PERFORMANCE EVALUATION OF NEURAL NETWORKS IN DAILY STREAMFLOW FORECASTING

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ABSTRACT: Stream flows are often treated as estimates of runoff from watershed of a stream. Stream flow information is required to reduce uncertainty and permit decisions on water resource planning and design. Neural Network model is formulated to predict daily river flows in river Godavari at Perur using Gradient Descent back propagation algorithm. To study the performance of the model developed, various statistical performance indices namely correlation coefficient, normalised root mean square error, coefficient of efficiency, average absolute relative error and threshold statistic are computed during training and testing phases. The results indicate that ANN can effectively be used to model daily streamflows.

Key words: Streamflow, forecasting, Neural networks, back propagation algorithm

I.INTRODUCTION:

Streamflow prediction is one of the most important aspects in hydrology, useful in water resources development, planning and management. A wide variety of models have been developed and used for flood forecasting. Recently, soft computing techniques such as fuzzy logic, Artificial Neural Networks, have emerged to model streamflows. Notable contributions are Poff et al. (1996), Muttiah et al. (1997), Tawfik et al. (1997) ,Karunanithi et al. (1994) and Thirumalaiah and Deo (1998) ,Jain et al. (1999), Jagadeesh et al. (2000), Amin et al. (2000), Birikundavyi et al. (2002) , Ozgur Kisi (2004), Cigizoglu (2005), Wu et al. (2005) , Francois et al. (2005).

II.ARTIFICIAL NEURAL NETWORKS BASED MODELING APPROACH:

An ANN is a massively parallel distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain (Haykin, 1994). ANN plays an important role in the field of hydrology, since the analysis of hydrologic systems deals with high degree of empiricism and approximation. As large number of publications has appeared in the recent past, to avoid duplication, the main concepts are highlighted in this section.

An ANN is composed of many non- linear and densely interconnected processing elements or neurons. In ANN architecture, neurons are arranged in groups called layers. Each neuron in a layer operates in logical parallelism. Information is transmitted from one layer to another in serial operations (Hecht- Nielsen, 1991). A network can have one or several layers. 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(s), where the data are processed, and the output layer, where the results for the given input are produced. The neurons in the hidden layer(s) are connected to the neurons of a neighboring layer by weighing factors that can be adjusted during the model training process. The networks are organized according to training methods for specific applications. Figure. 1 illustrates a three layer artificial neural network The most distinctive characteristic of an ANN is its ability to learn from examples. Learning or training of an ANN model is a procedure by which ANN repeatedly processes a set of test data (input – output data pairs) , changing the values of its weights. In the training or learning process, the target output at each output node is compared with the network output, and the difference or error is minimized by adjusting the weights and biases through some training algorithm. In the present study, the training of ANNs was accomplished by Gradient descent algorithm with back- propagation.

In Back-Propagation, each input pattern of the training data set is passed through the network from the input layer to the output layer. The network output is compared to the desired target output, and an error is computed. The error is propagated backward through the network to each node and correspondingly the connection weights are adjusted based on the equation,

$$\Delta W_{ij}(n) = \alpha \Delta W_{ij}(n-1) - \eta (\partial E / \partial W_{ij}) \qquad (1)$$

where $\Delta W_{ij}(n)$ and $\Delta W_{ij}(n-1)$ are the weight increments between nodes i and j during the n th and (n-1) th steps. 'α' is the momentum factor, used to speed up the training in flat regions of the error surface and to prevent oscillations in the weights. 'η' is the learning rate used to avoid the chance of being trapped in local minimum instead of global minima (ASCE Task Committee, 2000). In the present study the initial learning rate is taken as 0.01 and the momentum term as 0.9. Low value of learning rate takes more time for error convergence. Thus, a back propagation algorithm consists of two phases: a forward pass, during which the processing of information occurs from the input layer to the output layer; and a backward pass, when the error from the output layer is propagated back to the input layer and the interconnections are modified.

The back propagation algorithm was originally developed by Werbos in 1974. Rumelhart et al. (1986, reported in Haykin, 1994) rediscovered the algorithm and made it popular by demonstrating the training of hidden neurons for complex mapping problems. The algorithm is given by Fausett (1994), (Source: ASCE Task Committee, 2000).

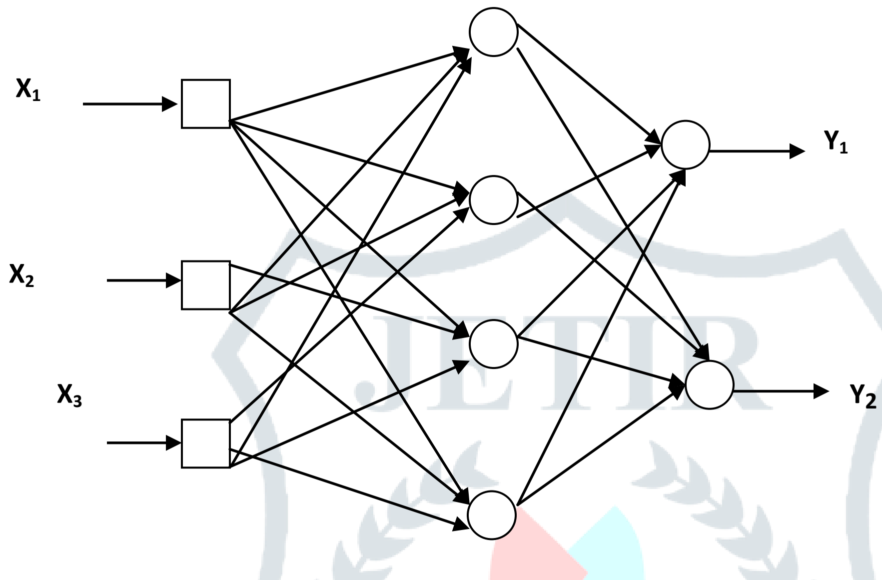

Fig. 1. A Typical Three Layer Feed forward ANN configuration

III.STUDY AREA:

To demonstrate the methodology for modeling daily streamflow using ANN technique, Perur gauging station on River Godavari is considered . The catchment of the Godavari at Perur is 2,68,200 km^2. The basin lies in the Deccan Plateau and is situated between latitude 16^o 16'N and 22^o 43'N and longitude 73^o 26'E and 83^o 07'E. The schematic representation of Godavari catchment plan with gauging stations are shown in Fig.2.

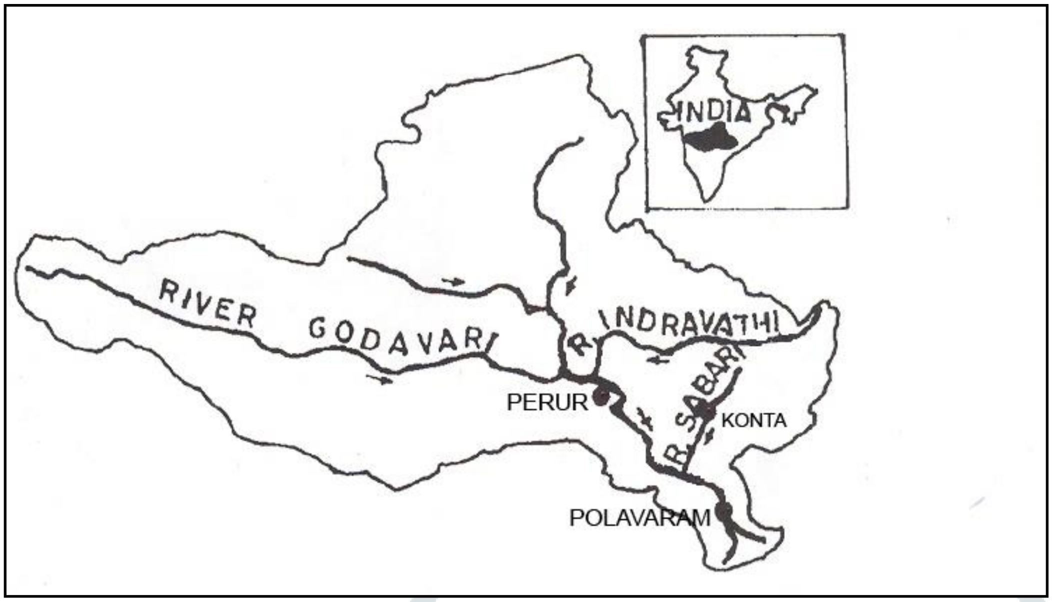

Fig: 2 Schematic representation of Godavari Catchment Plan
(Source: Konda Thirumalaiah et al. 2000)

IV. EVALUATION METHODOLOGY

The steps involved in the present study in the formulation of various hydrological models are as follows:

(1) Selection of data sets for calibration and validation of the model.
(2) Normalization of the selected data.
(3) Formulation of the model by the identification of the input and output vectors.
(4) Determination of the structure of the Artificial Neural Network i.e., number of neurons in the input layer, hidden layer and the output layer.
(5) Training the Artificial Neural Network model using Gradient Descent Back Propagation algorithm.
(6) Validation of the model by presenting the test data to the developed ANN model.
(7) Computation of the statistical performance indices for both training and validation phases.

V. DAILY STREAM FLOW MODEL FORMULATION

Daily stream flow data is available for the period 1996 to 2006. The model is trained using data for 7 years (1996-2002) and validated on 4 years (2003-2006). The input vector to the model is identified using the procedure outlined by Sudheer et al. (2002). The historical flow series was normalised between 0 and 1 using equation (2). Observed values of the river flow are used in model formulation.

$$(x_i)nor = \frac{(x_i)act - (x_i)min}{(x_i)\max - (x_i)min} \qquad (2)$$

Where, $(x_i)_{nor}$ is the normalized value of the variable under consideration, $(x_i)_{act}$ is the actual value of the variable, $(x_i)_{max}$ and $(x_i)_{min}$ are the maximum and minimum values in the data series of a variable under consideration.

The statistical analysis carried out indicated that, the most appropriate input vector includes antecedent flows upto a lag of 2 days. Thus the functional form of the ANN stream flow model is,

$$Q_t = f(Q_{t-1}, Q_{t-2}) \qquad (3)$$

Where Q_t represents the river flow at time t and Q_{t-1} and Q_{t-2} are river flows at time periods (t-1) and (t-2) respectively. Thus the input layer consists of 2 neurons and the output layer has one neuron for the current flow Q_t.

A three layer ANN model was employed to develop streamflow model. The number of neurons in the hidden layer is finalised by trial and error. The configuration that gives the minimum MSE and maximum correlation coefficient was selected for each of the options**.** Sigmoid function is used as the activation function in the network training process. The final ANN architecture arrived consists of nine hidden neurons. To test the robustness of the model developed the performance criteria such as Correlation coefficient, Average absolute relative error (AARE), Nash coefficient of efficiency, Threshold Statistics (TS_x), Normalised Root Mean Square Error (NRMSE), Normalised Mean Bias Error (NMBE), are evaluated during training and testing.

STATISTICAL PERFORMANCE INDICES

(1)Correlation Coefficient (R): The correlation coefficient is given as,

$$R = \frac{[y_o(t) - y'_o(t)] * [y_p(t) - y'_p(t)]}{\sqrt{\Sigma[\mathrm{yo(t)} - \mathrm{y'o(t)}]2 * \sqrt{[\mathrm{y_p(t)} - \mathrm{y'_p(t)}]2}}} \quad (4)$$

Where $y_o(t)$ and $y_p(t)$ are the observed and computed values of a variable and $y'_o(t)$, $y'_p(t)$ are the mean of the observed and computed values.

. **(2) Average Absolute Relative Error (AARE):**

Average Absolute Relative Error gives average error prediction. It is the average of the absolute values of the relative errors in forecasting. Mathematically AARE is calculated using the following equations.

$$RE(t) = \frac{y_p(t) - y_o(t)}{y_o(t)} * 100 \quad (5)$$

$$AARE = \frac{1}{n}\sum |RE(t)| \quad (6)$$

where $y_o(t)$ and $y_p(t)$ are the observed and computed values of a variable at time t, *RE(t)* is the relative error in predicting the variable at time t and n, the number of observations. Smaller the value of *AARE* better is the performance of the model.

(3) Threshold Statistics (TS_x):

This performance index gives the distribution of the errors. The threshold statistic for a level of x% is a measure of the consistency in forecasting errors from a particular model (Nayak et al. 2005). It is designated by TS_x and is expressed in percentage. This criterion can be expressed for different levels of absolute relative error from the model. It is computed for x% level as,

$$TS_x = \left[{}^{Y_x}/_N\right] * 100 \quad (7)$$

where 'Y_x' number of data points forecasted whose absolute relative error is less than *x%* and *N* the total number of data points predicted.

Threshold Statistics were computed for absolute relative error levels of 1%, 5%, 10%, 25%, 50%, and 100% in this study. Higher the value of threshold statistic better is the model performance.

(4) Nash- Sutcliffe coefficient of efficiency (η):

The Nash coefficient of efficiency (Nash- Sutcliffe, 1970) compares the computed and the observed values of the variable and evaluates how far the model is able to explain the total variance in the data set.

The Nash coefficient of efficiency is calculated as,

$$\eta = \frac{[\Sigma y_o(t) - y'_o(t)]^2 - y_p(t) - y_o(t)]^2}{\Sigma[y_o(t) - y'_o(t)]^2} * 100 \quad (8)$$

where $y'_o(t)$ is the mean of observed values and all other variables are same as explained earlier. Higher the value of efficiency better is the model performance.

(5) Normalised Mean Bias Error (NMBE):

The Normalised Mean Bias Error (Nayak et al. 2005) indicates whether the modeled values of the output are under or over predicted**.** It is computed as,

$$\mathrm{NMBE} = \frac{{}^1/_n\,\Sigma[y_p(t) - y_o(t)]}{{}^1/_n\,\Sigma y_o(t)} \quad (9)$$

Positive NMBE would indicate overall over prediction while negative value would mean overall under prediction from the model.

(6)Normalised Root Mean Square Error (NRMSE):

The Normalised Root Mean Square Error is computed using the following equation.

$$NRMSE = \frac{1/_{n}\sqrt{\sum[y_p(t) - y_o(t)]^2}}{1/_{n}\sum y_o(t)} \qquad (10)$$

Better model performance is indicated by lower value of NRMSE.

VI.RESULTS AND DISCUSSION:

In the stream model, it is found that the model with architecture, 2 input neurons, 9 hidden neurons, 1 output neuron is the most suitable model. The correlation coefficient is found to be 0.76, 0.81 and the Mean Square error is 0.006013, 0.006398 during training and testing phases at 100 epochs. With increase in epochs to 1000, the correlation coefficient improved to 0.939 and 0.949 during training and testing respectively. MSE further decreased to 0.00078 and 0.00064 during training and testing.

For the selected models, the computed stream flows are denormalized and the performance criteria such as R, AARE, coefficient of efficiency, NMBE, NRMSE, and TS_x are evaluated during training and testing and are presented in Table 1.

Based on the performance evaluation criteria, it can be concluded the model using Gradient descent algorithm performed well. The linear scale plot of the observed and modeled flows v/s time during training and testing phases is shown in Fig. 3 and Fig. 4. The graphs show a good match between modeled and observed flow values. However, the peak flows are slightly over estimated, both during training and testing. The scatter plots of the modeled flow versus observed flows for the training and testing phases are shown in Fig. 5and Fig. 6.

Table. 1 Statistical Performance Indices during Training & Testing for 2-9-1 configuration

Phase	Threshold Statistics						R	η (%)	NRMSE	AARE (%)	NMBE (%)
	TS1	TS5	TS10	TS25	TS50	TS100					
Training	1.92	9.28	20.23	73.66	94.09	99.64	0.939	88.24	0.711	20.85	0.500
Testing	0.80	5.86	13.49	65.86	91.16	96.70	0.949	90.09	0.674	28.22	-0.012

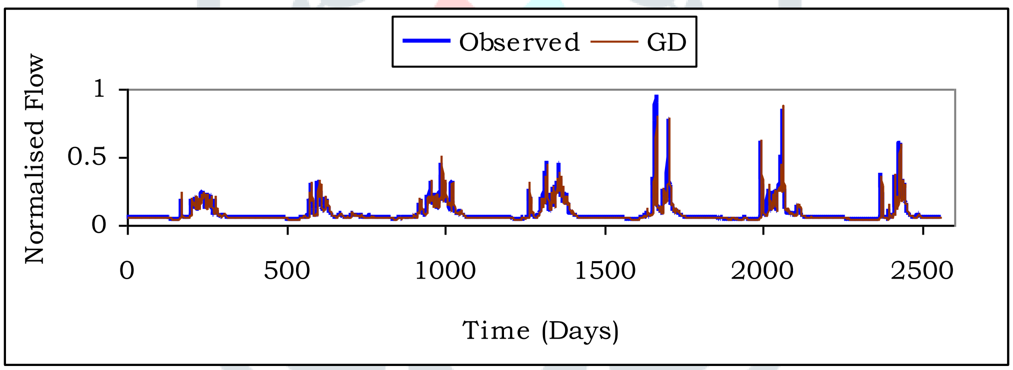

Fig: 3 Hydrograph during Training

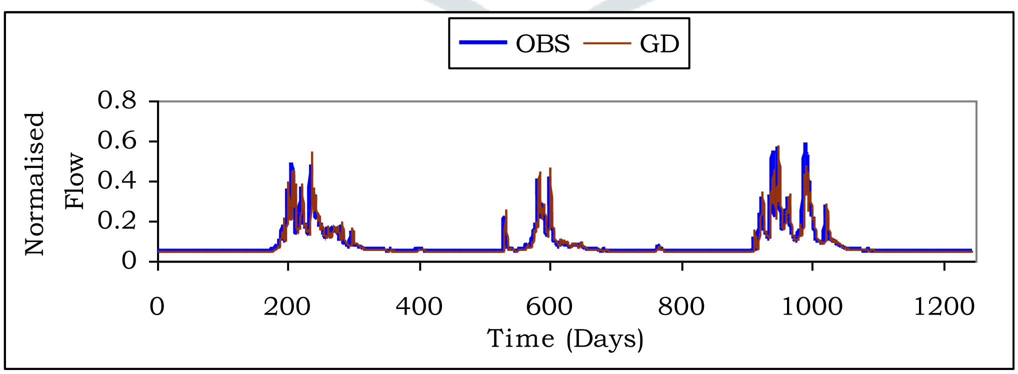

Fig: 4 Hydrograph during Testing

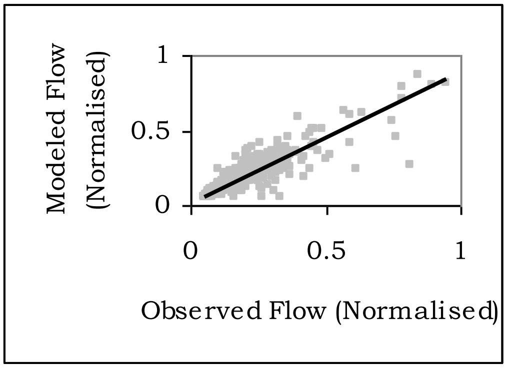

Fig. 5 Scatter plot comparing the modeled and observed flows during training

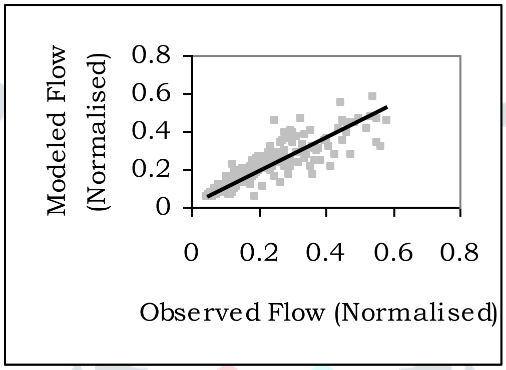

Fig. 6 Scatter plot comparing the modeled and observed flows during testing

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