in order to Rainfall-Runoff forecasting. In this research, we present two types of models for daily Rainfall-Runoff process. The first type of models employ ANNs technique using total rainfall and discharge data. The second type of model use a conjugate method with using wavelet and ANNs that called neural wavelet networks (NWNs) or wavelet.

ARTIFICIAL NEURAL NETWORKS

The application of ANNs has been the topic of large number of paper. Use of neural network techniques to solve hydrologic engineering problem began in the late 1992. As shown in Fig. 1, three-layered feed forward neural networks which have been usually used in forecasting hydrologic time series, provide a general framework for representing nonlinear functional mapping between a set of input and out variables (Kim and Valdes, 2003).

The output $\hat{y}_k$ is determined by the architecture of the networks. The number of hidden layer which serve as links between the input and output layers determined with trial and error rule. Each input or signal $x_i = (i = 1,....,n)$ is attenuated or amplified by a factor w_{ji} the explicit expression for an output value of ANN is given by following Equation.

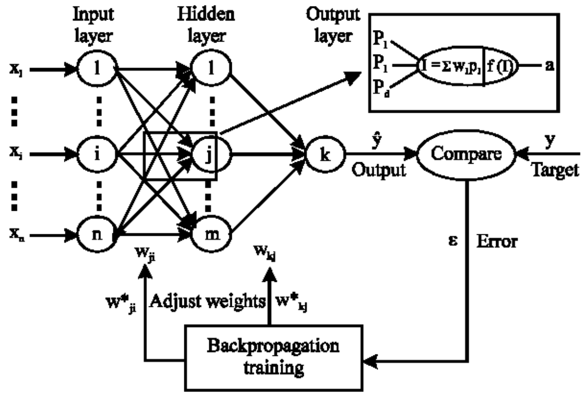

Fig. 1: Typical three-layered feed forward neural networks with back propagation algorithm

$$\hat{y}_k = f_o\left[\sum_{i=1}^{m} w_{kj} f_h\left(\sum_{i=1}^{n} w_{ji} x_i + b_i\right) + b_k\right]$$

Where:

w_{ji} = Weight in the hidden layer connecting the ith neuron in the layer
J_{th} = Neuron in the hidden neuron
f_h = Activation function of the hidden neuron
w_{kj} = Weight in the output layer connecting the jth neuron in the hidden layer
K_{th} = Neuron in the output layer
b_k = Bias for the K_{th} output neuron
f_o = Activation function for the output neuron

The values of weights are different in the layers and can be updated during the process of network training. The activation function f_h that will be used is the log sigmoid function given by:

$$f = \frac{1}{1 + e^{-x}}$$

We need to determine the optimum of weights and biases that will yield the least mean square value of the desired response $\hat{y}_k$, thus we must satisfy the following performance criterion:

$$\min_{w_{ji}, b_o, b_k} \frac{1}{2} E\left[(\hat{y}_k - y)^2\right]$$

where, E is statistical expectation operator and the factor 1.2 is included for convenience of Presentation (Birkunavyi, 2002).

NEURAL WAVELET NETWORK

The term wavelet as it implies means a little wave. This little wave must have at least a minimum oscillation and a fast decay to zero, in both the positive and negative directions, of its amplitude. This property is analogous to an admissibility condition of a function that is required for the wavelet transform (Thuillard, 2000). Sets of wavelets are employed to approximate a signal and the goal is to find a set of daughter wavelets constructed by a dilated and translated original wavelets or mother wavelets that best represent the signal. The daughter wavelets are generated from a single mother wavelet h (t) by dilation and translation:

$$h_{a,b}(t) = \frac{c}{\sqrt{a}} h\left(\frac{t-b}{a}\right)$$

where, a>0 is the dilation factor, b is the translation factor and c is correction factor (Lekutai, 1977).

Neural Wavelet networks employing wavelets as the activation functions recently have been researched as an alternative approach to the neural networks with sigmoid activation functions. The combination of wavelet theory and neural networks has lead to the development of wavelet networks. Wavelet networks are feed forward neural networks using wavelets as activation function. In wavelet networks, both the position and the dilation of the wavelets are optimized besides the weights. Wavelet is another term to describe wavelet networks. Originally, Neural Wavelet networks did refer to neural networks using wavelets. In NWN, the position and dilation of the wavelets are fixed and the weights are optimized (Thuillard, 2000).

NWN BACK PROPAGATION (NWNBP)

Back Propagation (BP) neural network is now the most popular mapping neural network. But BP neural network has few problems such as trapping into local minima and slow convergence. Wavelets are a powerful tool signal analysis. They can approximately realize the time-frequency analysis using a mother wavelet. The mother wavelet has a square window in the time-frequency space. The size of the window can be freely variable by two parameters. Thus, wavelets can identify the localization of unknown signals at any level. Activation function of hidden layer neurons in Back-Propagation network is a sigmoidal function shown in Fig. 2a. This type of activation function provides a global approximation on the search space. In this study we have substituted hidden layer sigmoidal activation function of Back Propagation neural network with POLYWOG and other wavelets.

$$h_{POLYWOG1}(t) = \sqrt{e}.(t).e^{(-(t)^2)/2}$$

Diagram of POLYWOG1 with a = 1 and b = 0, is shown in Fig. 1b.

This type of activation function provides a local approximation to the experimental data. In Back Propagation NWN (BPW), the position and dilation of the wavelets as activation function of hidden layer neurons are fixed and the weights of network are optimized using Scaled Conjugate Gradient (SCG) algorithm. In this study we suppose a = 1 and b = 0.2, 2.5,10

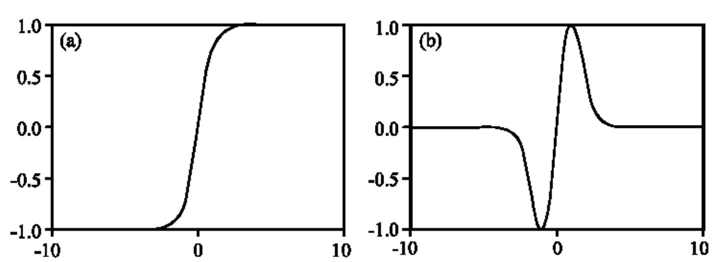

Fig. 2: (a) Sigmoidal function and (b) POLYWOG mother wavelet

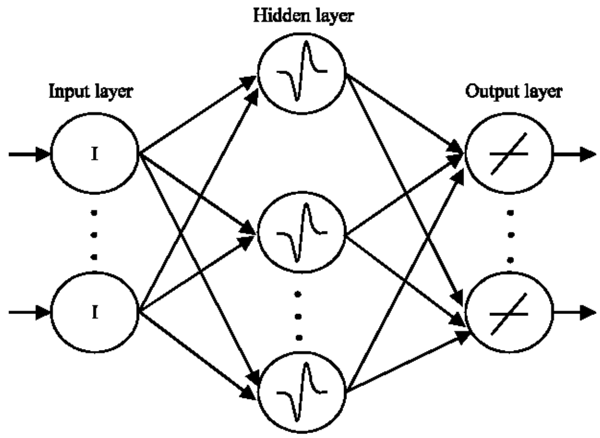

Fig. 3: Structure of BPW

$$h_{POLYWOG1}(t) = \sqrt{e}.(\frac{t}{8}).e^{(-(\frac{t}{8})^2)/2} \quad (1)$$

Therefore, BPW is a modified Back-Propagation neural network with local approximation property and POLYWOG1 hidden layer neurons activation function. And adjusting the weights of network are done using Scaled Conjugate Gradient (SCG) algorithm. Structure of BPW is shown in Fig. 3.

PREPARATION OF DATA

First, time series data are divided to two sets; 80% for training and 20% for testing. Then we normalized data prepared the files associated MATLAB software for using them in wavelet neural network and neural network.

In this study, based on correlation analysis, proper input variables are selected from a set of potential inputs.

CASE STUDY APPLICATION

A multi-layer artificial neural networks and a neuro-wavelet hybrid system were used. The proposed conjunction model based on use of wavelet transform and artificial neural networks for predicting runoff hydrograph has been applied to Halil River in Jiroft Dam located in the South of Iran (Fig. 4).

The Halil River watershed has five rainfall stations named Baft-Soltani, Baft-Zirpol, Meidan, Henjan and Cheshmeharoos. The stream flow measurement station named Konaroeih which is close to Jiroft Dam, where natural flow measurements are available, has been selected as a site to estimate runoff hydrograph. The rainfall information of the stations, were chosen as input data. Therefore, hourly rainfall from a gauging station of five stations (Baft-Soltani, Baft-Zirpol, Meidan, Henjan, Cheshmeharoos) are used as input data and hourly discharge from a gauging station Konaroeih as output data for the artificial neural networks and a neuro-wavelet hybrid approach. Using the input and output data to train the artificial neural network model by trail and error procedure for different

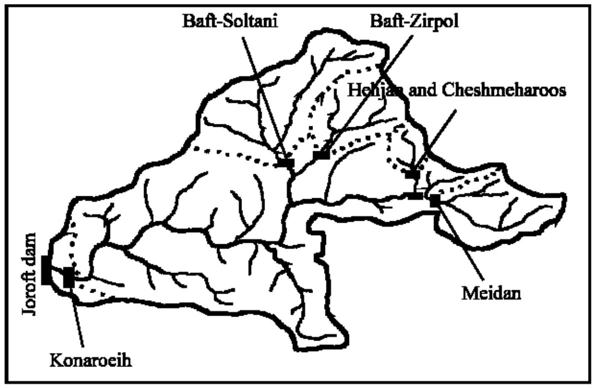

Fig. 4: Halil River watershed and location of the rainfall and hydrometrics stations

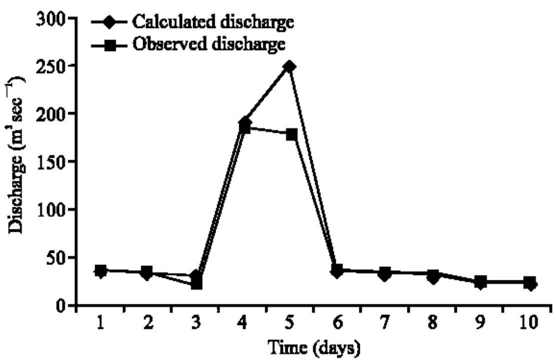

Fig. 5: Comparison between calculated and observed discharge, flood date December 8 through 17, 1376

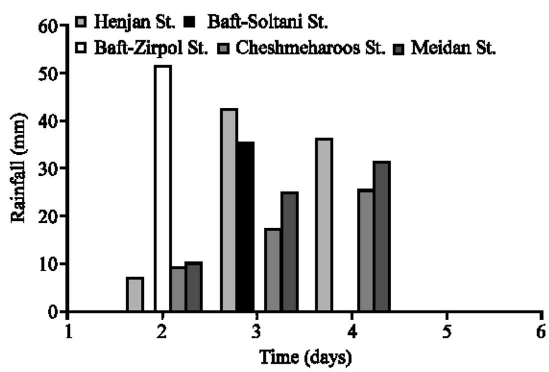

Fig. 6: Rainfall as an input information of the 5 station, flood date December 8 through 17, 1376

number of hidden layer(s), it was concluded that the model with appropriate 7-8-1 structures has the best topology. The model results and the actual data of the stream flow discharge of Konaroeih station in (m^3/s) (for two flood date December 8 through 17, 1376 and December 25, 1376 through January 5, 1377) are shown in Fig. 5-8.

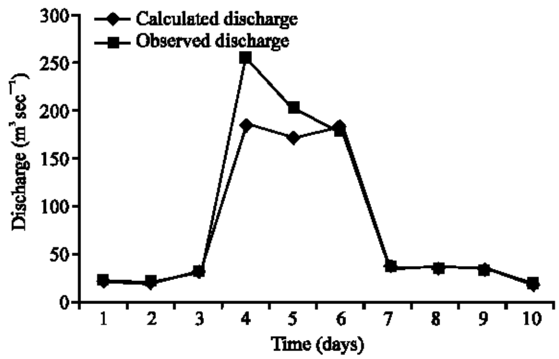

Fig. 7: Comparison between calculated and observed discharge, flood date December 25, 1376 through January 5, 1377

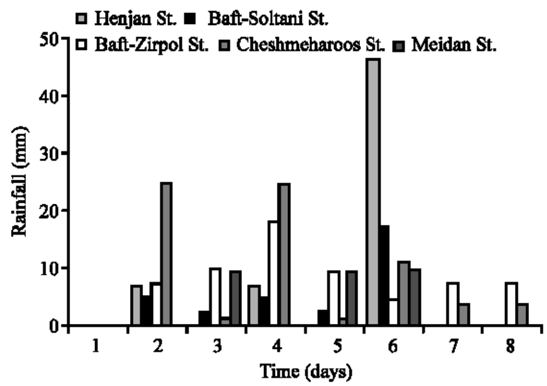

Fig. 8: Rainfall as an input information of the five stations, flood date December 25, 1376 through January 5, 1377

RESULTS

As shown in Table 1 different wave exert with various delay and transmission. The considerable point is that the more coefficient related to transmission was smaller, the better result have obtained. Of course we should say this problem is not a general real. Analysis with wavelet that is considered

Table 1: Results of the wavelet models

				R^2		RMSE	
		Dilation	Transmission	------------------------		------------------------	
Wavelet	Structure	a	b	Test	Train	Test	Train
POLYWOG2	7-8-1	1	0.2	0.98	0.953	0.53	0.009
		1	2.5	0.97	0.932	0.46	0.009
		1	10.0	0.96	0.912	0.68	0.009
POLYWOG3	7-8-1	1	0.2	0.95	0.940	0.78	0.009
		1	2.5	0.97	0.932	0.46	0.009
		1	10.0	0.96	0.912	0.68	0.009
POLYWOG4	7-8-1	1	0.2	0.96	0.950	0.78	0.009
		1	2.5	0.96	0.930	0.75	0.009
		1	10.0	0.95	0.930	0.81	0.009
Morlet	7-8-1	1	0.2	0.95	0.930	0.81	0.010
		1	2.5	0.90	0.870	0.72	0.010
		1	10.0	0.91	0.850	0.95	0.010

Table 2: Comparison of the results between the ANN mode and wavelet model

Type of model	Structure	Step	RMSE	R^2
ANN	7-8-1	Train	0.009	0.93
	7-8-1	Test	0.850	0.91
NWN	7-8-1	Train	0.009	0.95
	7-8-1	Test	0.460	0.92

as an proposed of this research, register of time record in train phase that this fact see when we use the software but with attention to the probable changes in software and hardware situation, this investigation needs excellence situation.

CONCLUSION

The use of neural wavelet network is a new method in improving the result of neural networks. In this paper use a multilayer network structure to predict daily stream flow. With the operation of NWN in Table 2 also compares the yield result with observance can say: NWN can be become a good alternative for ANN in predict daily stream flow. Suggested that other wavelet with large extend exert in changing the translation and dilation parameter and also NWN can uses in the other result science in water resources.

REFERENCES

Anctil, F. and D. Tape, 2004. Exploration of artificial neural network rain fall-runoff forecasting combined with wavelet decomposition. J. Environ. Sci., 3: s121-s128.

Birkunavyi, S., 2002. Performance of neural networks in daily stream flow forecasting. J. Hydrol. Eng., 7 (5): 392-398.

Danh, N.T., H.N. Phien and A.D. Gupta, 1999. Neural network models for river flow forecasting. Water SA., 25 (1): 33-39.

Gorr, W.L., D. Nagind and J. Szczypula, 1994. Comparative study of artificial neural networks and statistical models for predicting student grade point average. Int. J. Forecasting, 10: 17-34.

Govindaraju, R.S., 2000. Artificial neural networks in hydrology, I: Preliminary concepts. J. Hydrol. Eng., 5 (2): 115-123.

Hsu, K., H.V. Gupta and S. Soorooshian, 1995. Artificial neural network modeling of the rainfall runoff process. J. Water Resour. Res., 31 (100): 2517-2530.

Jain, A. and S. Srinivasulu, 2004. Development of effective and efficient rainfall-runoff models using interaction of deterministic, real-coded genetic algorithms and artificial neural network techniques. J. Water Resour. Res., 40: w04302.

Kim, T. and B. Valdes, 2003. Nonlinear model for drought forecasting based on a conjunction of wavelet transforms and neural networks. J. Hydrol. Eng., 8 (6): 319-328.

Lachtermacher, G. and J. Fuller, 1995. Back propagation in time series forecasting. J. Forecasting, 14: 381-393.

Lekutai, G., 1997. Adaptive self-tuning neuron wavelet network controllers. Ph.D Thesis, Virginia, Polytechnic Institute and State University.

Maier, H. and G. Dandy, 1996. The use of artificial neural networks for the prediction of water quality parameters. Water Resour. Res., 32 (4): 1013-1022.

Ozgur, K., 2004. River flow modeling using artificial neural networks. J. Hydraulic Eng., 9 (1): 60-63.

Phien, H. and N. Danh, 1997. A hybrid model for daily flow forecasting. Water SA., 23 (3): 201-108.

Shamseldin, A., 1997. Application of a neural networks technique to rainfall-runoff modeling. J. Hydrol., 199 (3-4): 272-294.

Thuillard, M., 2000. A review of wavelet networks, wavelets, fuzzy wavelets and their applications. ESIT, Aachen, Germany, Presented in Conference 14-15 September.