Modular neural network approach for short term flood forecasting a comparative study

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Abstract— **The artificial neural networks (ANNs) have been applied to various hydrologic problems recently. This research demonstrates static neural approach by applying Modular feedforward neural network to rainfall-runoff modeling for the upper area of Wardha River in India. The model is developed by processing online data over time using static modular neural network modeling. Methodologies and techniques for four models are presented in this paper and a comparison of the short term runoff prediction results between them is also conducted. The prediction results of the Modular feedforward neural network with model two indicate a satisfactory performance in the three hours ahead of time prediction. The conclusions also indicate that Modular feedforward neural network with model two is more versatile than other and can be considered as an alternate and practical tool for predicting short term flood flow.**

Keywords- Artificial neural network, Forecasting, Rainfall, Runoff, Models.

I. Introduction

The main focus of this research is development of Artificial Neural Network (ANN) models for short term flood forecasting, determining the characteristics of different neural network models. Comparisons are made between the performances of different artificial neural network models of Modular feedforward neural network for optimal result.

The field engineers face the danger of very heavy flow of water through the gates to control the reservoir level by proper operation of gates to achieve the amount of water flowing over the spillway. This can be limited to maximum allowable flood and control flood downstream restricting river channel capacity so as to have safe florid levels in the river within the city limits on the downstream [21].

By keeping the water level in the dam at the optimum level in the monsoon the post monsoon replenishment can be conveniently stored between the full reservoir level and the permissible maximum water level. Flood estimation is very essential and plays a vital role in planning for flood regulation and protection measures.

The total runoff from catchment area depends upon various unknown parameters like Rainfall intensity, Duration of rainfall, Frequency of intense rainfall, Evaporation, Interception, Infiltration, Surface storage, Surface detention, Channel detention, Geological characteristics of drainage basin, Meteorological characteristics of basin, Geographical features of basin etc. Thus it is very difficult to predict runoff at the dam due to the nonlinear and unknown parameters.

In this context, the power of ANNs arises from the capability for constructing complicated indicators (non-linear models). Among several artificial intelligence methods artificial neural networks (ANN) holds a vital role and even ASCE Task Committee Reports have accepted ANNs as an efficient forecasting and modeling tool of complex hydrologic systems[22].

Neural networks are widely regarded as a potentially effective approach for handling large amounts of dynamic, non-linear and noisy data, especially in situations where the underlying physical relationships are not fully understood. Neural networks are also particularly well suited to modeling systems on a real-time basis, and this could greatly benefit operational flood forecasting systems which aim to predict the flood hydrograph for purposes of flood warning and control[16].

Artificial neural netwark are applied for flood forecasting using different models.

Multilayer perceptrons (MLPs) are feedforward neural networks trained with the standard backpropagation algorithm. They are supervised networks so they require a desired response to be trained. They learn how to transform input data into a desired response, and widely used for modeling prediction problems [2].

Backpropagation computes the sensitivity of the output with respect to each weight in the network, and modifies each weight by a value that is proportional to the sensitivity.

Radial basis functions networks have a very strong mathematical foundation rooted in regularization theory for solving ill-conditioned problems. The mapping function of a radial basis function network, is built up of Gaussians rather than sigmoids as in MLP networks [7].

A subset of historical rainfall data from the Wardha River catchment in India was used to build neural network models for real time prediction. Telematic automatic rain gauging stations are deployed at eight identified strategic locations which transmit the real time rainfall data on hourly basis. At the dam site the ANN model is developed to predict the runoff three hours ahead of time.

In this paper, we demonstrate four different models of Modular feedforward neural network (M FF) models for real time prediction of runoff at the dam and compare the effectiveness of these methods. As the name indicates, the modular feedforward networks are special cases of MLPs, such that layers are segmented into modules. This tends to create some structure within the topology, which will foster specialization of function in each sub-module.

At a time when global climatic change would seem to be increasing the risk of historically unprecedented changes in river regimes, it would appear to be appropriate that alternative representations for flood forecasting should be considered.

II. METHODOLOGY

In this study four methods are employed for rainfall-runoff modeling using Modular feedforward neural network model.

Of the entire learning algorithm, the error backpropagation method is the most widely used. Although this algorithm has been successful in many applications, it has disadvantages such as the long training time that can be inconvenient in practical and on-line applications. This necessitates the improvement of the basic algorithm or integration with other forms of network configurations such as modular networks studied here.

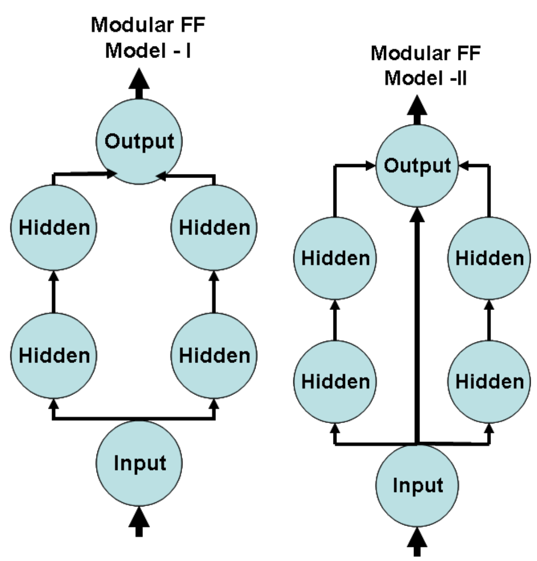

Figure 1. The Modular feedforward model I and II neural network

The modular architecture allows decomposition and assignment of tasks to several modules. Therefore, separate architectures can be developed to each solve a sub-task with the best possible architecture, and the individual modules or building blocks may be combined to form a comprehensive system. The modules decompose the problem into two or more subsystems that operate on inputs without communicating with each other. The input unites are mediated by an integrating unit that is not permitted to feed information back to the module (Jacobs, Jordan, Nowlan, and Hinton, 1991).

Four different models as shown in Figure 1 and Figure 2 are studied. We use two hidden layers, tanh activation function with 0.7 momentum and mean squared error of the cross validation set as stopping criteria which give the optimal results.

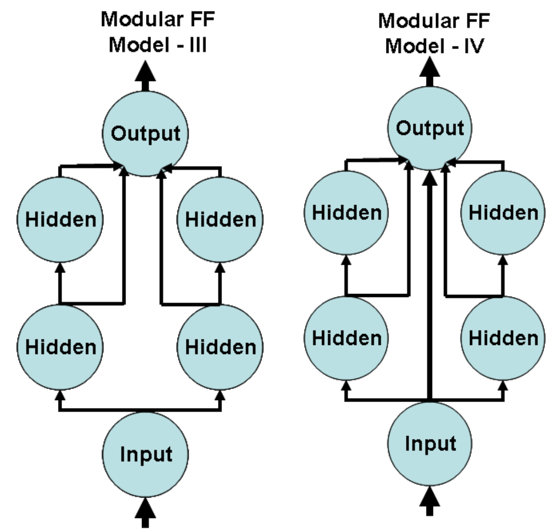

Figure 2. The Modular feedforward model III and IV neural network

Performance Measures:

The learning and generalization ability of the estimated NN model is assessed on the basis of important performance measures such as MSE (Mean Square Error), NMSE (Normalized Mean Square Error) and r (Correlation coefficient)

A. MSE (Mean Squzre Error) :

The formula for the mean square error is:

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}\left(d_{ij} - y_{ij}\right)^2}{NP} \quad \ldots \quad (1)$$

Where

P = number of output PEs,

N = number of exemplars in the data set,

y_{ij} = network output for exemplar i at PE j,

d_{ij} = desired output for exemplar i at PE j.

B. NMSE (Normalized Mean Square Error:

The normalized mean squared error is defined by the following formula:

$$NMSE = \frac{P\,N\,MSE}{\sum_{j=0}^{P} \frac{N\sum_{i=0}^{N} d_{ij}^{2} - \left(\sum_{i=0}^{N} d_{ij}\right)^{2}}{N}} \quad \dots (2)$$

Where

P = number of output processing elements,

N = number of exemplars in the data set,

MSE = mean square error,

d_{ij} = desired output for exemplar i at processing element j.

C. r (correlation coefficient) :

The size of the mean square error (MSE) can be used to determine how well the network output fits the desired output, but it doesn't necessarily reflect whether the two sets of data move in the same direction. For instance, by simply scaling the network output, the MSE can be changed without changing the directionality of the data. The correlation coefficient (r) solves this problem. By definition, the correlation coefficient between a network output x and a desired output d is:

$$r = \frac{\dfrac{\sum_i \left(x_i - \bar{x}\right)\left(d_i - \bar{d}\right)}{N}}{\sqrt{\dfrac{\sum_i \left(d_i - \bar{d}\right)^2}{N}}\sqrt{\dfrac{\sum_i \left(x_i - \bar{x}\right)^2}{N}}} \quad \dots (3)$$

where $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$ and $\bar{d} = \frac{1}{N}\sum_{i=1}^{N} d_i$

The correlation coefficient is confined to the range [-1, 1]. When r = 1 there is a perfect positive linear correlation between x and d, that is, they co-vary, which means that they vary by the same amount.

III. Study Area and Data Set

The Upper Wardha catchment area lies directly in the path of depression movements which originates in the Bay of Bengal. When the low pressure area is formed in the Bay of Bengal and cyclone moves in North West directions, many times this catchment receives very heavy intense cyclonic precipitation for a day or two. Occurrence of such events have been observed in the months of August and September. Rainfall is so intense that immediately flash runoff, causing heavy flood has been very common feature in this catchment.

For such flashy type of catchment and wide variety in topography, runoff at dam is still complicated to predict. The conventional methods also display chaotic result. Thus ANN based model is built to predict the total runoff from rainfall in Upper Wardha catchment area for controlling water level of the dam.

In the initial reaches, near its origin catchment area is hilly and covered with forest. The latter portion of the river lies almost in plain with wide valleys.

The catchment area up to dam site is 4302 sq. km. At dam site the river has wide fan shaped catchment area which has large variation with respect to slope, soil and vegetation cover.

Figure 3- Location of Upper Wardha dam on Indian map

Data: Rainfall runoff data for this study is taken from the Wardha river catchment area which contains a mix of urban and rural land. The catchments is evenly distributed in eight zones based on the amount of rainfall and geographical survey. The model is developed using historical rainfall runoff data , provided by Upper Wardha Dam Division Amravati, department of irrigation Govt. of Maharashtra. Network is trained by rainfall information gathered from eight telemetric rain-gauge stations distributed evenly throughout the catchment area and runoff at the dam site.

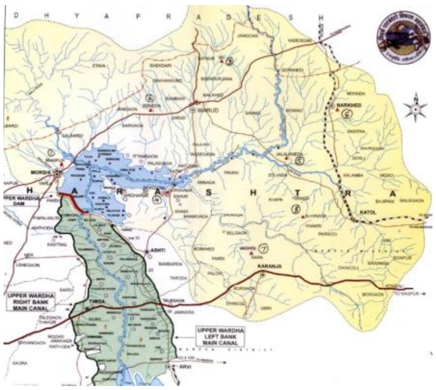

Figure 4- The Wardha river catchment

The data is received at the central control room online through this system on hourly basis. The Upper Wardha dam reservoir operations are also fully automated. The amount of inflow, amount of discharge is also recorded on hourly basis. From the inflow and discharge data the cumulative inflow is calculated. The following features are identified for the modeling the neural network .

TABLE I. THE PARAMETERS USED FOR TRAINING THE NETWORK

Month	RG1	RG2	RG3	RG4	RG5	RG6	RG7	RG8	CIF

- Month – The month of rainfall
- Rain1 to Rain8 – Eight rain gauging stations.
- Cum Inflow – Cumulative inflow in dam

Seven years of data on hourly basis from 2001 to 2007 is used. It has been found that major rain fall (90%) occurs in the month of June to October Mostly all other months are dry hence data from five months. June to October is used to train the network

IV. RESULT

The neural network structure is employed to learn the unknown characterization of the system from the dataset presented to it. The dataset is partitioned into three categories, namely training, cross validation and test. The idea behind this is that the estimated NN model should be tested against the dataset that was never presented to it before. This is necessary to ensure the generalization. An experiment is performed at least twenty five times with different random initializations of the connection weights in order to improve generalization.

The data set is divided in to training , testing and cross validation data and the network is trained for all models of Modular feedforward neural network model for 5000 epochs. Fig 5 to Fig 8 shows the plot of actual Vs predicted values for runoff for Modular feedforward neural network models.

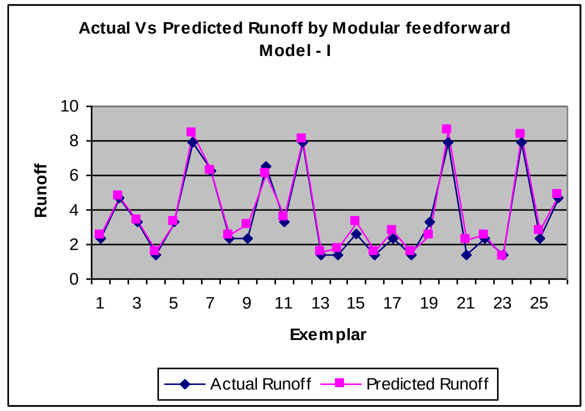

Figure 5- Actual Vs. Predicted runoff by MFF M-I

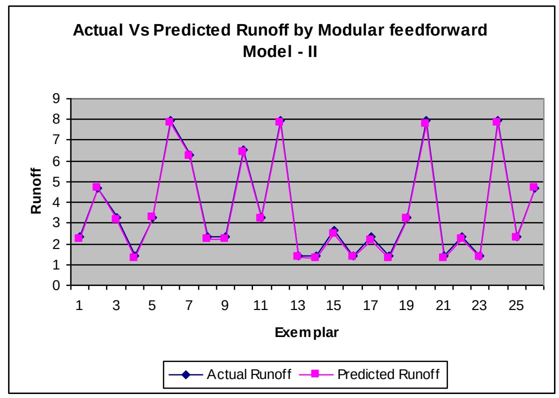

Figure 6.– Actual Vs. Predicted runoff by M FF M-II

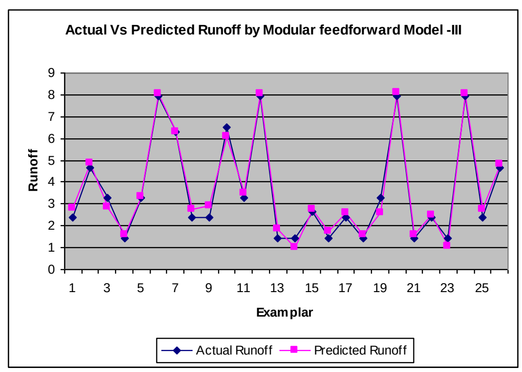

Figure 7.– Actual Vs. Predicted runoff by M FF M-III

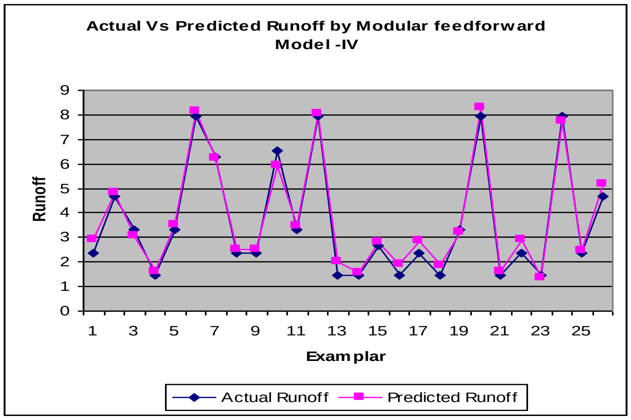

Figure 8.– Actual Vs. Predicted runoff by M FF M-IV

The error found in the actual and predicted runoff at the dam site is plotted for all four models of M FF neural networks as shown in the Figure 9 to Figure 12.

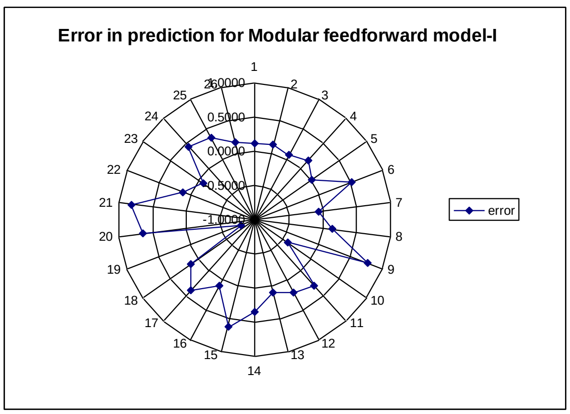

Fig 9 – Error graph of MLP Model

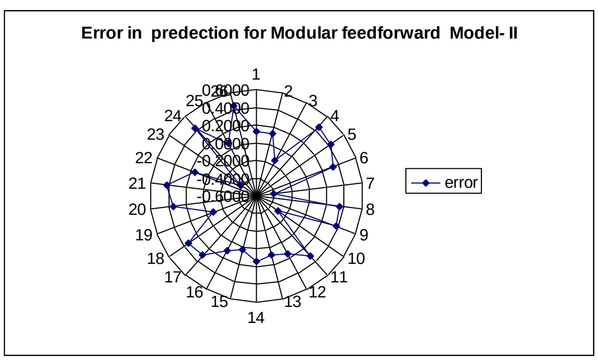

Fig 10 – Error graph of M FF Model

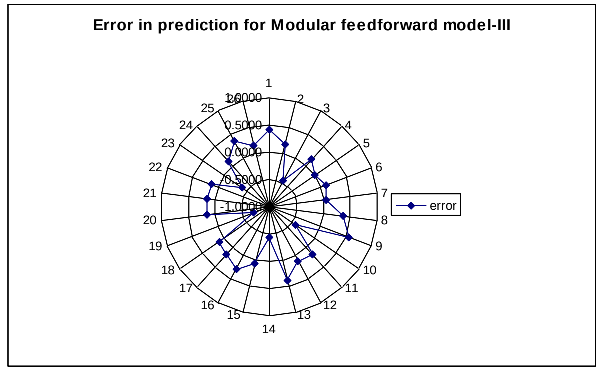

Fig 11 – Error graph of M FF Model

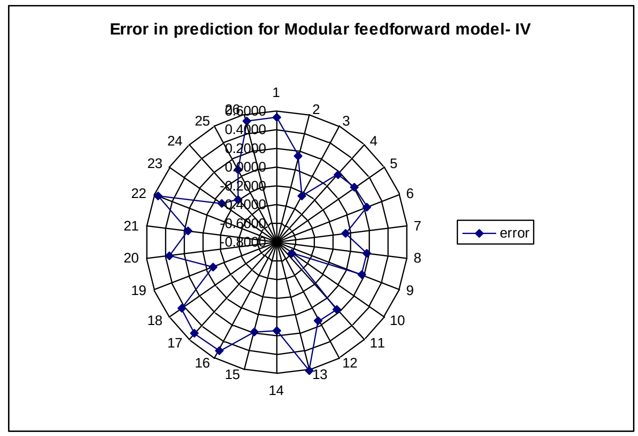

Fig 12 – Error graph of M FF Model

After training the network the performance is studied and in the Table-2 to Table-5 the parameters and the performances of four different models of Modular feedforward neural network are listed.

TABLE II. M FF M-I NETWORK PERFORMANCE

Parameter	Performance- M-I
MSE	0.1547
NMSE	0.1436
Min Abs Error	0.0652
Max Abs Error	0.8193
r	0.4619

TABLE III. M FF M-II NETWORK PERFORMANCE

Parameter	Performance-M-II
MSE	0.0872
NMSE	0.0764
Min Abs Error	0.0246
Max Abs Error	0.4601
r	0.8106

TABLE IV. MFF M-III NETWORK PERFORMANCE

Parameter	Performance-M-III
MSE	0.0968
NMSE	0.1196
Min Abs Error	0.0342
Max Abs Error	0.6904
r	0.7342

TABLE V. M FF M-IV NETWORK PERFORMANCE

Parameter	Performance-M-IV
MSE	0.1068
NMSE	0.1263
Min Abs Error	0.0519
Max Abs Error	0.6036
r	0.6184

The parameters and performance for all four models of M FF model are compared on the performance scale and are listed in the Table 6 shown below. The comparative analysis of the MSE, NMSE and r (the correlation coefficient) is done.

TABLE VI. COMPARISON OF PERFORMANCE PARAMETERS

TABLE VII.

Module / Parameter	M-I	M-II	M-III	M-IV
MSE	0.1547	0.0872	0.0968	0.1068
NMSE	0.1436	0.0764	0.1196	0.1263
Min Abs Error	0.0652	0.0246	0.0342	0.0519
Max Abs Error	0.8193	0.4601	0.6904	0.6036
r	0.4619	0.8106	.7342	0.6184

The main advantage of M FF is that in contrast to the MLP, modular feedforward networks do not have full interconnectivity between the layers. Therefore, a smaller number of weights are required for the same size network (the same number of PEs). This tends to speed the training and reduce the number of examples needed to train the network to the same degree of accuracy.

V. CONCLUSION

An ANN-based short-term runoff forecasting system is developed in this work. A comparison between four different models of Modular feedforward neural network model is made to investigate the performance of four distinct approaches. We find that Modular feedforward neural network with model-II approach is more versatile than others. Modular feedforward neural network with module-II is performing better as compare to other approaches studied as far as the overall performance is concerned for forecasting runoff for 3 hrs lead time. Other models of Modular feedforward neural network are also performing optimally. Which means that static model of Modular feedforward neural network with model-II is powerful tool for short term runoff forecasting for Wardha River basin

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