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Prediction of Rainfall Using MLP and RBF Networks

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ABSTRACT

Prediction of rainfall for a region is of utmost importance for planning, design and management of irrigation and drainage systems. This can be achieved by different approaches such as deterministic, conceptual, stochastic and Artificial Neural Network (ANN). This paper illustrates the use of ANN for prediction of rainfall at Atner, Multai and Dharni stations. Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) networks are applied to train the network data. Model performance indicators such as correlation coefficient, model efficiency and root mean square error are used to evaluate the performance of the MLP and RBF networks. The paper presents the MLP network is better suited for prediction of rainfall for Atner and Multai whereas RBF network for Dharni.

Keywords - Correlation, Mean Square Error, Model Efficiency, Neural Network, Rainfall

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1. INTRODUCTION

Prediction of rainfall for a region is of utmost importance for planning, design and management of irrigation and drainage systems. Since the distribution of rainfall varies over space and time, it is required to analyze the data covering long periods and observed at various locations to arrive at reliable information for decision support. Further, such data need to be analyzed in different ways, depending on the issue under consideration [1]. Approaches such as deterministic, conceptual, stochastic and Artificial Neural Network (ANN) are commonly used for prediction of rainfall. Past research experience shows that there is an abundance of literature on development of deterministic, conceptual and stochastic models [2]. In this context, ANN is considered an effective tool for prediction of meteorological variables such as rainfall, temperature and wind speed, etc; and hence used in the present study.

ANN modelling procedures adapt to complexity of input-output patterns and accuracy goes on increasing as more and more data become available. Fig. 1 shows the architecture of ANN that consists of input layer, hidden layer, and output layer. In turn, these layers have a certain number of neurons or units, so the units are called as input units, hidden units and output units. From ANN structure, it can be easily understood that input units receive data from external sources to the network and send them to the hidden units, in turn, the hidden units send and receive data only from other units in the network, and output units receive and produce data generated by the network, which goes out of the system. In this process, a typical problem is to estimate the output as a function of the input. This unknown function may be approximated by a superposition of certain activation functions such as tangent, sigmoid and polynomial. A common threshold function used in ANN is the sigmoid function (f(S)) expressed by Eq. (1), which provides an output in the range of 0<f(S)<1 [3].

$$f(S) = \left[1 + \exp(-S_i)\right]^{-1} \qquad \ldots (1)$$

$$S_i = \sum_{i=1}^{N} I_i W_{ij} + O_i, \; j=1,2,3,\ldots..M \qquad \ldots (2)$$

where S_i is the characteristic function of i^{th} layer, I_i is the input unit of i^{th} layer, O_i is the output unit of i^{th} layer, W_{ij} is the synaptic weights between i^{th} input and j^{th} hidden layers, N is the number of observations and M is the number of neurons in the hidden layer. The sigmoid function is chosen for mathematical convenience because it resembles a hard-limiting step function for extremely large positive and negative values of the incoming signal and also gives sufficient information about the response of the processing unit to inputs that are close to the threshold value.

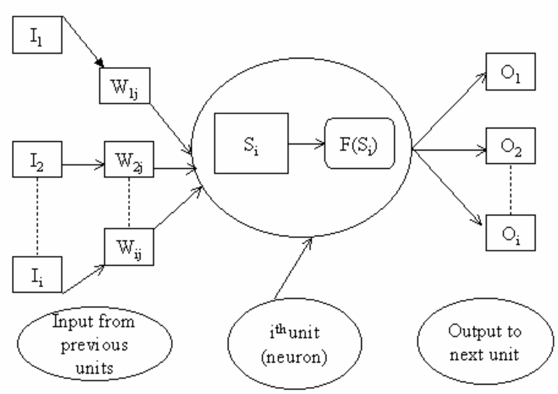

Figure1: Architecture of ANN

Number of networks such as Multi-Layer Perceptron (MLP), Cascade Correlation, Conjugate Gradient, Radial Basis Function (RBF), Bayesian, etc is commonly used for training the network data [4-6]. The objective in training the network is to reduce the global error between the

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predicted and targeted outputs. From the research reports on ANN, it is understood that number of researchers has applied different networks for prediction of rainfall for various regions [7-14]. But there is no general agreement in applying particular network for rainfall prediction for a region though different networks are available for training the network data. In this paper, an attempt has been made to train the network data with MLP and RBF networks for prediction of rainfall at Atner, Multai and Dharni stations. Model Performance Indicators (MPIs) such as Correlation Coefficient (CC), Model Efficiency (MEF) and Root Mean Square Error (RMSE) are used to evaluate the performance of the models with a specific objective to identify the most suitable network for rainfall prediction. The procedures adopted in training the network data with MLP and RBF networks, and computation of MPIs is briefly described in the ensuing sections.

2. METHODOLOGY

2.1 Multi-Layer Perceptron Network (MLPN)

MLPN is the most widely used for rainfall prediction and its architecture with single hidden layer is shown in Fig.1. Gradient descent is the most commonly used supervised training algorithm in MLPN [15]. Each input unit of the training data set is passed through the network from the input layer to output layer. The network output is compared with the desired target output and output error (E) is computed using Eq. (3). This error is propagated backward through the network to each neuron, and the connection weights are adjusted based on Eq. (3).

$$E = \frac{1}{2}\sum_{i=1}^{N}\left(P_i - P_i^*\right)^2 \quad \ldots (3)$$

where P_i is the observed rainfall for i^{th} sample and P_i^* is the predicted rainfall for i^{th} sample.

$$\Delta W_{ij}(M) = -\varepsilon\frac{\partial E}{\partial W_{ij}} + \alpha\Delta W_{ij}(M-1) \quad \ldots (4)$$

where W_{ij} is the synaptic weights between input and hidden layers, $\Delta W_{ij}(M)$ is the weight increments between i^{th} and j^{th} units during M neurons (units) and $\Delta W_{ij}(M-1)$ is the weight increments between i^{th} and j^{th} units during M-1 neurons. In MLPN, momentum factor (α) is used to speed up training in very flat regions of the error surface to prevent oscillations in the weights and learning rate (ε) is used to increase the chance of avoiding the training process being trapped in local minima instead of global minima [16].

2.2 Radial Basis Function Network (RBFN)

RBFN is supervised and three-layered feed forward neural network. The hidden layer of RBFN consists of a number of nodes and a parameter vector called a 'center', which can be considered the weight vector. In RBFN, the standard Euclidean distance is used to measure the distance of an input vector from the center. The design of neural networks is a curve-fitting problem in a high dimensional space in RBFN. Training the RBFN implies finding the set of basis nodes and weights. Therefore, the learning process is to find the best fit to the training data [17]. The transfer functions of the nodes are governed by nonlinear functions that is assumed to be an approximation of the influence that data points have at the center. The transfer function of a RBFN is mostly built up of Gaussian rather than sigmoid. The Gaussian functions decrease with distance from the center. The transfer functions of the nodes are governed by nonlinear functions that is assumed to be an approximation of the influence that data points have at the center.

The Euclidean length is represented by r_j that measures the radial distance between the datum vector $\underline{p}(p_1, p_2, \ldots p_M)$; and the radial center $\underline{P}^{(j)} = (w_{1j}, w_{2j}, \ldots w_{Mj})$ can be written as:

$$r_j = \left\|\underline{p} - \underline{P}^{(j)}\right\| = \left[\sum_{i=1}^{M}\left(p_i - w_{ij}\right)^2\right]^{1/2} \quad \ldots (5)$$

where $r_j = \| \ \|$ is the Euclidean norm, $\Phi()$ is the activation function and w_{ij} is the connecting weight between the i^{th} hidden unit and j^{th} output unit. A suitable transfer function is then applied to r_j to give $\Phi(r_j) = \Phi\left\|\underline{p} - \underline{P}^{(k)}\right\|$. Finally, the output layer (k-1) receives a weighted linear combination of $\Phi(r_j)$,

$$P^{(k)} = w_0 + \sum_{j=1}^{N} c_j^{(k)}\Phi(r_j) = w_0 + \sum_{j=1}^{N} c_j^{(k)}\Phi\left(\left\|\underline{p} - \underline{P}^{(j)}\right\|\right) \quad \ldots (6)$$

where c_j is the centre of the neuron in the hidden layer and $\Phi(r_j)$ is the response of the j^{th} hidden unit and w_0 is the bias term [18].

2.3 Normalization of Data

By considering the nature of sigmoid function adopted in ANN, the training data set values are normalized between 0 and 1 by Eq. (7) and passed into the network [19]. After the completion of training, the output values are denormalized to provide the results in original domain.

$$NOR(P_i) = \frac{P_i - Min(P_i)}{Max(P_i) - Min(P_i)} \quad \ldots (7)$$

where $NOR(P_i)$ is the normalized value of P_i, $Min(P_i)$ is the series minimum value of P_i and $Max(P_i)$ is the series maximum value of P_i.

2.4 Model Performance Analysis

The performance of predicted rainfall using MLP and RBF networks are analyzed by MPIs and are:

$$CC = \frac{\sum_{i=1}^{N}\left(P_i - \overline{P}\right)\left(P_i^* - \overline{P^*}\right)}{\sqrt{\left(\sum_{i=1}^{N}\left(P_i - \overline{P}\right)^2\right)\left(\sum_{i=1}^{N}\left(P_i^* - \overline{P^*}\right)^2\right)}} \quad \ldots (8)$$

$$MEF\ (\%) = \left(1 - \frac{\sum_{i=1}^{N}\left(P_i - P_i^*\right)^2}{\sum_{i=1}^{N}\left(P_i - \overline{P}\right)^2}\right)*100 \quad \ldots (9)$$

$$RMSE = \left(\left(1/N\right)\sum_{i=1}^{N}\left(P_i - P_i^*\right)^2\right)^{1/2} \quad \ldots (10)$$

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where $\overline{P}$ is the average observed rainfall and $\overline{P^*}$ is the average predicted rainfall [20].

3. APPLICATION

An attempt has been made to predict the rainfall at Atner, Dharni and Multai stations using MLP and RBF networks. Fig. 2 shows the location map of the study area. The drainage area of Atner, Multai and Dharni are 650 km^2, 932 km^2 and 2860 km^2 respectively. The annual rainfall recorded at the stations during the period 1943-2004 is used. The data for the period 1943-1984 is used for training the network and the data for the period 1985-2004 is used for testing the network.

Figure 2: Location map of the study area

4. RESULTS AND DISCUSSIONS

Statistical software, namely, SPSS Neural Connection was used to train the network data with different combinations of parameters to determine optimum network architecture of MLP and RBF networks for prediction of rainfall for the stations under study.

4.1 Prediction of Rainfall using MLP and RBF Networks

For Atner and Multai stations, the parameters of α=0.7 and ε=0.08 were used in optimizing the network architecture of MLP. Similarly, the factors of α=0.8 and ε=0.10 were used in optimizing the MLP network architecture of Dharni. The optimum network architectures with model parameters were used for prediction of rainfall. The model performance of MLP and RBF networks were evaluated by MPIs and given in Tables 1 and 2 for the stations under study.

Table 1: Network architecture and MPIs given by MLPN

Network Architecture and MPIs	Atner		Multai		Dharni	
	Training	Testing	Training	Testing	Training	Testing
Network Architecture	1-15-1		1-18-1		1-21-1	
Model Performance Indicators						
CC	0.966	0.971	0.994	0.986	0.995	0.997
MEF (%)	91.9	92.9	96.3	97.0	98.7	99.3
RMSE (mm)	76.3	62.4	60.1	62.3	36.1	28.2

Table 2: Network architecture and MPIs given by RBFN

Network Architecture and MPIs	Atner		Multai		Dharni	
	Training	Testing	Training	Testing	Training	Testing
Network Architecture	1-18-1		1-21-1		1-25-1	
Model Performance Indicators						
CC	0.966	0.971	0.994	0.986	0.995	0.997
MEF (%)	92.5	92.7	98.6	96.1	98.8	99.4
RMSE (mm)	73.3	63.0	67.4	66.4	33.8	25.6

From Tables 1 and 2, it may be noted that: (i) The RMSEs on the predicted rainfall using MLPN are lesser than the corresponding values of RBFN during testing and therefore the architecture of MLPN is better suited network for rainfall prediction for Atner and Multai; (ii) The RMSE value of RBFN is comparatively better than the corresponding value of MLPN for prediction of rainfall for Dharni; (iii) There is generally a good correlation between the observed and predicted rainfall using MLP and RBF networks, with CC values are in the range of 0.966 to 0.997 for Atner, 0.986 to 0.994 for Multai and 0.995 to 0.997 for Dharni; and (iv) The percentages of MEF vary from about 92% to 99% when MLP and RBF networks applied for rainfall prediction for the stations under study. Based on performance analysis, it may be noted that the MLPN could be used for rainfall prediction for Atner and Multai whereas RBFN for Dharni. Figs. 3-5 show the plots of observed and predicted rainfalls (using MLP and RBF networks) for Atner, Multai and Dharni stations respectively.

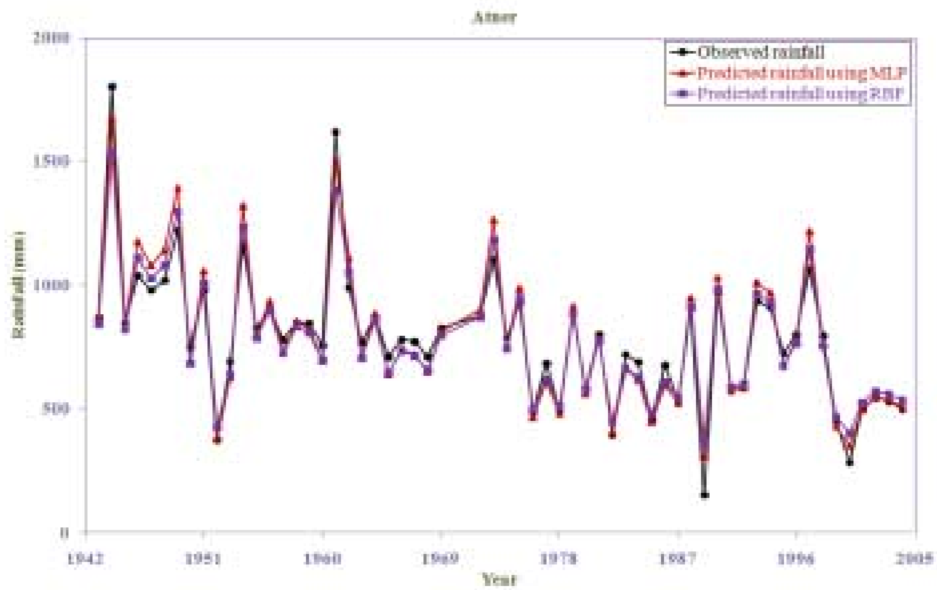

Figure 3: Observed and predicted rainfall (using MLP and RBF networks) for Atner

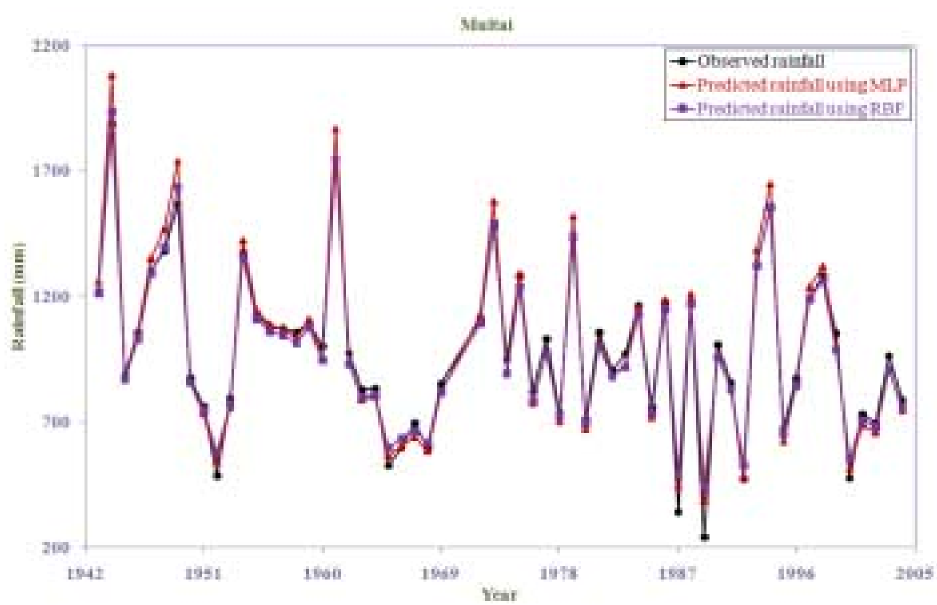

Figure 4: Observed and predicted rainfall (using MLP and RBF networks) for Multai

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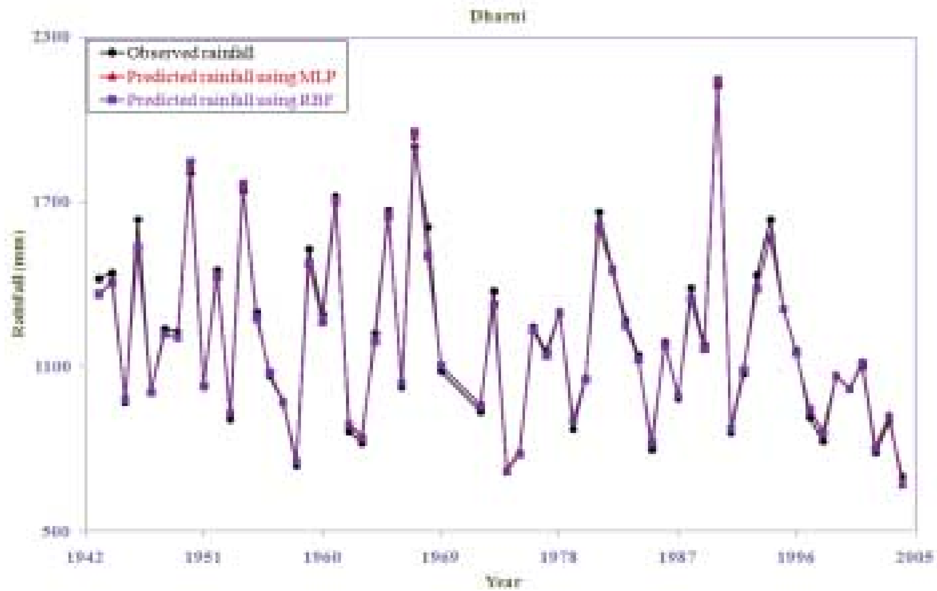

Figure 5: Observed and predicted rainfall (using MLP and RBF networks) for Dharni

From Figs. 3 and 4, it can be seen that the predicted rainfall using MLPN is generally higher than the corresponding values of RBFN. Similarly, from Fig. 5, it can be seen that there is no appreciable difference between the predicted values using MLP and RBF networks for Dharni though the RMSE on the predicted rainfall (using RBFN) is minimum when compared to MLPN values.

4.2 Analysis Based on Statistical Parameters

The summary statistics such as average, Standard Deviation (SD), skewness and kurtosis for the observed and predicted rainfall were computed and given in Tables 3 and 4. From the results, it may be noted that the percentages of variation on the average predicted rainfall, with reference to average observed rainfall, are about 0.2% to 3.0% for Atner, 0.8% to 0.9% for Multai and 0.1% to 0.8% for Dharni.

Table 3: Summary statistics of observed and predicted rainfall (using MLPN) for Atner and Multai

Summary statistics	Atner				Multai			
	Observed rainfall		Predicted rainfall		Observed rainfall		Predicted rainfall	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Average(mm)	855.6	646.0	857.4	665.6	1035.3	884.0	1044.1	892.4
SD(mm)	271.5	239.5	293.4	251.7	317.8	346.8	364.6	348.9
Skewness	1.432	-0.064	0.849	0.719	0.660	-0.050	0.986	0.485
Kurtosis	4.061	-0.479	0.575	-0.411	0.431	-0.522	0.741	-0.527

Table 4: Summary statistics of observed and predicted rainfall (using RBFN) for Dharni

Summary statistics	Dharni			
	Observed rainfall		Predicted rainfall	
	Training	Testing	Training	Testing
Average(mm)	1242.0	1122.6	1232.3	1121.7
SD(mm)	318.1	336.7	308.2	327.5
Skewness	0.256	0.300	0.250	0.292
Kurtosis	0.274	1.499	0.457	1.656

5. Conclusions

The paper described the procedures involved in prediction of rainfall using MLP and RBF networks for Atner, Multai and Dharni stations. The performance analysis (using MPIs) showed that the MLPN architectures of 1-15-1 (for Atner) and 1-18-1 (for Multai); and RBFN architecture of 1-25-1 (for Dharni) are better suited for training the network data. The results obtained from MPIs indicated that the MLPN is comparatively better than RBFN for Atner and Multai. The performance analysis also showed that the RBFN is considerably better than MLPN for Dharni through there is no appreciable difference between the observed and predicted rainfall. Based on the performance analysis (using MPIs), the study suggested that MLPN could be used for rainfall prediction for Atner and Multai whereas RBFN for Dharni. The paper presented that the percentages of variation on the average predicted rainfall, with reference to the average observed rainfall, are about 0.2% to 3.0% for Atner, 0.8% to 0.9% for Multai and 0.1% to 0.8% for Dharni. The results presented in the paper would be helpful to the stakeholders for planning, design and management of irrigation and drainage systems in Atner, Multai and Dharni stations.

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