Time Series Modelling of Reservoir inflows through back Propagation Artificial Neural Network

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ABSTRACT

Artificial neural network (ANN) is an efficient and useful technique and gaining popularity in hydrological modeling and forecasting. This paper presents the application of ANNs to hydrologic time series modeling, and is illustrated by an application to model the monthly reservoir inflow of Gandhi Sagar reservoir. The advantage of the ANN method is that it does not require the artificial neural network model structure to be known a priori, in contrast to most of the time series modeling techniques. The results showed that the ANN forecasted reservoir inflow series preserves the statistical properties of the original inflow series. The model also showed good performance in terms of various statistical indices. The results are highly promising.

INTRODUCTION

Stream flow forecasting is of vital importance for the efficient reservoir management and control. In case of already existing reservoirs better management means better reservoir yields and greater flood protection through better operation policy. The operation policy for the reservoir may be daily, weekly or monthly depending on the main goals of the reservoir. The interval at which a reservoir is to be controlled depends on the purpose of control. A multipurpose reservoir can have varied purposes such as flood control, water supply to industry, agriculture or municipality, flow augmentation etc. If the reservoir operation is for flood control during the months of heavy flows the operation may be at vary short intervals such as a day or even several hours. However, for other purposes a larger interval of operation may be more practical. The monthly forecasts are useful in determining the monthly operation policy of a multipurpose reservoir particularly involving an allocation problem. A widely used practice is monthly operation over a twelve-month horizon for managing reservoirs with agricultural allocation as the basic goal. The important aspects of the monthly flows are worth noting. First of all the seasonality of the time series is to be preserved and secondly the correlation structure with the preceding months is to be incorporated.

Traditionally, regression or a time series model is used to carry out stream flow forecasting. However, such models do not attempt to represent the non-linear dynamics inherent in the hydrologic processes, and may not always perform well. On the other hand, artificial neural networks (ANNs) can approximate virtually any (measurable) function up to an arbitrary degree of accuracy. The advantage of ANN is that one need not have a well defined physical relationship for converting an input to an output. Artificial neural networks provide a quick and flexible means of creating models for hydrological forecasting. In the present paper artificial neural network approach is chosen for forecasting inflows into the Gandhi Sagar Reservoir. This is because ANNs belong to the class of data driven approaches that have the capability to recognize the hidden pattern in the data and make forecasts accordingly. The forecast of flow is restricted to a single-space i.e. the reservoir site. Interval for forecasting is chosen as a month and the analysis is based on the data from 1961 to 1986. The most popular back prorogation algorithm has been used to train artificial neural networks. The analysis has been carried out considering various model structures and a suitable model structure have been suggested.

APPLICATION OF ANN TO TIME SERIES ANALYSIS

Time series is one of the methods to quantify predictions and it can be interpreted as an output of an unknown system (Lopez, 1996). In situations when both the system characteristics and the input functions are not known, a time series analysis provides future output values by means of extrapolation from their own past. Many of the time series analysis techniques assume linear relationships among variables. For describing time series data using linear relationship is often found to be inadequate. A neural network model generally offer several advantages over the more conventional approaches to computing. The most frequently cited of these are their ability to develop a generalised solution to a problem from a set of examples. The attribute of generalisation permits them to be applied to problems other than those used for training and to produce valid solutions even when there are errors in the training data (Hecht-Nelson, 1991; Haykin, 1994).

A number of studies demonstrate the applicability of ANN in time series and other hydrological modeling. For forecasting rainfall in space and time, French et al. (1992) developed an ANN model. Kang (1993) used multi-layer perception model to forecast stream flows at Pyunchang river basin in Korea. They showed that the rainfall-and runoff simulation problem can be considered as a pattern recognition problem. Buch et al. (1993) have used ANN in runoff simulation of a Himalayan glacier. An ANN model for the simulation and prediction of daily flow of Huron river at Dexter sampling station was developed by Karunanithi et al. (1994). Raman and Sunil Kumar (1995) compared the performance of neural network with the statistical method for synthesising monthly inflow records for two reservoir sites.

ANN AND BACK PROPOGATION ALGORITHM

Mathematical models of biological neurons (called artificial neurons) mimic the functionality of biological neurons at various levels of detail. The basic function of a neural network, which consists of a number of simple processing nodes or neurons, is to map information from an input vector space onto an output vector space. A typical model is basically a static function with several inputs (representing the dendrites) and one output (the axon). Each input is associated with a weight factor (synaptic strength). The weighted inputs are added up and passed through a nonlinear function, which is called the *activation function* (ASCE, 2000). A neural network learns to solve a problem by modifying the values of the weighted connections through either supervised or unsupervised training. Most widely applied network is the multilayer perceptron using a supervised training algorithm, known as backpropagation. Once trained, the network is validated with a testing dataset to assess how well it can generalise to unseen data. A three-layer neural network consisting of input layer (L_i), hidden layer (L_H) and the output layer (L_o) with the inter-connection weights W_{ih} and W_{ho} between layers of neurons is shown in Fig. 1.

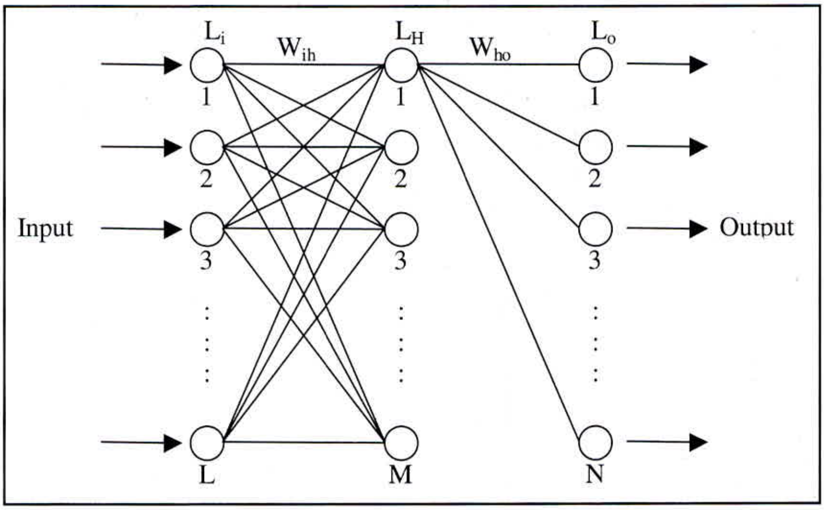

Fig. 1: Configuration of Three-Layer Neural Network

The performance of a backpropagation ANN algorithm depends on the initial setting of the weights, learning rate, output function of the units (sigmoidal, hyperbolic tangent etc.) and the presentation of training data. During training of an ANN the initial weights should be randomized and uniformly distributed in a small range of values while the learning rate is important for the speed of convergence. A small value of learning parameter may result in smooth trajectory in the weight space but on the other hand it takes long time to converge. Similarly a large value of learning parameter may increase the learning speed but result in large random fluctuations in the weight space. It is desirable to adjust the weights in such a way that all the units learn nearly at the same rate. The selection of training data should be made in such a way so that it represents all data and the process adequately. The generalized delta rule determines the appropriate weight adjustments necessary to minimize the errors. The total input H_{ij} to hidden units j is a linear function of outputs x_i of the units that are connected to j and of the weights w_{ij} on these connections i.e.

$$H_{ij} = \sum_i x_i \; w_{ij} \qquad (1)$$

A hidden unit has a real-value output H_{oj}, which is a non-linear function of its total input. Biases (q_j) is introduced as an extra input to each unit.

$$H_{oj} = \frac{1}{1 + e^{-(H_i j + \theta_j)}} \qquad (2)$$

The use of a linear function for combing the inputs to a unit before applying the non-linearity greatly simplifies the learning procedure.

The aim is to find a set of weights that ensure that for each input vector, the output vector produced by the network is the same as (or sufficiently close to) the desired output vector. If there is a fixed, finite set of input-output cases, the total error in the performance of the network with a particular set of weights can be computed by comparing the actual and desired output vectors for every case. The total error E, is defined as:

$$E = \frac{1}{2} \sum_c \sum_f (O_{j,c} - T_{j,c})^2 \qquad (3)$$

where 'c' is an index over cases (input-output pairs), j is an index over output units, 'O' is the actual state of an output neuron in the output layer and T is its targeted state. To minimise E by gradient descent, it is necessary to compute the partial derivative of E with respect to each weight in the network i.e. ¶E/¶W_{ji}. The simplest version of gradient descent is to change each weight by an amount proportional to the accumulated ¶E/¶w. This proportional constant is called learning rate.

Dw = -Î ¶E/¶w (4)

The convergence of Eqn (4) can be significantly improved, by an acceleration method wherein the incremental weights at t can related to the previous incremental weights as shown in Eqn (5).

$$\Delta w(t) = \in \frac{\partial E}{\partial w(t)} + \alpha \Delta w(t-1) \qquad (5)$$

where, a is an exponential decay factor between '0' and '1' that determines the relative contribution of the current gradient and earlier gradients to the weight change.

STUDY AREA

The Gandhi Sagar reservoir, one of the first major reservoirs of the State of Madhya Pradesh (M.P.), is the uppermost dam in a series of three dams (Gandhi Sagar, Rana Pratap Sagar, and Jawahar Sagar) and a barrage (Kota barrage) of Chambal Valley Project. The dam was a joint venture of the States of M.P. and Rajasthan and was completed in the year 1960. It is the main storage dam constructed across river Chambal, intercepting a catchment area of about 23025 sq. km. The dam serves as a backup storage for power generation in the three dams and irrigation through canal systems taking off from Kota Barrage. Monthly reservoir inflow into the Gandhi Sagar dam has been taken for the analysis. Period for analysis has been selected from 1961 to 1986. Data from 1961 to 1970 have been used for training and rest of the data for testing the ANN model structure.

NETWORK TRAINING AND IDENTIFICATION OF ANN MODEL

Using the available historical inflow data series the following neural network models have been considered to forecast monthly reservoir inflows:

(a) X_{t-1}, X_{t-2}
(b) X_{t-12}, X_{t-13}
(c) $X_{t-1}, X_{t-2}, X_{t-12}, X_{t-13}$

The time series was normalized and standarised prior to training the model. The architecture of the network in the present study consisted of an input layer, a hidden layer and an output layer. In the process of model development the data have been divided into two statistically similar parts for supervised training. One part is used for training and the other part is used for testing the performance of the ANN. The training of the neural network is accomplished by adjusting the inter-connecting weights till such time that the root mean square error (r.m.s.e.) between the observed and the predicted set of values is minimized. The adjusting of inter-connecting weights is accomplished by using the back propagation algorithm. In the process of model development several network architectures with different number of input neuron in input layer, and different number of hidden layer with varying number of hidden neurons have been considered to select the optimal architecture of the network. A trial and error procedure based on the minimum r.m.s.e. criterion is used to select the best network architecture.

RESULTS

The ANN model structure given by (c) has shown a best fit model to the training data set when compared using with other model structures. A comparison of the selected model structures has been done using the evaluation criteria such as coefficient of correlation, and model efficiency. Table 1 indicates that the coefficient of correlation of the ANN models (a) to (c) ranges from 0.57 to 0.82 during calibration and 0.59 to 0.83

during validation. While models efficiency of the ANN models (a) to (c) ranges from 58.2% to 83.4% during calibration and 59.4% to 84.6% during validation. Input model structure (a) gives lowest coefficient correlation and model efficiency. Model structure (c) has the coefficient of correlation 0.82 and model efficiency 83.4% during calibration and coefficient of correlation 0.83 and model efficiency 84.6% during validation. These values are better than the values obtained using other two model structures. Further, the training model results were also compared on the basis of statistical parameters. In the time series modeling it is important to preserve the statistical properties of the monthly inflow series. Therefore, statistical parameters viz. mean and standard deviation of the generated and actual flow series are compared (Table 2). In general the ANN model based on the input model structure (c) shows that the statistical properties of the monthly inflow series are well preserved. These results also indicated that the ANN model (c) can be taken as a suitable model for generating reservoir inflows.

Table 1 : Comparison of correlation and model efficiency of ANN models

Model	Model Structure	Coefficient Correlation	Model Efficiency
(a)	$X(t) = f(X_{t-1},\ X_{t-2})$	0.57 (Calibration) 0.59 (Validation)	58.2 (Calibration) 59.4 (Validation)
(b)	$X(t) = f(X_{t-12},\ X_{t-13})$	0.68 (Calibration) 0.67 (Validation)	74.5 (Calibration) 73.2 (Validation)
(c)	$X(t) = f(X_{t-1},\ X_{t-2}, X_{t-12},\ X_{t-13})$	0.82 (Calibration) 0.83 (Validation)	83.4 (Calibration) 84.6 (Validation)

Further, using the data set selected for the model testing, the inflow is synthesized. The time series plot of historic monthly inflows superimposed with simulated inflows using the ANN model is shown in Figure 2. It is evident from this figure that the inflow series generated using the ANN model (c) generates the inflows similar to the observed inflows. Further, Table 3 gives the comparison of the monthly statistical properties of the generated series using ANN and the actual observed data series for the test period. It is observed from Table 3 that both mean and standard deviation of generated and actual observed series are almost in the same order. This indicates that the ANN model preserved the statistical properties of the monthly inflow series.

CONCLUSIONS

In this paper, the use of artificial neural network model for the reservoir inflow is investigated by developing a back propagation ANN model for Gandhi Sagar reservoir

Table 2 : Comparison of statistical parameters of historic and generated series

Month	Mean (1000 m^3)				Standard Deviation			
	Historical Data	Model (a)	Model (b)	Model (c)	Historical Data	Model (a)	Model (b)	Model (c)
January	36.88	34.7	36.2	37.1	24.18	16.65	20.7	23.4
February	23.06	28.0	26.6	24.1	14.57	13.12	14.9	15.4
March	39.95	46.3	41.8	37.5	21.94	17.58	19.3	21.2
April	38.43	35.1	36.9	37.4	27.11	16.51	22.3	24.4
May	25.86	27.7	27.3	26.6	21.93	18.61	27.3	23.3
June	211.12	180.1	192.7	198.0	225.95	143.65	172.4	184.8
July	1003.61	832.5	1100.1	1023.6	1142.16	921.65	1002.1	1069.1
August	1467.66	1891.9	1435.9	1454.5	1255.48	1217.9	1277.2	1243.5
September	1615.16	1821.7	1552.0	1582.6	1975.32	1218.9	1523.4	1771.6
October	300.86	419.2	332.4	321.9	430.82	243.20	331.2	361.2
November	50.52	72.3	80.4	61.5	51.38	64.39	61.3	60.4
December	35.59	47.0	47.2	42.0	21.46	35.00	32.7	28.4

Table 3 : Comparison of statistical parameters of historic and generated series

Month	Mean (1000 m^3)		Standard Deviation	
	Historical Data	Model (c)	Historical Data	Model (c)
January	36.93	42.2	29.17	20.1
February	37.82	39.9	13.73	17.4
March	43.62	55.1	24.18	24.2
April	44.27	53.9	26.69	24.2
May	41.00	37.3	28.22	27.3
June	118.12	139.4	115.00	187.3
July	646.48	833.4	879.73	1021.4
August	2537.30	2456.9	1455.31	1430.2
September	876.51	716.7	946.79	1054.3
October	234.01	320.1	250.89	241.8
November	74.42	80.0	84.88	70.2
December	45.11	52.3	30.27	27.3

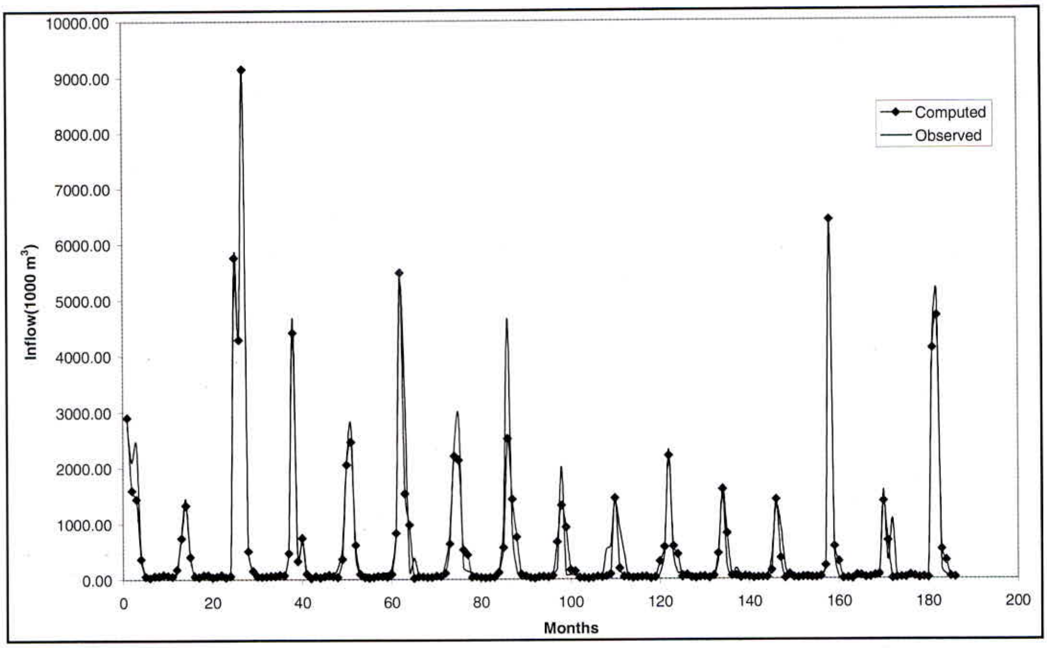

Fig. 2 : Time series plot of historic monthly flows superimposed with simulated flows

inflow. It is observed that the ANN model is capable of preserving the statistical properties of the reservoir inflow time series. The results of the study are very encouraging as indicated by the model performance indices and statistical properties of the modeled time series data both for training and testing periods. The study suggests that an ANN based model is a useful soft computing technique for modelling hydrological time series.

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