LOWLAND TECHNOLOGY INTERNATIONAL Vol. 4, No. 2, 17-26, December 2002
International Association of Lowland Technology (IALT), ISSN 1344-9656

APPLICATION OF ANN FOR RESERVOIR INFLOW FORECASTING USING SNOWMELT EQUIVALENT IN THE KARAJ RIVER WATERSHED

H. R. Eslami[1] and K. Mohammadi[2]

ABSTRACT: Three different methods were used to predict the spring inflow into the Amir Kabir reservoir, which is located near Tehran, Iran. The spring inflow accounts for almost 60 percent of annual inflow to the reservoir. Utilizing the results of an artificial neural network (ANN) model, the inflow to Amir Kabir reservoir is predicted. It will be compared with two other methods: ARIMA time series and regression analysis between some hydroclimatological data and inflow. Using the thirty years of observed data proved that the ANN has a better performance than that the other methods have.

INTRODUCTION

New theories of the human brain introduced a new approach to motivate our conventional digital computers to a new computation and computer architecture. One such computational system, an artificial neural network (ANN), learns to solve a problem by developing a memory capable of associating a large number of input patterns with a resulting set of outputs or effects. The ANN develops a solution system by training on examples given to it. In this paper, ANNs were studied in the context of reservoir inflow prediction using the snowmelt equivalent in a watershed.

Inflow is an important data to have for an optimal reservoir operation. There are several inflow forecasting methods to do this task including time series analysis approach, rainfall-runoff process, and regression analysis (Hsu et al. 1995). Recently, the ANN models have attracted increased attention due to their effectiveness and viability. While traditional models are of importance in the understanding of hydrologic processes, there are many practical situations where the main concern is with making accurate predictions at specific watershed locations (Hsu et al. 1995). In such a situation, using a simpler system that relates some available data to inflow may be preferred.

The Karaj river watershed, located in northwest of Tehran, Iran, was selected to demonstrate the methodology for predicting spring inflow. The watershed has a drainage area of 850 km^2 and the average elevation is 2806 m above sea level. The monthly stream flow at Amir Kabir Dam has been recorded for the period between 1970 and 1999. The precipitation and snowmelt equivalent data are collected as daily and monthly averages in the Karaj basin in five stations.

The main purpose of the Amir Kabir reservoir is to provide drinking water to Tehran. A small percentage of its storage is used for irrigation. As 60 percent of the reservoir inflow happens in spring, the prediction of the inflow in this season is very important for the reservoir operation (Fig. 1). Most of the inflow is caused by melting of the snow that falls during winter in the watershed.

1 Senior Engineer, Water Resources Planning Dept., Jamab Consulting Engineers Co., Tehran 14157, IRAN.
2 Assistant Professor, Faculty of Agriculture, University of Tarbiat Modarres, Tehran, IRAN.
Note: Discussion on this paper is open until June 1, 2003.

The first objective of this paper was to develop an ANN model and to predict the inflow to the Karadj reservoir. The second objective was to compare the ANN model with two other methods: Auto Regressive Integrated Moving Average (ARIMA) and regression analysis.

ANN: AN OVERVIEW

The ANN approach is based on the highly interconnected structure of the brain cells. This approach is faster in comparison to its conventional counterparts, robust in noisy environments, flexible in the range of problems it can solve, and highly adaptive to the newer environments (Jain et al. 1999). Due to these established advantages, currently the ANN has extensive applications in the system engineering-related fields such as time series prediction, rule-based control, and rainfall-runoff modeling.

Early work in the ANN technology was done by Rosenblatt (1962) on the perceptron. Rumelhart et al. (1986) and McClelland et al. (1986) are often credited with leading the modern renaissance in ANN technology. The addition of more complexity in the networks, specifically in adding middle (hidden) layers to multi-layer perceptron networks, together with a clear explanation of the back propagation learning algorithm, overcame many of the limitations of the one or two-layered perceptron neural networks.

Since 1986, the variety of ANNs has rapidly expanded. Maren et al. (1990) described about 24 ANNs. There is currently a vast array of ANN applications in the cognitive sciences, the neurosciences, engineering, computer science, and the physical sciences.

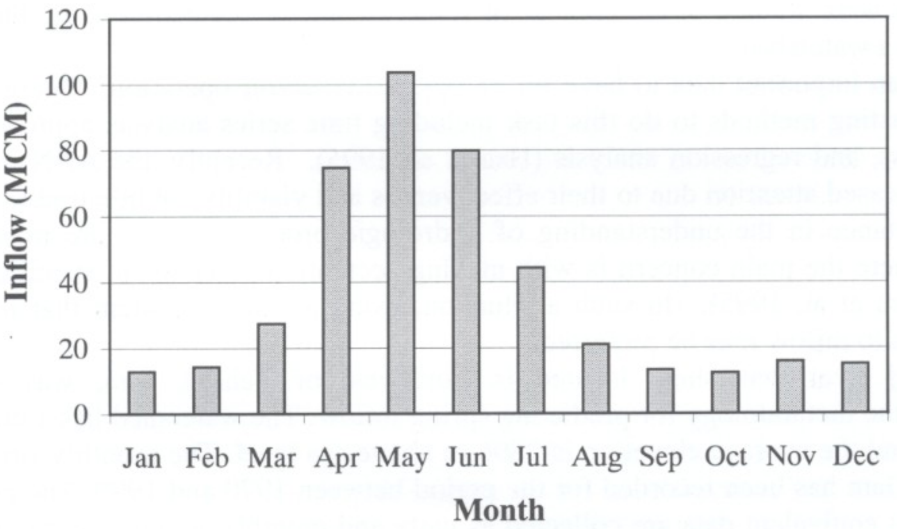

Fig. 1 Average monthly inflow to Amir-Kabir dam (year)

The basic structure of a network usually consists of three layers: the input layer, where the data are introduced to the network; the hidden layer or layers, where data are processed; and the output layer, where the results for given inputs are produced (Fig. 2). The architecture of ANN is designed by the number of layers, number of neurons in each layer, weights between neurons, a transfer function that controls the generation of output in a neuron, and learning laws that define the relative importance of weights for input to a neuron (Caudill 1987).

In recent years, ANN methods have been successfully applied to a number of multivariate forecasting problems in the field of water resources engineering. The ANN models have many advantages over other methods. Some of them are as follows (Jaın et al. 1999):

1. The data used do not have to follow a Gaussian distribution.
2. The data used may possess irregular seasonal variation.
3. ANNs are nonlinear models and perform well even when limited data are available.
4. They are very robust and are able to deal with outliers and noisy or incomplete data.

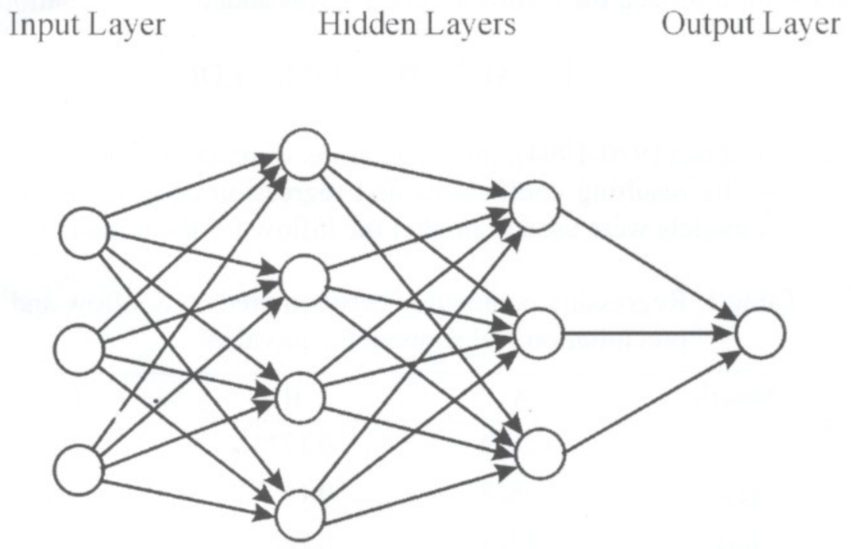

Fig. 2 The basic structure of an artificial neural network

RESEARCH METHODS

Three approaches were adopted for reservoir inflow forecasting: ARIMA time series modeling, regression analysis between some hydrometeorological data and inflow, and the ANN model. Forecasts for the seasonal average of three months of spring, April, May, June, were obtained from all models and compared with the actual inflow to investigate which approach gives better predictions. From the first two methods, the three monthly average inflows were estimated and added together to compare with the ANN method which forecasts the average seasonal inflow

FORECASTING USING REGRESSION ANALYSIS

Three models were selected to predict the monthly streamflow in spring (Jamab 1997). The first one was selected by representing stream flow at the present time, t, as a function of snowmelt equivalent for watershed in winter and rainfall at time t-1:

$$I_i = AP_{i-1} + BS_{i-1} \tag{4}$$

where I_i is the inflow to the reservoir in month i [million cubic meter (MCM)/month], P_{i-1} is the average rainfall over the watershed [mm], S_{i-1} is the snowmelt equivalent [mm], A and B are constant coefficients. Snowmelt equivalent data is only available for March and April, so, in order to estimate the inflow in May and June, the snowmelt equivalent in April is used.

For the second model an additional parameter was added to the previous model, which is the temperature in the previous month:

$$I_i = AP_{i-1} + BS_{i-1} + CT_{i-1} \tag{5}$$

where T_{i-1} is the temperature in the previous month [°C] and C is the coefficient of temperature.

To develop the third model, the inflow at time t-1 was added to the equation 5:

$$I_i = AP_{i-1} + BS_{i-1} + CT_{i-1} + DI_{i-1} \tag{6}$$

Using 25 years of data (1970-1994), three equations were adapted for each month in spring. Tables 1 to 3 show the resulting coefficients and regression coefficients for the calibration period. Then, these models were used to predict the inflow for the remaining 5 years of data.

Table 1 Regression parameters between predicted inflow and precipitation and snowmelt equivalent

Month	**A**	**B**	**R**
April	0.2412	0.1270	0.96
May	0.3824	0.1191	0.96
June	0.6725	0.1057	0.92

Table 2 Regression parameters between predicted inflow and precipitation, snowmelt equivalent, and temperature

Month	**A**	**B**	**C**	**R**
April	0.2227	0.1012	1.2636	0.96
May	0.1151	0.0791	3.7211	0.95
June	0.3083	0.0541	2.3356	0.95

Table 3 Regression parameters between predicted inflow and precipitation, snowmelt equivalent, temperature, and previous inflow

Month	**A**	**B**	**C**	**D**	**R**
April	0.1117	0.0983	-0.7126	1.1232	0.98
May	0.2149	0.0371	-0.9954	1.0884	0.98
June	0.3269	0.0031	-0.3140	0.7272	0.99

FORECASTING WITH ARIMA MODELS

A time series is a set of observations generated sequentially in time. If a stationary stochastic process, a process whose parameters do not change over time can describe the stream flow population, and if a long historic stream flow record exists, then a statistical stream flow model may be fitted to the historic flows. This statistical model can then generate synthetic sequences that reproduce selected characteristics of the historic flows. An auto regressive integrated moving average (ARIMA) method was used to model the historic flows and predict the future stream flows based on the past stream flows only.

The method of least squares was used to estimate the parameters. The accuracy of a forecast is best assessed by comparison of forecasts made and the values observed during the forecast periods.

The general class of ARIMA model can be written as (Box and Jenkins 1976):

$$\phi_p(B)\Phi_P(B^{12})Z_t = \theta_q(B)\Theta_Q(B^{12})a_t \tag{7}$$

where ϕ_p , Φ_P , θ_q , Θ_Q are polynomials of order p, P, q, and Q, respectively; and a_t is independent random variable series with mean zero and variance σ_a^2. A number of models were applied to the series and finally a mixed ARIMA (1,0,1)(0,1,1) model was selected.

FORECASTING THROUGH THE ANN MODEL

In this study, the training of the ANN model was accomplished by a back propagation algorithm. Back propagation is the most commonly used supervised training algorithm (Sezin et al. 1999). Werbos (1974) presented the back propagation learning algorithm for the first time but his dissertation received little attention. The algorithm was independently developed again and documented by two researchers in 1985 (Parker 1985; Le Cun 1985). With the development of a back propagation algorithm, the network weights are modified by minimizing the error between a target and computed outputs. In the back propagation networks, the information about the error is provided from the output layer, backwards to the input layer. The objective of a back propagation network is to find the weight that approximate target values of output with a selected accuracy.

Knowledge learned by an ANN is encoded in the interconnected weights of the network. The success of ANN learning can be thought of as the appropriate evaluation of the interconnecting weights in order to result in the correct output for a given input pattern. The input values, x_i, are multiplied by weights, w_{ij}, and summed in the neuron forming $z_j = \sum_{i=1}^{n} x_i w_{ij}$. This result is then acted upon by an activation function, yielding the output of the jth neuron $z_j = f\left(\sum_{j=1}^{n} x_i w_{ij}\right)$. One of the important factors in ANN models is to choose the optimal network's topology. An understanding of the topology as a whole is needed before the number of hidden layers and the number of processing elements (PEs) in each layer can be estimated.

A multilayer perceptron with two hidden layers has the power of solving any problem if the number of PEs in each layer and the training time is not constrained. This is a very important result but it is only an existence proof, so it does not say how such networks can be designed. The problem left to the experimentalist is to find out what is the right combination of PEs and layers to solve the problem with acceptable training times and performance (Lefebvre & Principe 1998). Training is the process by which the free parameters of the network (i.e. the weights) get optimal values. The weights are updated using either supervised or unsupervised learning. In this research, a supervised approach was used to train the ANN models.

The structure of the applied ANN model consisted of a 7-7-1 layer, which means seven neurons in the input layer, seven neurons in one hidden layer and one neuron in the output layer. The parameters chosen as inputs were snowmelt equivalent depth at five stations in the watershed and the average rainfall in six months from September to March in each year. It was observed during training that a better fitting between observed and computed data is achieved by adding a descriptive hydrological parameter into the model. Hydrological condition of the year was divided into two categories: above or equal average and below average. By adding this parameter to the input layer, which is very easy for user to select based on the average rainfall of the previous year, the average percentage error was decreased by 5 percent. The output was the average seasonal flow.

After the training was over using the 25 years of data, the model was used to predict the last 5 years, which were not included in the training process. MATLAB 5.3 was used to construct the ANN model using a feedforward backpropagation network. During test period, weights were kept constant and then river flow was estimated. Trained back propagation networks tend to give reasonable answers when presented with inputs that they have never seen.

RESULTS ANALYSIS

Three criteria, namely, average percentage error, average seasonal deviation, and root mean square (RMS) error between observed and calculated inflow were used to monitor the performance of the forecast models. Average percentage error is equal to

$$\frac{1}{n}\sum_{i=1}^{n}\left[\frac{ABS(Q_{obs}(i)-Q_{cal}(i))}{Q_{obs}(i)}\times 100\right] \tag{1}$$

average seasonal deviation was calculated by

$$\frac{1}{n}\sum_{i=1}^{n}[Q_{obs}(i)-Q_{cal}(i)] \tag{2}$$

and RMS error is

$$\left[\frac{1}{n}\sum_{i=1}^{n}[Q_{obs}(i)-Q_{cal}(i)]^2\right]^{1/2} \tag{3}$$

where, Q_{obs} and Q_{cal} represent the observed and calculated flows, respectively and n is the number of data. The RMS error is more pronounced by higher deviations, whereas the average percentage error is influenced by low flows. The average seasonal deviation is an unbiased interpreter of the forecast performance. The data from 1970 to 1994 was used for model calibration and training. Then, models were used to predict the spring inflow from 1995 to 1999.

The comparison between observed and computed inflows in correspondence of both calibration and validation data for the three methods of regression analysis are shown in Figs 3 to 5, respectively and Figs 6 and 7 show the comparison between observed and computed seasonal, from April to June, inflow values in Amir-Kabir Dam station using ARIMA and ANN method, respectively. Table 4 shows the computed error percentages for all methods in calibration period. It may be seen that among the regression analysis method the second equation has better performance with an average percentage error of 17.34 percent compare to 23.38 and 22.3 for the first and the third equations, respectively. ARIMA method produced 30.78 percent error but ANN had significantly low error compare with other methods. Its average percentage error was 7.35 percent. Another indicator which was calculated during calibration of different models was correlation coefficient between the observed and calculated data. This coefficient for RA1, RA2, RA3, ARIMA, and ANN models was 0.710, 0.665, 0.485, 0.175 and 0.937, respectively.

Table 4 Calculated errors for different prediction methods in calibration period

	RA1	RA2	RA3	ARIMA	ANN
APE	23.38	17.34	22.30	30.78	7.35
ADE	24.76	32.46	-10.29	-10.99	-3.58
RMSE	69.85	56.67	67.01	95.03	22.09

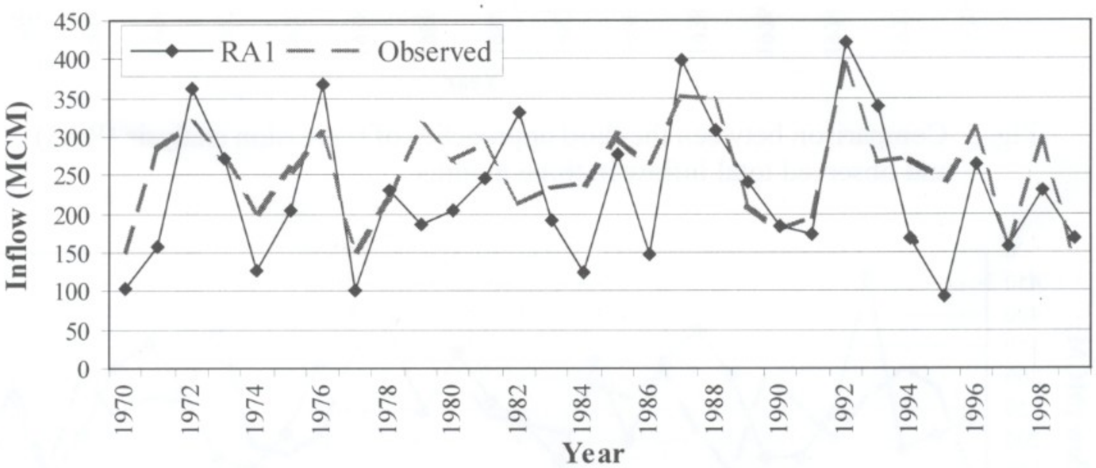

Fig. 3 Comparison between the first approaches of regression analysis (RA1) and observed total inflow in three months

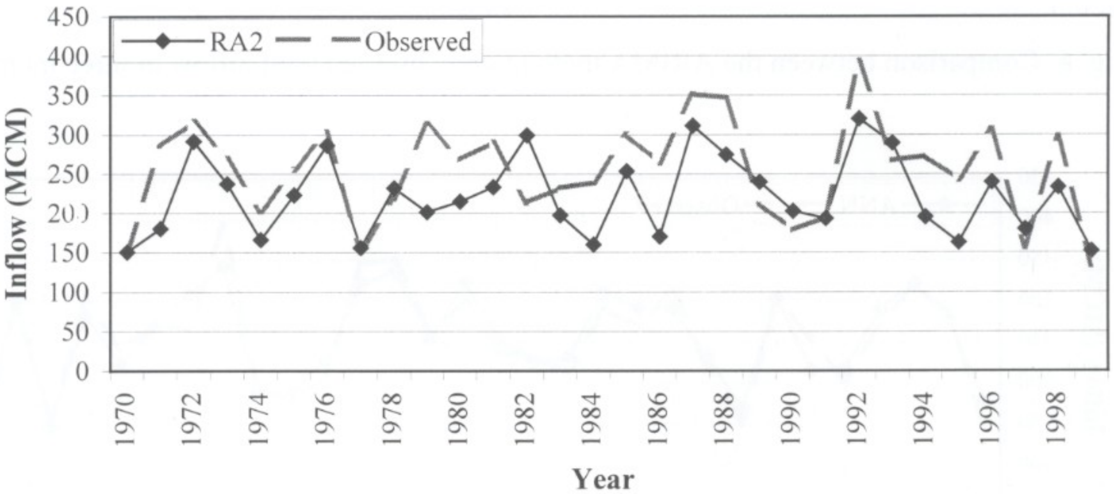

Fig. 4 Comparison between the second approaches of regression analysis (RA1) and observed total inflow in three months

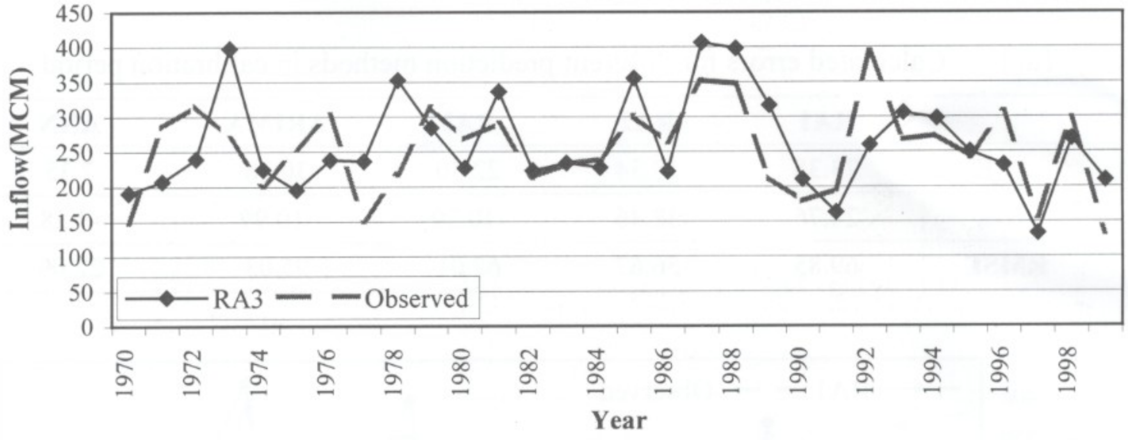

Fig. 5 Comparison between the third approaches of regression analysis (RA3) and observed total inflow in three months

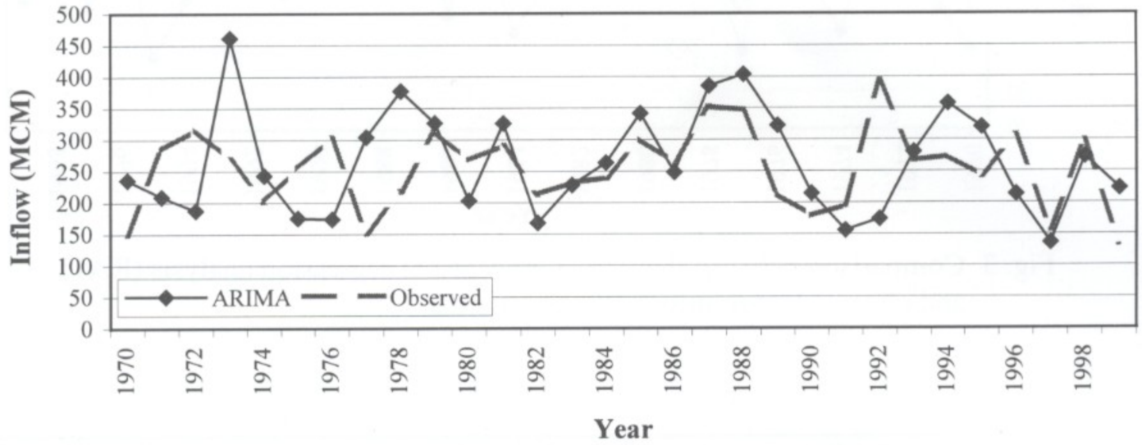

Fig. 6 Comparison between the ARIMA method and observed total inflow in three months

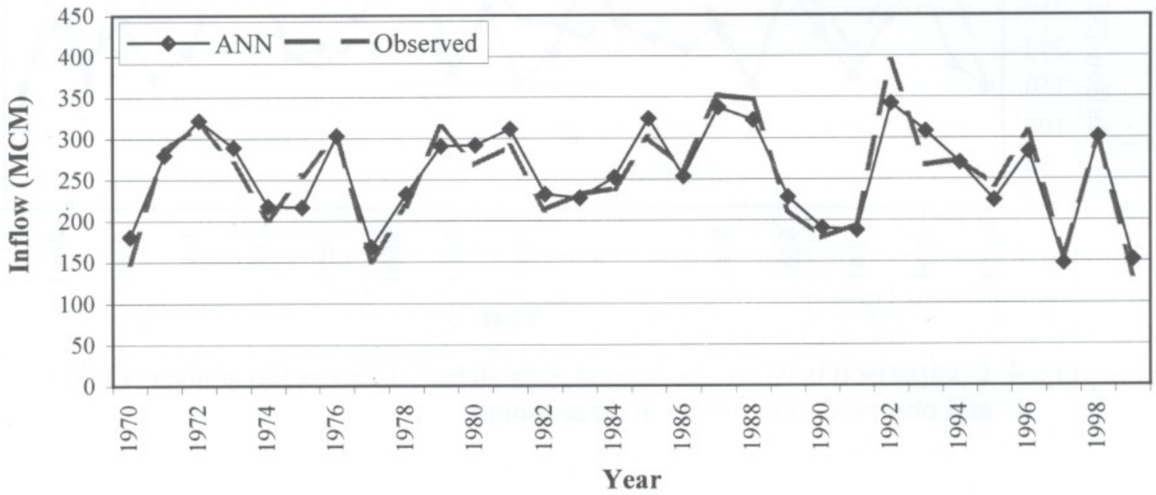

Fig. 7 Comparison between the ANN model and observed total inflow in three months

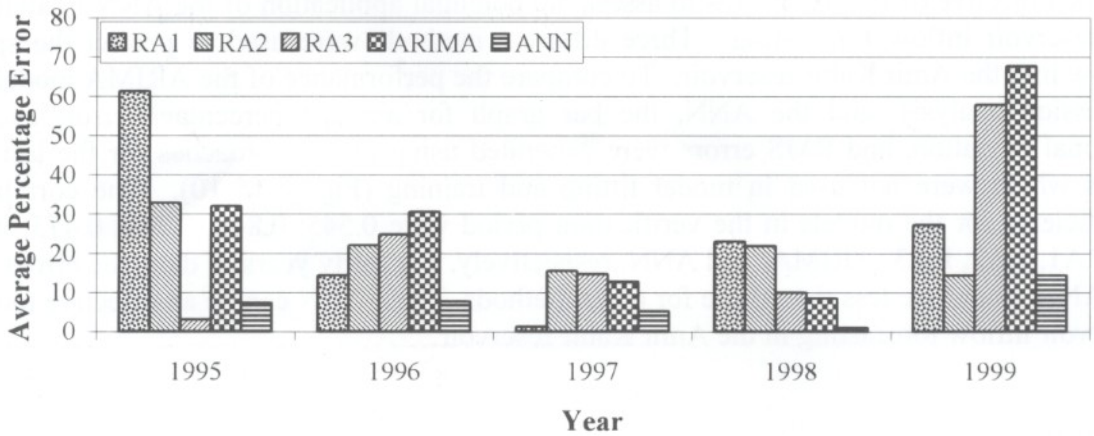

Fig. 8 Average percentage error of different methods for the last five years

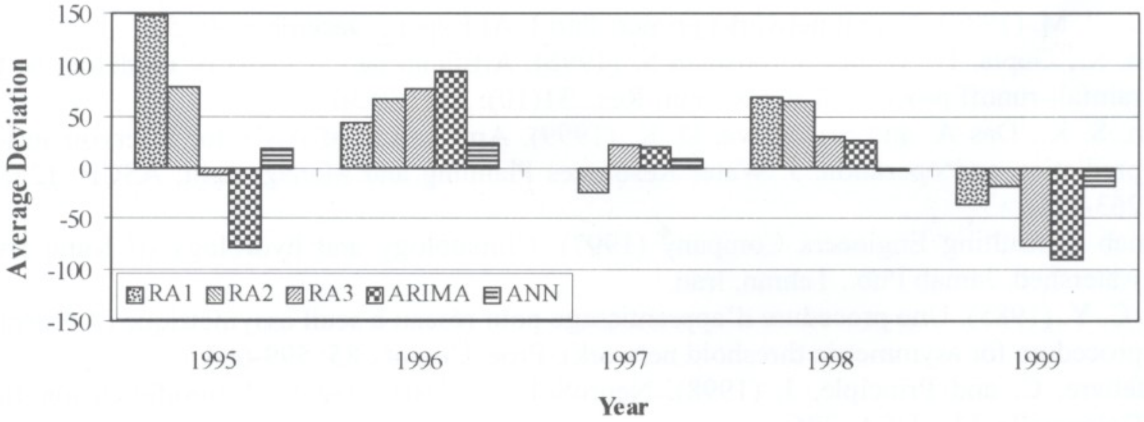

Fig. 9 Average seasonal deviation of different methods for last five years

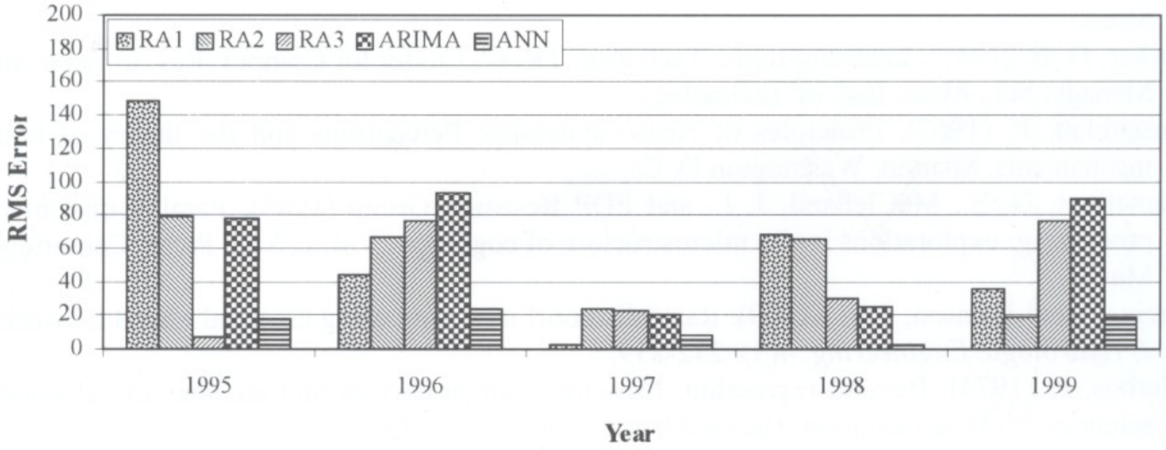

Fig. 10 RMS error of different methods for last five years

CONCLUSION

The objective of this study was to assess the potential application of the ANN in attaining the reservoir inflow forecasting. Three different methods were used to predict the spring inflow into the Amir Kabir reservoir. To compare the performance of the ARIMA model, the regression analysis, and the ANN, the bar graph for average percentage error, average seasonal deviation, and RMS errors were generated using three approaches for the last five years which were not used in model fitting and training (Figs 8 to 10). The correlation coefficients for the models in the verification period were 0.545, 0.844, 0.711, 0.475, 0.981 for RA1, RA2, RA3, ARIMA, and ANN, respectively. For thirty years of data, the errors with the ANN model are less than those for other methods. Thus, ANN can be an effective tool for reservoir inflow forecasting in the Amir Kabir reservoir.

REFERENCES

Box, G. E. P. and Jenkins, G. M. (1976). Time series analysis: Forecasting and control. Holden-Day Pub., Oakland, USA.

Caudill, M. (1987). Neural networks primer: Part I, AI Expert, December, 46-52.

Hsu, K., Gupta, H. V. and Sorooshian S. (1995). Artificial neural network modeling of the rainfall-runoff process. Water Resour. Res.. 31(10): 2517-2530.

Jain, S. K., Das A. and Srivastava, D. K. (1999). Application of ANN for reservoir inflow prediction and operation. J. Water Resources Planning and Management, ASCE. 125(5): 263-271.

Jamab Consulting Engineers Company (1997). Climatology and hydrology of Karaj river watershed. Jamab Pub., Tehran, Iran.

Le, C. Y. (1985). Une procedure d'apprentissage pour réseau à seuil assymetrique (A learning procedure for asymmetric threshold network). Proc. Cognit., 85: 599-604.

Lefebvre, C. and Principle, J. (1998). NeuroSolution User's Guide. Neurodimension Inc., Gainesville, FL., USA: 786.

Maren, A. J., Harston, C. T. and Pap, R. M. (1990). Handbook of neural computing applications. Academic Press, San Diego, Calif..

McClelland, J. L., D. E. Rumelhart and the PDP research Group (1986). Parallel distributed processing: Explorations in the microstructure of cognition. Vol. 2, MIT Press, Cambridge, Mass..

Parker, D. B. (1985). Learning-logic. Tech Rep. TR-47, Center for Comput. Res. in Econ. and Manage. Sci., Mass. Inst. of Technology.

Rosenblatt, F. (1962). Principles of Neuro-dynamics: Perceptrons and the theory of brain mechanisms. Spartan, Washington D. C.

Rumelhart, D. E., McClelland, J. L. and PDP Research Group (1986). Parallel distributed processing: explorations in the microstructure of cognition. Vol. 1, MIT Press, Cambridge, Mass..

Sezin, A and Johnson, P. A. (1999). Rainfall-runoff modeling using artificial neural networks. *J. Hydrologic Engineering.* 4(3): 232-239.

Werbos, P. (1974). Beyond regression: New tools for prediction and analysis in behavioral sciences. Ph.D. dissertation, Harvard Univ., Cambridge, Mass..