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ARTIFICIAL NEURAL NETWORK APPROACH FOR RESERVOIR STAGE PREDICTION

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ABSTRACT

Feed forward multilayer neural networks are widely used as predictors in several fields of water resources applications . The present study demonstrates the application of neural networks to real time prediction of daily reservoir stage. Prediction of reservoir stage helps in operational planning of water resources systems like reservoirs. The Artificial Neural Network (ANN) stage prediction model was developed using stage data for a period of 76 years. The ANN model was trained using data for a period of 50 years. The trained ANN was then tested for 26 years and the results were compared with the observed values of the corresponding period. The results suggests that a three layer feed forward ANN having single hidden layer with two neurons in the hidden layer can effectively be used to predict the reservoir stage The Nash coefficient of efficiency of the ANN model were found to be 0.971 and 0.987 during training and testing The correlation coefficient between the observed and computed stage series is 0.986 during training and 0.994 during validation. The study revealed that ANN model developed gives the best prediction of reservoir stage.

Introduction : With increase in population, urbanization, rapid industralisation and over exploitation of water resources, the management of water resources is very important. Management of water resources can be carried out from the hydrological studies. This is mainly carried in the form of estimation or forecasting the magnitude of a hydrological variable like rainfall, runoff using the past experience. Such forecasts and predictions provide a warning of the extreme flood or drought situations. Such studies help in optimal operation of water resources systems such as reservoirs and power plants.

Many approaches have emerged over the past few decades which are deterministic as well as stochastic in nature. Both these approaches include conceptual and statistical methods. Distributed models require large number of parameters. In situations where adequate information regarding meteorological and topographic is not available, development of models require more time and effort. In such situations development of ANN seems attractive in hydrological modeling. The other benefits include data error tolerance, adaptability, lack of any exogenous input, and less computer storage space.

In the present study an attempt is made to apply ANN to predict the daily reservoir stage in Osmansagar reservoir, Hyderabad, A.P, India.

Artificial Neural Networks (ANN): ANN is a computing technique designed to mimic the human brain and the nervous system. 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 resent past, to avoid duplication, the main concepts are highlighted. in this section.

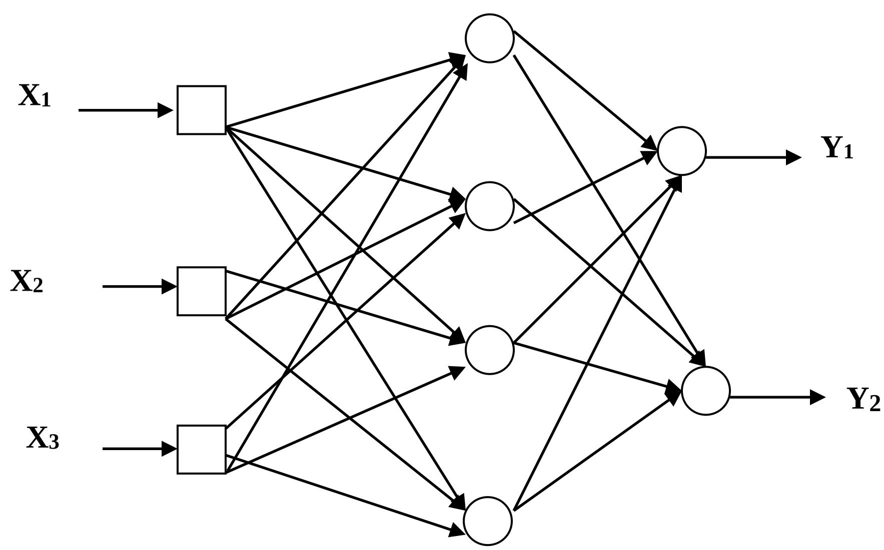
A three layer feed- forward ANN is shown in Fig.1. It consists of input, output and hidden layers. Each neuron in a layer is connected to all the neurons in the next layer, and the neurons in one layer are not connected among themselves. All the nodes within a layer act synchronously. In a feed- forward network, the input quantities are fed to the input nodes, which in turn pass them on to the hidden layer nodes after multiplying by a weight. A hidden layer node adds up the weighted input received from each input node, associates it with a bias, and then passes the result on through a non- linear transfer function. This process is repeated by the output nodes.

Training of ANN: In any hydrologic problem using ANN, the network is first trained, 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 Levenberg- Marquardt algorithm with back- propagation (LMBP). Back- propagation is the most commonly used supervised training algorithm in the multilayer feed forward networks.

Levenberg- Marquardt algorithm is one method which uses second order derivatives of the error function and can be used as a variant of back propagation to improve the learning rate. The weight update rule of this algorithm is given by (in vector notation)

$$\Delta W = (H + \mu \times I)^{-1} \times J^T \times e \quad (1)$$

Where $\mathbf{H} = \mathbf{J^T \times J}$ is the Hessian matrix of error vector and is equal to $\Delta^2\mathbf{E}$, is the Jacobian matrix of derivatives of each error to each weight, $\boldsymbol{\mu}$ is a small value which controls the learning process, $\mathbf{e}$ is an error vector, $\Delta\mathbf{W}$ is the change in weights, $\mathbf{J^T}$ is the transpose of the Jacobian matrix and $\mathbf{I}$ is the identity matrix. If the scalar μ is very large, the above expression approximates gradient descent method, while if it is very small the above expression becomes Gauss- Newton method. The Gauss- Newton method is faster and more accurate near an error minimum. Hence it is decreased after each successful step and is increased only when error is increased. In practice, Levenberg- Marguardt algorithm with back propagation is faster and finds better optima for a variety of problems.



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

Study Area: Osmansagar reservoirt in Hyderabad, A.P, India, was selected to demonstrate the methodology for predicting daily stage in the reservoir during monsoon using an ANN. The catchment has a drainiage area of 285 sq miles. The area is situated between 17.2° – 17.5° N latitude and 78.25° to 78.35°E longitude. The climate in the study area is semi arid and the average annual rainfall is around 800mm

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Design of ANN: A three layer ANN model was adopted in this study. The number of neurons in the hidden layer is finalised by trial and error. In the trial process during training, the number of neurons in the hidden layer was varied between 1 and 3. The configuration that gives the minimum MSE and maximum correlation coefficient was selected for each of the options. Before applying the ANN, the input data was normalized to fall in the range of 0 and 1. The reservoir stage was normalized using the following relation,

$$RE = (RV - MIN\ R) / (MAX\ R - MIN\ R) \quad (2)$$

Where **RE** is normalized value of the reservoir stage, **RV** the initial value of reservoir stage, **MIN R** is the smallest value of reservoir stage, **MAX R** is the greatest value of reservoir stage.

Let E_t represent the reservoir stage at time t. In the present study, the following combinations of input data of reservoir stage were presented to the network.

1. E_{t-1}
2. E_{t-1}, E_{t-2},
3. E_{t-1}, E_{t-2}, E_{t-3}

Where E_{t-1}, E_{t-2}, and E_{t-3} are the reservoir stages at time periods (t-1), (t-2) and (t-3) respectievely.

The ANN model was trained using daily reservoir stage during monsoon period (June – October) for a period of 50 years (1931 – 1980) and then tested or validated for a period of 26 years (1981 – 2006). For each combination of inputs, the number of nodes in the hidden layer that gave the best MSE and correlation coefficient was determined. The number of nodes in the hidden layer varied between 1 and 3. Table.1. gives the statistical performance indices for each combination.

Based on the performance criteria, the final architecture arrived in the present study is 2- 2- 1, i.e., model 2. The graphical representation of the output of model 2 during training and testing phases is presented in Fig.2 and Fig.3. The scatter plots of the computed / predicted versus observed stage values during training and testing phases are shown in Fig.4 and Fig.5.

Table.1. Statistical performance indices

Model Name	ANN model inputs	Nodes in the hidden layer	Reservoir Stage					
			Training Phase			Testing Phase		
			Mean square error (MSE)	Correlation coefficient (R)	Nash coefficient (η)	Mean square error (MSE)	Correlation coefficient (R)	Nash coefficient (η)
Model1	E_{t-1}	3	1.10	0.985	0.972	2.00	0.989	0.976
Model2	E_{t-1}, E_{t-2}	2	1.16	0.986	0.971	$4.52 * 10^{-5}$	0.994	0.987
Model3	E_{t-1}, E_{t-2} E_{t-3}	2	1.13	0.985	0.97	1.07	0.993	0.987

Conclusions : The potential of ANN model which belongs to the class of data- driven approaches for predicting daily reservoir stage in Osmansagar reservoir, Hyderabad has been presented in the paper. An ANN using Levenberg- Marquardt algorithm with back- propagation (LMBP) is adopted in the study. Various combinations of ANN inputs were tried and for each combination, the optimum number of nodes in the hidden layer was determined. The ANN with input nodes consisting of E_{t-1}, E_{t-2}, and E_t as output node with two nodes in the hidden layer is the best match among the combinations tried. For this combination, the MSE is found to be 1.16 and $4.52 * 10^{-5}$

during training and testing periods. The correlation coefficient is 0.986 and 0.994 and the Nash Coefficient is 0.971 and 0.987 respectively during both the phases. Based on the results, it is clear that ANN predictions are better and these predictions are very near to the observed values. It is concluded that ANN provides systematic approach and shortened time spent on training of the model compared to the development and calibration of the conceptual models.

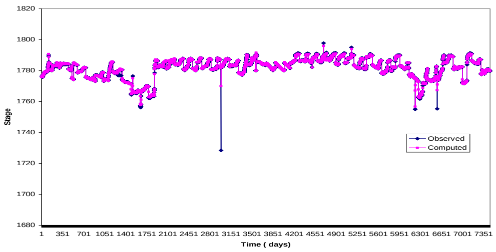

Fig.2 Variation of observed & computed stage values

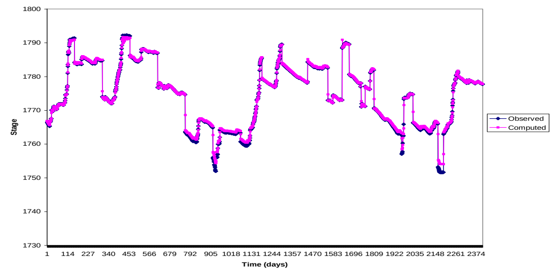

Fig.3 Variation of observed & computed stage values

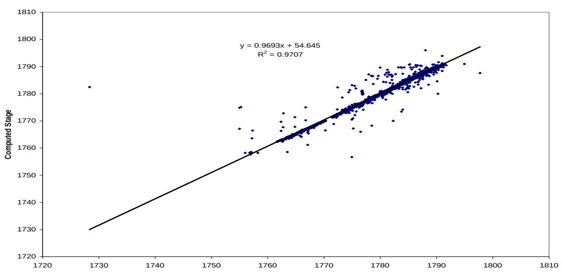

Fig.4 Scatter plot of observed & computed stage values

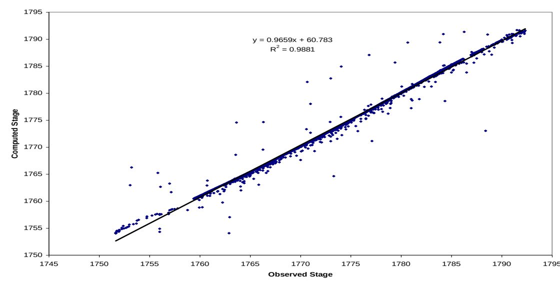

Fig.5 Scatter plot of observed & computed stage values

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