DEVELOPMENT OF SEDIMENT TRANSPORT MODEL USING ARTIFICIAL NEURAL NETWORKS

[1]Dr.C.S.V. Subrahmanya Kumar [2]Dr.G.K.Viswanadh
[1]Professor, [2]Professor & OSD to VC
[1]Department of Civil Engineering [2]Department of Civil Engineering
[1]ACE Engineering College, Hyderabad, India, [2]J.N.T.U College of Engineering, Hyderabad, India

ABSTRACT: The assessment of the volume of sediment transported by a river is of vital interest in hydraulic engineering. Neural Network model is formulated to predict daily suspended sediment yield in river Godavari at Perur using Gradient Descent back propagation algorithm. To test the robustness of the model formulated, statistical performance indices namely, Correlation coefficient (R), Average Absolute Relative Error (AARE), Nash coefficient of efficiency (η) and Normalised Root Mean Square Error (NRMSE) are computed during training and testing. The results indicate that ANN can be effectively used to model daily suspended sediment yield.

Key words: Suspended sediment yield, catchment, Atrificial Neural Networks, Gradient descent back propagation algorithm

I.INTRODUCTION

Soil erosion occurring in different forms on the earth surface is an unavoidable phenomenon that is deteriorated by human activities. Knowledge of the erosion status and its prediction has always been a general concern. Correct estimation of sediment yield or sediment concentration carried by a river is very important for many water resources projects. The assessment of the volume of sediment transported by a river is of vital interest in hydraulic engineering. Its assessment is important in the design of life of the reservoirs. Sediment transport in rivers is associated with a wide variety of environmental and engineering issues which are outlined in Table.1 (Ongley, 1996).

There are many parameters like rainfall, moisture content of the soil, land use pattern, slope of the catchment, soil characteristics etc. that affect the sediment load. Although it is possible to identify sophisticated models taking into consideration the hydrological hydro meteorological variables, it is economically preferable to have a model that can simulate the sediment variations on the basis of flow discharge and sediment records (Ozgur Kisi, 2007).

Table.1 Issues associated with sediment transport in rivers

Type of sediment	Environmental issues	Associated engineering issues
Silts and clays	Erosion, especially loss of top soil in agricultural areas, gullying.	
	High sediment loads to reservoirs.	Reservoir siltation
	Chemical transport of nutrients, metals and chlorinated organic compounds	Drinking water supply
	Accumulation of contaminants in organisms at the bottom of the food chain	
	Silting of fish spawning beds and disturbance of habitats (by erosion or siltation) for benthic organisms	
Sand	River bed and Bank erosion	River channel deposition: navigation problems Instability of river cross sections.
	River bed and Bank erosion	Sedimentation in the reservoirs
	Habitat disturbance	
Gravel	Channel instability when dredged for aggregate	Instability of river channel leads to problems of navigation and flood control
	Habitat disturbance	

A plethora of models and procedures have so far been adopted for sediment computations. These models are mostly derived from statistical methods and therefore lack the required accuracy. The earlier studies (Ozgur Kisi, 2007), carried out on sediment predictions indicated that ANN based models performed better when compared to the regression based methods. Chang et al. (1965) studied total bed- material discharge relation in Alluvial Channels. Ackers and White (1973) developed Sediment Transport models. The works by some investigators using the regression techniques for sediment prediction coefficients are those by Shen and Hung (1972), Ackers and White (1973), Brownlie (1982), Karim and Kennedy (1990). Ariffin (2004) developed Sediment Transport Models for Selected Rivers in Malaysia using Regression Analysis and Artificial Neural Network. Ozgur Kisi (2007) studied the abilities of Neuro-Fuzzy (NF) and Neural Network (NN) approaches to model the streamflow–suspended sediment relationship at two stations namely, Quebrada Blanca station and Rio Valenciano station.

Thus the present study investigates and forecasts the scale of sedimentation with the aid of an ANN technique in Godavari River basin at Perur station.

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 have 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 an 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 neighbouring layer by weighing factors that can be adjusted during the model training process. The networks are organized according to training methods for specific applications. Fig. 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).

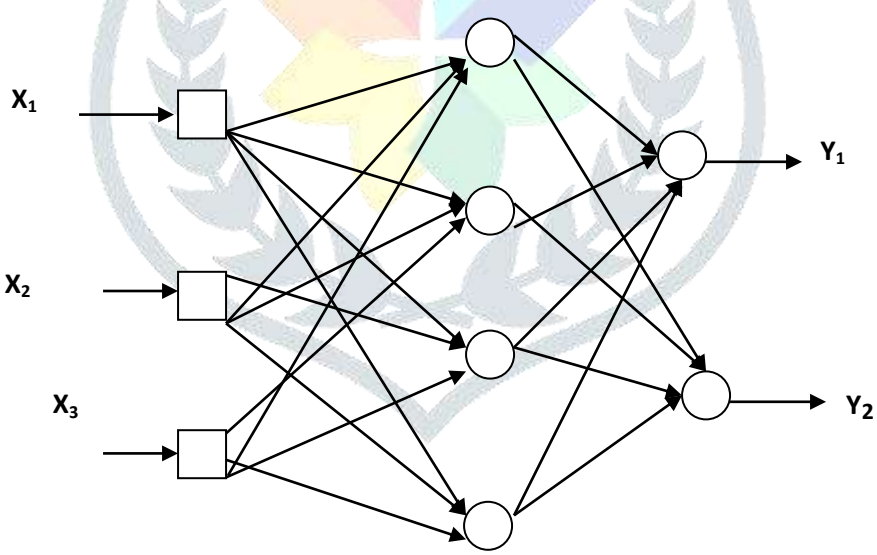

Fig. 1. A Typical Three Layer Feed forward ANN configuration

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° 16'N and 22° 43'N and longitude 73° 26'E and 83° 07'E. The schematic representation of Godavari catchment plan with gauging stations are shown in Fig. 2.

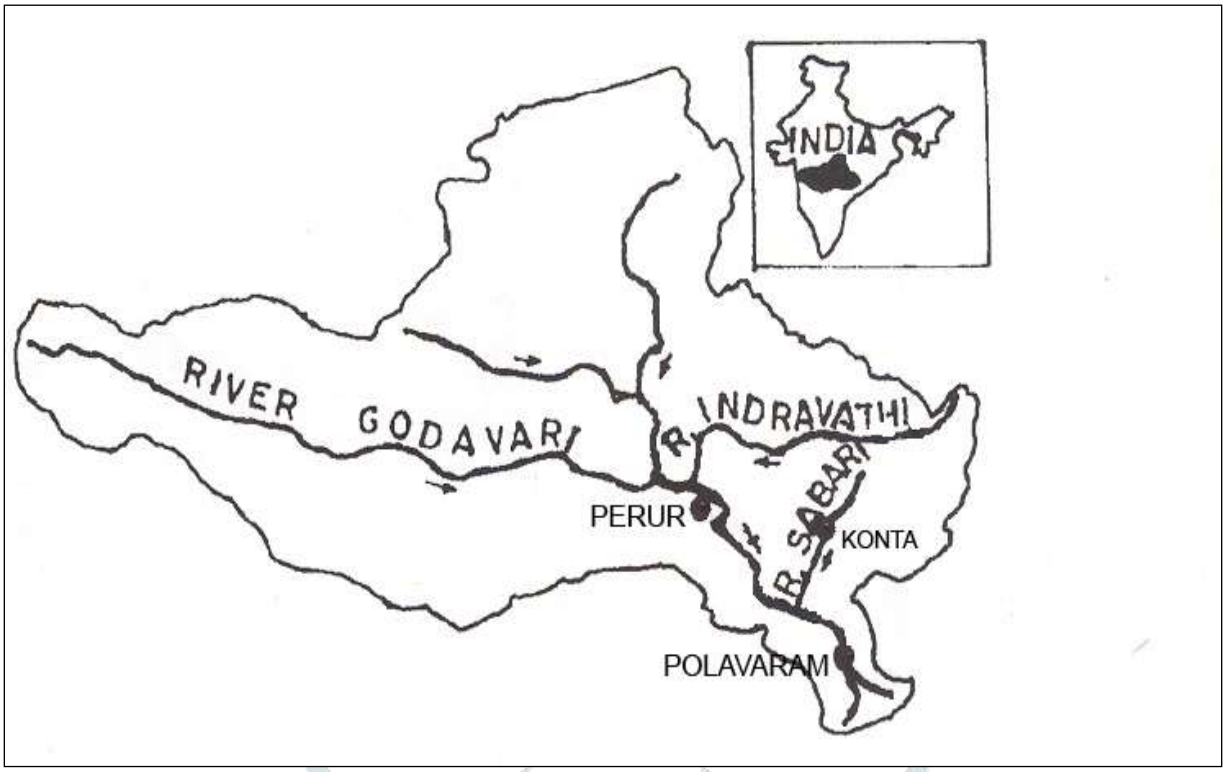

Fig: 2 Schematic representation of Godavari Catchment Plan
(Source: Konda Thirumalaiah et al. 2000)

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.

Daily Suspended Sediment Yield Prediction Model:

Daily suspended sediment 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 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 study was focused on sediment predictions using the past discharge and sediment records at station Perur. A network involving 3 input nodes of suspended sediment and stream flows at Perur and one output node corresponding to the sediment yield forecast at time t was developed. The functional form of the sediment yield ANN model is,

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

Where S_t represents the sediment yield at time t , Q_t, Q_{t-1}, are stream flows at time periods t, (t-1) and S_{t-1}, the sediment yield at time (t-1) .

A three layer ANN model was employed to develop daily sediment yield 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.

To test the robustness of the model developed the performance criteria such as Correlation coefficient, Average absolute relative error (AARE), Nash coefficient of efficiency, Normalised Root Mean Square Error (NRMSE), are evaluated during training and testing.

STATISTICAL PERFORMANCE INDICES

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

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

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.

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

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

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) 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,

$$\eta = \frac{[\sum y_o(t) - y'_o \quad (t)]^2 - y_p(t) - y_o \quad (t)]^2}{\sum[y_o(t) - y'_o \quad (t)]^2} * 100 \qquad (7)$$

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.

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

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

$$\mathrm{NRMSE} = \frac{1/n\,\sqrt{\sum[y_p\,(t) - y_o\,(t)]^2}}{1/n\,\sum y_o(t)} \qquad (8)$$

Better model performance is indicated by lower value of NRMSE.

RESULTS AND DISCUSSION

In the prediction model, it is found that the model with architecture, 3 input neurons, 3 hidden neurons, 1 output neuron is the most suitable model. The correlation coefficient is found to be 0.886, 0.904 and the Mean Square error is 0.00433, 0.00421 during training and testing phases at 100 epochs. With increase in epochs from 100 to 2000, the correlation coefficient has increased to 0.9982 during training and to 0.9990 during testing phase. The MSE has further decreased to 8.92 E-07 during training and to 6.06E-07 during testing.

For the selected models, the computed sediment yield values are denormalised and the performance criteria such as correlation coefficient, NRMSE, AARE, Nash coefficient of efficiency are evaluated during training and testing and are presented in Table 2.

The values of the performance criteria namely R and coefficient of efficiency are very good and consistent for the sediment yield model both during and testing.

The linear scale plot of the observed and modeled values v/s time during training and testing phases is shown in Fig. 3 & Fig. 4. The graphs show a good match between modeled and observed values both during training and validation periods. The scatter plots of the modeled versus observed sediment yield for the training and testing phases are shown in Fig. 5 and Fig. 6.

Table.2 Statistical Performance Indices during Training & Testing.

Phase	ANN Configuration			R	η (%)	NRMSE	AARE (%)
	Input	Hidden	Output				
Training	3	3	1	0.9982	99.63	0.0002	1.99
Testing				0.9990	99.74	0.0005	2.14

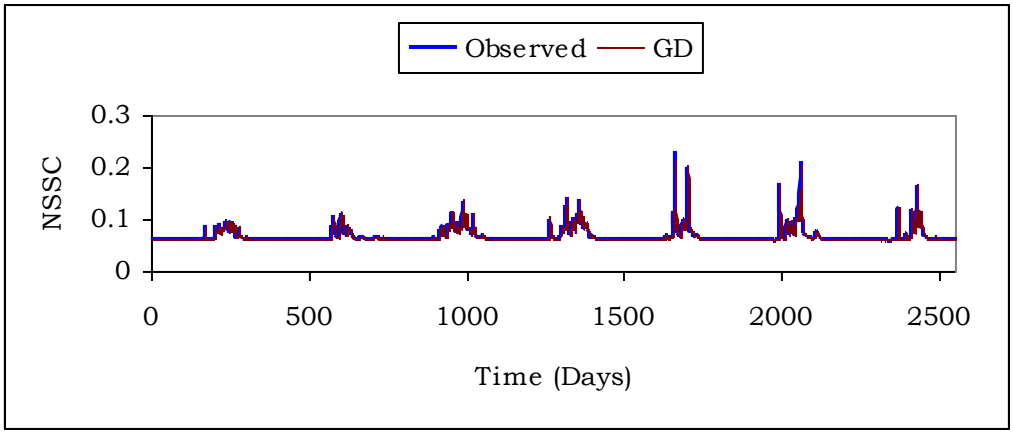

Fig 3: Daily Predicted Sediment Yield during Training

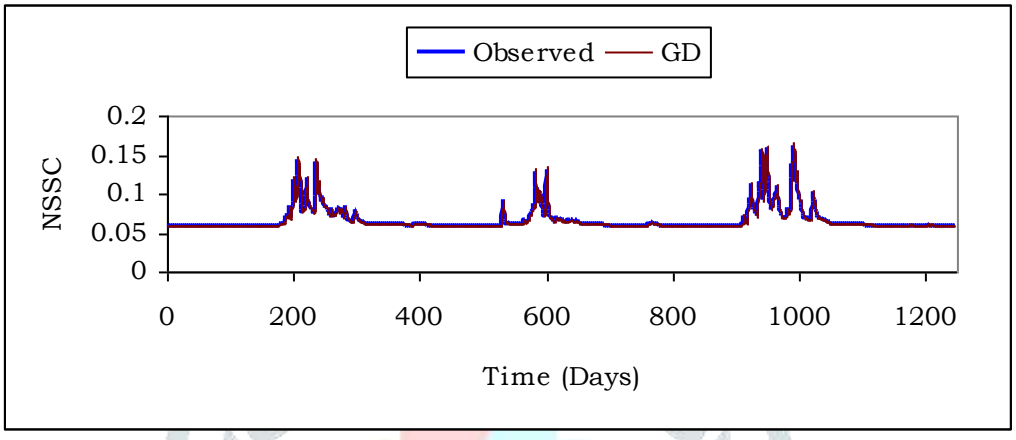

Fig 4: Daily Predicted Sediment Yield during Testing

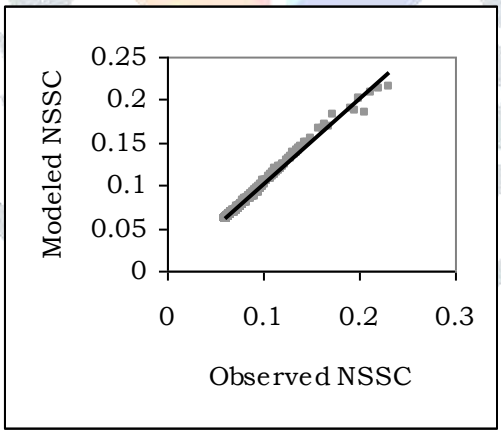

Fig:5 Scatter Plots comparing Modeled & Observed Sediment Yield during Training

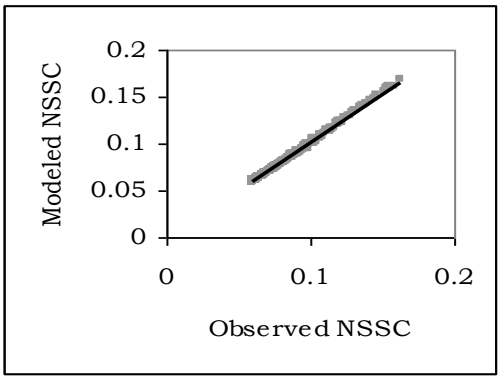

Fig: 6 Scatter Plots comparing Modeled & Observed Sediment Yield during Testing

REFERENCES

[1] Ackers, P., and White, W.R. (1973). "Sediment Transport: New Approach and Analysis." Journal of the Hydraulics Division, ASCE, 2041- 2060

[2] Amin Elshorbagy., Simnovic, S.P., Panu, U.S. (2000). "Performance Evaluation of Artificial Neural Networks for Runoff Prediction." Journal of Hydrologic Engineering, 4(5), 424-427.

[3] Ariffin, J. (2004). "Development of Sediment Transport Models for Selected Rivers in Malaysia using Regression Analysis and Artificial Neural Network." Ph.D Thesis, University of Science Malaysia, Penang, Malaysia.

[4] ASCE Task Committee (2000a). "Artificial neural networks in Hydrology I Journal of Hydrologic Engineering, 5(2), 115- 123.

[5] ASCE Task Committee (2000b). "Artificial neural networks in Hydrology II, Journal of Hydrologic Engineering, 5(2), 124- 132.

[6] Birikundavyi,S., Labib,R., Trung,H.T., Rousselle.J. (2002). "Performance of Neural Networks in Daily Streamflow Forecasting." Journal of Hydrologic Engineering, 5(7), 392- 399.

[7] Brownlie,W. (1982). "Prediction of Flow Depth and Sediment Discharge in Open Channels." Reports of the California Institute of Technology, Pasadena, Report No. NSF/CEE-82090, 73- 154.

[8] Chang,F.M., Simons, D.B., and Richardson, E.V. (1965). "Total Bed Material Discharge in Alluvial Channels." U.S.Geological Survey Water Supply Paper 1498-I.

[9] Cigizoglu., (2005). "Application of Generalized regression Neural Networks to Intermittent Flow Forecasting and Estimation." Journal of Hydrologic Engineering, 4(10), 336-341.

[10] Fausett,L. (1994). "Fundamental of Neural Networks." Prentice Hall, Englewood Cliffs,N.J.

[11] Francois Anctil, Alexandre Rat. (2005). "Evaluation of Neural Network Streamflow Forecasting on 47 Watersheds." Journal of Hydrologic Engineering, 1(10), 85-88.

[12] French,M.N., Krajewski.W.F., and Cuykendall R.R. (1992). "Rainfall forecasting in space and time using a neural network." Journal of Hydrology, Amsterdam, 137, 1-31.

[13] Haykin, S. (1994). "Neural networks: A comphrensive foundation." Mac Millan, New York.

[14] Hect- Nielson, R.(1990). "Neuro Computing." Addison-Wesley, New York.

[15] Hsu.K.,Gupta.V.H., and Sorooshian,S. (1995). "Artificial Neural Network Modeling of the Rainfall -Runoff Process." Water Resource Research, 31(10), 2517-2530.

[16] Jagadeesh Anmala, Bin Zhang, Rao S. Govindaraju. (2000), "Comparison of ANNs and Emperical Approaches for Predicting Watershed Runoff." Water Resources Planning and Mangement, 3(126), 156-166.Jain.S.K., Das.A., Srivastava.D.K. (1999). "Application of ANN for Reservoir Inflow Prediction and Operation." Water Resources Planning and Mangement, 5(125), 263- 271.

[17] Jain .A, Ormsbee L.E., (2002). "Evaluation of short term water demand forecast modeling techniques: conventional methods versus AI." Journal of the American Water Works Association, 94(7), 64 – 72.

[18] Jain.A, Varshney.A.K, Joshi.U.C., (2001). "Short term water demand forecast modeling at IIT Kanpur using artificial neural networks." Water Resources Management, 15(5), 299 – 321.

[19] Karim,M.F., and Kennedy,J.F. (1990). "Menu of Coupled Velocity and Sediment-Discharge Relationship for River." Journal of Hydraulic Engineering, 116(8), 987- 996.

[20] Karunanithi,N., Grenney,W.J., Whitley,D., and Bovee,K. (1994). " Neural Networks for River flow Prediction." J. Comp. in Civil Engg., ASCE, 8(2), 201- 220.

[21] Muttiah,R.S., Srinivasan,R., and Allen,P.M. (1997). "Prediction of two- year PeakStream Discharges using Neural Networks." Journal of American Water Resources Association, 33(3), 625-630.

[22] Ongley,E. (1996). "Water Quality Monitoring- A Practical Guide to the Design and Implementation of Freshwater Quality Studies and Monitoring Programmes".

[23] Ozgur Kisi. (2007). "Development of Streamflow- Suspended Sediment Rating Curve using a Range Dependent Neural Network." International Journal of Science and Technology, 1(2), 49-61.

[24] Prakash,A.,(1986). "Current state of hydrologic modeling and its limitations." Proceedings International Symposium on Flood Frequency and Risk Analysis, Louisiana State University, Baton Rouge, Louisiana, USA.

[25] Poff,L.N., Tokar and Johnson. P.A (1996). "Stream Hydrological and Ecological Responses to Climatic change assessed with an Artificial Neural Network." Limnol and Oceanogr., 41(5), 857- 863.

[26] Raman.H., Sunil Kumar.N. (1995). " Multivariate Modelling of Water Resources Time Series using Artificial Neural Networks." Hydrological Sciences, 2(40), 145-163.

[27] Roger,L.L., Dowla,F.U. (1994). "Optimization of Groundwater Remediation using ANNwith Parallel Solute Transport Modeling." Water Resources Research, 30(2), 457-481.

[28] Rumelhart,D.E., Hinton,G.E., and Williams,R.J. (1986). "Learning Representations by Back- Propagating Errors." Nature, 323, 533-536.

[29] Shen,H.W., and Hung, C.S. (1972). "An Engineering Approach to Total Bed Material Load by Regression Analysis." Proceedings Sedimentation Symposium, Chapter14, 14.1-14.7.

[30] Subrahmanya Kumar. C.S.V., (2009), Ph.D dissertation on Performance Evaluation and Comparison of Different types of Hydrological Models using Artificial Neural Networks, JNTU, Hyderabad.

[31] Subrahmanya Kumar. C.S.V & Viswanadh G.K (2008) Artificial Neural Network Approach for Reservoir Stage Prediction, International Journal of Applied Mathematical Analysis and Applications, pp 13- 19, Vol 3, No.1, Jan - June 2008.

[32] Subrahmanya Kumar. C.S.V & Viswanadh G.K (2009), Performance Evaluation of Rainfall-Runoff Modeling using Artificial Neural Networks**,** International Journal of Scientific Computing, pp 245- 250, Vol 3, No.2, July – December, 2009.

[33] Tawfik,M., Ibrahim,A., and Fahmy,H. (1997). "Hysteresis Sensitive Neural Network for Modeling Rating Curves." Journal of Comp. in Civil Engineering, 11(3), 206- 211.

[34] Thirumalaiah,K., and Deo,M.C. (1998). "River Stage Forecasting using Artificial Neural Networks." Hydrologic Engineering, 3(1), 26-32.

[35] Tokar,A.S.(1996). "Rainfall -Runoff Modeling in an Uncertain Environment." Ph.D dissertation, University of Maryland, College Park.

[36] Werbos,P. (1974). "Beyond Regression: New Tools for Prediction and Analysis in the behavioral Sciences." Ph.D dissertation, Harvard University, Cambridge.

[37] Wu., Jun Han., Shastri Annambhotla., Scott Bryant. "Artificial Neural Networks for Forecasting Watershed Runoff and Stream Flows." Journal of Hydrologic Engineering, 3(10), 216-222.