

Static and Dynamic 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 and dynamic neural approach by applying Time lagged recurrent neural network and Radial basis function 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 and dynamic connections. Methodologies and techniques of the two 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 Time lagged recurrent neural network indicate a satisfactory performance in the three hours ahead of time prediction. The conclusions also indicate that Time lagged recurrent neural network is more versatile than Radial basis function neural network and can be considered as an alternate and practical tool for predicting short term flood flow.

General Terms:- Prediction, Radial basis function neural network, Time lagged recurrent neural network.

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.

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 flood levels in the river within the city limits on the downstream.

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].

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 the use of time lagged recurrent neural network (TLRNN) and Radial basis function neural network (RBF) model for real time prediction of runoff at the dam and compare the effectiveness of these two methods. Time lagged recurrent neural network is dynamic model which extend the multilayer perceptron with context units, which are PE's that remember past activity. Whereas Radial basis function neural network is a static model having a feed-forward structure consisting of hidden layer for a given number of locally tuned units which are fully interconnected to an output layer of linear units

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 two methods employed for rainfall-runoff modeling namely Time lagged recurrent neural network and Radial basis function neural network models using artificial neural network [4].

TLRNs are MLPs extended with short term memory structures that have local recurrent connections. The TLRN is a very appropriate model for processing temporal (time-varying) information.

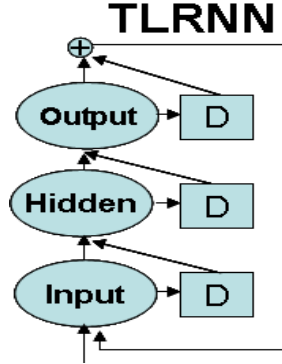


Figure 1. The TLRNN model

There are three memory structures to choose from. The TDNN memory structure is simply a cascade of ideal delays (a delay of one sample). The gamma memory is a cascade of leaky integrators. The Laguerre memory is slightly more sophisticated than the gamma memory in that it orthogonalizes the memory space

The Focused topology only includes the memory kernels connected to the input layer. This way, only the past of the input is remembered. If the Focused topology is not applied, then the hidden layers' PEs will also be equipped with memory kernels.

We use TDNN axon with Levenberg Marquardt with tanh activation function which give the optimal results.

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. Learning in RBF network is carried out in two phases: first for the hidden layer, and then for the output layer. The hidden layer is self-organising; its parameters depend on the distribution of the inputs, not on the mapping from the input to the output. The output layer, on the other hand, uses supervised learning (gradient or linear regression) to set its parameters.

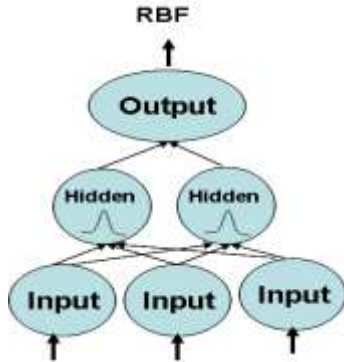


Figure 2. The Radial basis function neural network

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 Square Error):

The formula for the mean square error is:

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

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:

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

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

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



Figure 4- The Wardha river catchment

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 [3].

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 1- The parameters used for training the network

Month	RG1	RG2	RG3	RG4	RG5	RG6	RG7	RG8	CIF
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- 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 both Time lagged recurrent neural network and Radial basis function neural network model for 5000 epochs. Fig 5 shows the plot of actual Vs predicted values for runoff for TLRNN, where as Fig 6 shows the plot for Radial basis function neural network.

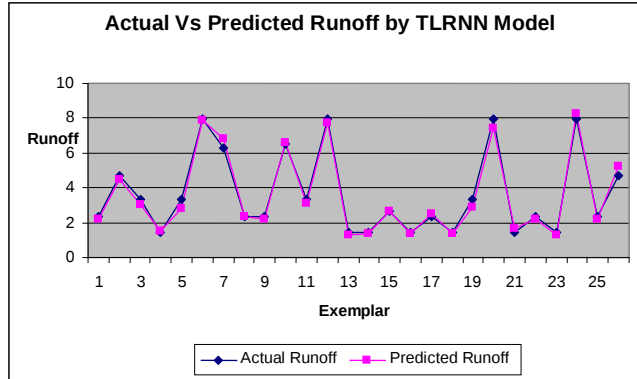


Figure 5- Actual Vs. Predicted runoff by TLRNN

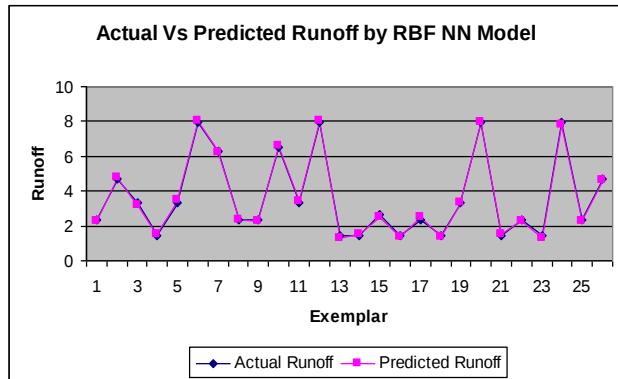


Figure 6.– Actual Vs. Predicted runoff by RBF

The error found in the actual and predicted runoff at the dam site is plotted for both TLRNN and RBF network as shown in the Figure 7 and Figure 8 respectively.

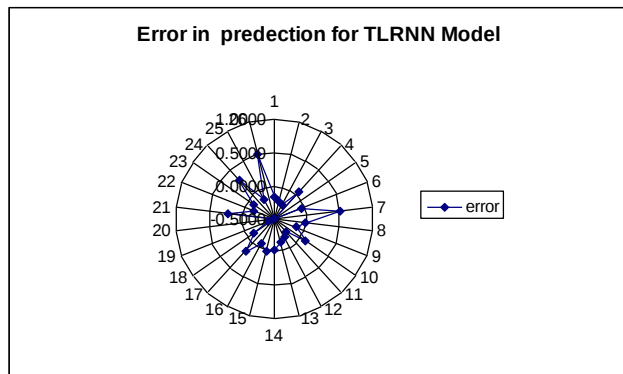


Fig 7 – Error graph of TLRNN Model

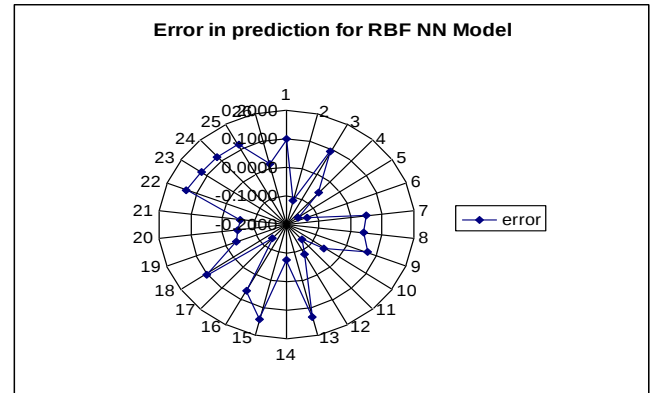


Fig 8 – Error graph of RBF Model

After training the network the performance is studied and in the Table-2 and Table-3 the parameters and the performances of time lagged recurrent neural network and Radial basis function neural network are listed.

Table 2- TLRN network parameters

Parameter	Performance
MSE	0.00587
NMSE	0.00378
Min Abs Error	0.00381
Max Abs Error	0.51340
r	0.9604

Table 3- RBF network parameters

Parameter	Performance
MSE	0.07629
NMSE	0.06431
Min Abs Error	0.01943
Max Abs Error	0.14387
r	0.85437

The parameters and performance for TLRNN and RBF model is compared on the performance scale and are listed in the Table 4 shown below. The comparative analysis of the MSE, NMSE and r (the correlation coefficient) is done.

Table 4 – Comparison of performance parameters

S.No.	N N Model	Performance measure		
		MSE	NMSE	r
1	TLRNN	0.00587	0.0037	0.9604
2	RBF NN	0.07629	0.0643	0.8543

The main advantage of RBF is that it finds the input to output map using local approximators. Each one of these local pieces is weighted linearly at the output of the network. Since they have fewer weights, these networks train extremely fast and require fewer training samples.

But the disadvantage is it requires a lot of radial basis function to cover a very large dimensionality space.

The main advantage of TLRNs is the smaller network size required to learn temporal problems when compared to MLPs that use extra inputs to represent the past samples (equivalent to time delay neural networks). An added advantage of TLRNs is their low sensitivity to noise. The recurrence of the TLRN provides the advantage of an adaptive memory depth (i.e., it finds the best duration to represent the input signal's past).

V. CONCLUSION

An ANN-based short-term runoff forecasting system is developed in this work. A comparison between Time lagged recurrent neural network (dynamic) model and Radial basis function neural network (static) model is made to investigate the performance of the two distinct approaches. We find that the Time lagged recurrent neural network is more versatile than the Radial basis function neural network. Time lagged recurrent neural network is performing better as compare to Radial basis function neural network as far as the overall performance is concerned for forecasting runoff for 3 hrs lead time. Radial basis function neural network is also performing optimally. Which means that dynamic model of Time lagged recurrent neural network is powerful tool for short term runoff forecasting for Wardha River basin

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