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Prediction of Annual Maximum Rainfall Using Artificial Neural Network Approach

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ABSTRACT
Prediction of rainfall on a given time period (daily, monthly, seasonal and annual) is of utmost importance for planning of irrigation and drainage system as also for command area development. With the development of Artificial Intelligence (AI), number of AI methods such as Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System, Fuzzy Logic, Support Vector Machine and Evolutionary Optimization Algorithm are generally applied for rainfall prediction. Out of which, ANN has an ability to obtain complicated non-linear relationship between the variables, which is suitable to predict the rainfall. This paper presented a study on prediction of annual maximum rainfall (AMR) of Gaganbawada, Lanja and Radhanagari using Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) networks of ANN. For this purpose, the annual maximum series of meteorological data viz., rainfall, minimum and maximum temperature and average wind speed was generated from the daily data observed at Gaganbawada (1950 to 2020), Lanja (1950 to 2021) and Radhanagari (1950 to 2021), and used as an input for prediction of AMR through MLP and RBF. The performance of the MLP and RBF networks applied in rainfall prediction was evaluated by model performance indicators such as correlation coefficient, Nash-Sutcliffe model efficiency and root mean squared error. The study showed that MLP is better suited amongst two networks of ANN applied for prediction of AMR of Gaganbawada, Lanja and Radhanagari.

Keywords - Correlation Coefficient, Multi-Layer Perceptron, Radial Basis Function, Model Efficiency, Rainfall, Mean Squared Error

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I. INTRODUCTION

Prediction of rainfall in the particular area on a given time is a result of a complex natural process that has become a crucial part in various sectors such as agriculture, water resource management, flood management and transportation. Moreover, heavy rainfall may cause flooding, landslides and other hydrological disasters that disturb human activities, the social economy, and the environment. Hence, an appropriate rainfall prediction with a lead time is an essential and vital process in order to warn people about incoming natural disasters as it can provide an extension of lead-time for the strategic and tactical planning of activities as well as courses of action [1]. For this purpose, a number of approaches based on numerical, statistical, machine learning and empirical and are generally applied. Due to non-linear nature of rainfall, machine learning-based models are gaining more popularity over empirical, numerical and statistical methods for accurate prediction of rainfall events [2]. With more focus on Artificial Intelligence (AI) and availability of high computational devices, number of various AI methods such as Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Fuzzy Logic, Support Vector Machine (SVM) and Evolutionary Optimization Algorithm have gained a lot amount of attention in the field of prediction and estimation [3-5]. Out of these methods, ANN can represent a complex non-linear relationship and extract the dependence between the variables through the training process and hence used. In ANN, the training algorithms viz., Bayesian, cascade correlation, conjugate gradient, Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) networks are generally applied for training the network data [6-9]. However, in this paper, the MLP and RBF networks are applied for training the data.

Senthil Kumar et al. [10] used the RBF and MLP networks for rainfall-runoff modelling for the Malaprabha catchment in India. They also found that the RBF is a viable alternative to the MLP. Wu [11] developed a Modular-RBF-Neural Network model for real time rainfall forecasting and flood management in Liuzhou, Guangxi. Study by Nayak et al. [12] indicated that the rainfall prediction using ANN technique is more suitable than traditional statistical and numerical methods. Choubin et al. [13] carried out the study on drought index modeling based on large-scale climate indices by applying the Adaptive Neuro-Fuzzy Inference System (ANFIS), M5P model tree, and MLP. They also evaluated the performance of the models using error parameters andTaylor diagrams, which revealed that the MLP outperformed the other models. Sofian et al. [14] compared the results of BPN and RBF networks applied for prediction of monthly rainfall of Palembang City, South Sumatera Province, Indonesia and concluded that the RBF provide better results than BPN. Dash et al. [15]

applied K-Nearest Neighbour (KNN), ANN and extreme learning algorithms models to forecast the rainfall for the Indian state of Kerala and found that the ANN and extreme learning algorithm models performed well than KNN models. Chai et al. [16] examined the effect of hidden neuron number, training data size and input variables applied in RBF network model for rainfall intensity forecasting of Kuching, Sarawak, Malaysia. Liu et al. [17] made a comprehensive survey on rainfall forecasting using different training algorithms of ANN. They also concluded that ANN can greatly improve the accuracy and efficiency of prediction. Velasco et al. [18] applied the MLP network to forecast the week-ahead rainfall forecasting using historic rainfall data. They described that the outcomes of the study would be helpful to the organizations and individuals for the strategic and tactical planning of activities related to rainfall. Study by Endalie et al. [19] revealed that the long short-term memory based prediction model capable of forecasting Jimma's daily rainfall of Ethiopia. Dutta and Gouthaman [20] made an attempt to predict the rainfall using LASSO (Least Absolute Shrinkage and Selection Operator) regression and ANN approach, and analyzed that the accuracy of LASSO is better than those values of ANN. Nandakumar et al. [21] applied the Back Propagation Network (BPN), RBFN and SVM models for prediction of rainfall. They have also stated that the BPN, RBFN and SVM models are sufficient in order to forecast precipitation over other strategies such as statistics and statistical structures. Zhang et al. [22] applied the SVR (Support Vector Regression)-MLP method for prediction of annual and non-monsoon rainfall for Odisha. By considering the research works carried out by various researchers on rainfall prediction using ANN, it was noticed that the MLP and RBF networks are widely applied for prediction of rainfall and hence used in this paper. The performance of the MLP and RBF networks adopted in rainfall prediction was evaluated through Model Performance Indicators (MPIs) viz., Correlation Coefficient (CC), Nash-Sutcliffe Model Efficiency (MEF) and Root Mean Squared Error (RMSE). This paper presented the methodology adopted in prediction of AMR using MLP and RBF networks with an illustrative example and the results obtained thereof.

II. METHODLOGY

ANN modelling procedures adapt to complexity of input-output patterns and accuracy goes on increasing as more and more data become available. The ANN architecture (Figure 1) that consists of input layer, hidden layer, and output layer [23, 24]. From ANN structure, it can be easily understood that the input units receive the data from external sources to the network and send to the hidden units, in turn, the hidden units send and receive the data only from other units in the network, and output units receive and produce the 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 viz., tangent, sigmoid, polynomial and sinusoid in ANN. A common threshold function used in ANN [25] is the sigmoid function (f(S)) expressed by Eq. (1), which provides an output in the range of $0 \leq f(S) \leq 1$.

$$f(S) = [1 + \exp(-S_i)]^{-1} \text{ wherein}$$

$$S_i = \sum_{i=1}^{N} I_i W_{ij} + O_i, \ j = 1,2,3,......,M \tag{1}$$

Where, f(S) is the characteristic function of S, S_i is the characteristic function of i^{th} layer, I_i is the input (I) unit of i^{th} layer, O_i is the output (O) unit of i^{th} layer, W_{ij} is the synaptic weights between input (i) and hidden (j) layers, N is the number of observations and M is the number of neurons (or units) of hidden layer.

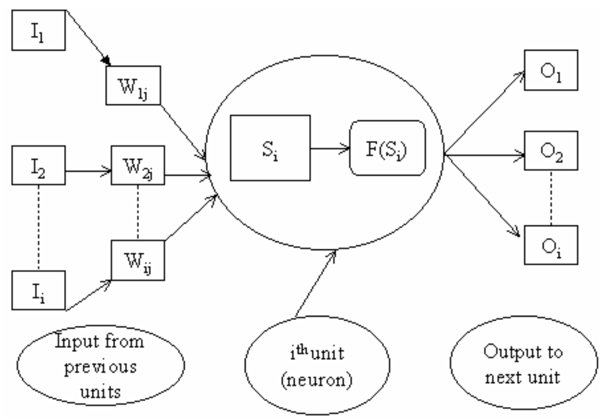

Figure 1. Architecture of ANN

Theoretical Description of MLP Network

MLP [26] network is based on architecture with single hidden layer as shown in Figure 1. Gradient descent is the most commonly used training algorithm in MLP in which 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 target output and output error (E) is computed using Eq. (2).

$$E = \frac{1}{2} \sum_{i=1}^{N} [X(i) - Y(i)]^2 \tag{2}$$

Where, X(i) is the observed value of i^{th} sample, Y(i) is the predicted value for i^{th} sample and N is the number of samples.

$$\Delta W_{ij}(M) = -\varepsilon \frac{\partial E}{\partial W_{ij}} + \alpha \Delta W_{ij}(M-1) \tag{3}$$

Where, $\Delta W_{ij}(M)$ is the weight increment between i^{th} and j^{th} layers during M neurons (units) and $\Delta W_{ij}(M-1)$ is the weight increments between i^{th} and j^{th} layers during M-1 neurons. In MLP, momentum factor (α) is used to speed up training in very flat region of the error surface to prevent oscillation in the weight and learning rate (ε) is used to increase the chance of avoiding the training process being trapped in local minima instead of global minima.

Theoretical Description of RBF Network

RBF network is supervised and three-layered feed forward neural network. The hidden layer of RBF network consists of a number of nodes and a parameter vector called a ‘centre’, which can be considered the weight vector. In RBF, the standard Euclidean distance is used to measure the distance of an input vector from the centre. The design of neural networks is a curve-fitting problem in a high dimensional space in RBF [27]. Training the RBF network implies finding the set of basis nodes and weights. Therefore, the learning process is to find the best fit to the training data. The transfer function of the nodes is governed by non-linear function that is assumed to be an approximation of the influence that data points have at the centre. The transfer function of a RBF is mostly built up of Gaussian rather than sigmoid. The Gaussian function decrease with distance from the centre. The transfer function of the nodes is governed by non-linear function that is assumed to be an approximation of the influence that data points have at the centre. The Euclidean length is represented by r_j that measures the radial distance between the datum vector $\underline{X}(X(1), X(2),\ldots,X(M)$ and the radial centre $\underline{X^{(j)}}(W_{1j}, W_{2j},\ldots\ldots,W_{Mj})$ can be written as:

$$r_j = \left\|\underline{X} - \underline{X^{(j)}}\right\| = \left[\sum_{i=1}^{N}(X(i) - W_{ij})^2\right]^{1/2} \quad (4)$$

Where, $r_j = \|\ \|$ is the Euclidean norm and M is the number of neurons [28]. A suitable transfer function is then applied to r_j to give $\Phi(r_j) = \Phi\left\|\underline{X} - \underline{X^{(k)}}\right\|$. Finally, the output layer (k-1) receives a weighted linear combination of $\Phi(r_j)$.

$$X^{(k)} = W_0 + \sum_{j=1}^{N} c_j^{(k)}\Phi(r_j) = W_0 + \sum_{j=1}^{N} c_j^{(k)}\Phi\left\|\underline{X} - \underline{X^{(j)}}\right\| \quad (5)$$

Where, c_j is the centre of the neuron in hidden layer, $\Phi(r_j)$ is the response of j^{th} hidden unit and W_0 is the bias term.

Model Performance Analysis

The performance of MLP and RBF networks adopted in rainfall prediction is evaluated by MPIs viz., Correlation Coefficient (CC), Nash–Sutcliffe Model Efficiency (MEF) and Root Mean Squared Error (RMSE). The theoretical descriptions of MPIs [29] are given as below:

$$CC = \frac{\sum_{i=1}^{N}[X(i) - \mu(X)][Y(i) - \mu(Y)]}{\sqrt{\sum_{i=1}^{N}[X(i) - \mu(X)]^2 \sum_{i=1}^{N}[Y(i) - \mu(Y)]^2}}$$

$$MEF(\%) = \left[1 - \frac{\sum_{i=1}^{N}[X(i) - Y(i)]^2}{\sum_{i=1}^{N}[X(i) - \mu(X)]^2}\right]*100 \quad (6)$$

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}[X(i) - Y(i)]^2\right]^{1/2}$$

Where, X(i) is the observed value of i^{th} sample, Y(i) is the predicted value of i^{th} sample $\mu(X)$ is the average of observed values and $\mu(Y)$ is the average of predicted values. The network model with high CC, better MEF and minimum RMSE is considered as better suited network for prediction of rainfall.

III. STUDY AREA AND DATA USED

In this paper, a study on prediction of annual maximum rainfall (AMR) using MLP and RBF networks of three rain gauge sites viz., Gaganbawada, Lanja and Radhanagari of Panchganga catchment was carried out. These rain-gauge sites are in and around the catchment of Panchganga Nadi, which is located at a distance of 1.5 km downstream of the railway bridge in Miraj-Kolhapur section near Rukadi village, Kolhapur. Figure 2 presents the index map of the study area with locations of Gaganbawada, Lanja and Radhanagari sites. In this paper, the annual maximum series (AMS) of meteorological data viz., rainfall (RFL), minimum and maximum temperature (Tmin and Tmax) and average wind speed (AWS) was generated from the daily data observed at Gaganbawada (1950 to 2020), Lanja (1950 to 2021) and Radhanagari (1950 to 2021) and used as input for prediction of AMR using MLP and RBF.

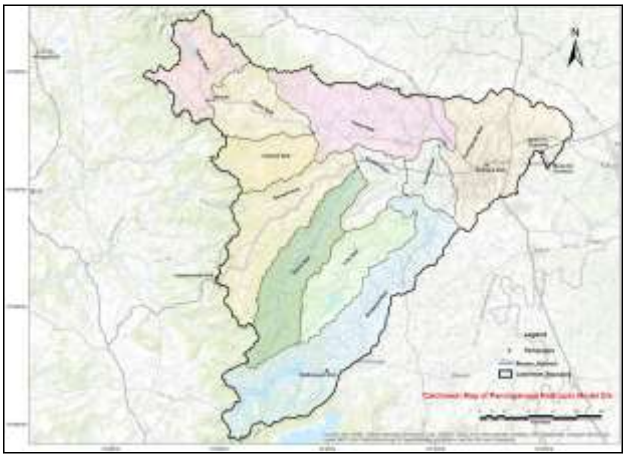

Figure 2. Index map of the study area

In the AMS of meteorological data, 80% of the data was used for training (TRG) the network through MLP and RBF and the remaining 20% of the data was used for testing (TES). From the scrutiny of the observed data, it was observed that the AMS of RFL (in mm), Tmin and Tmax (in ^oC), AWS (in km/hour) used in the rainfall prediction are of different units. Therefore, the data was normalized [30] and supplied to the MLP and RBF networks. After completion of the training and testing process of the network, the output data was denormalized through Eq. (7) to achieve the results in original domain.

$$Nor(X(i)) = \frac{X(i) - Min\,(X(i))}{Max\,(X(i)) - Min\,(X(i))} \quad (7)$$

Where, Nor(X(i)) is the normalized value of X(i), Min(X(i)) is the series minimum value of X(i) and Max(X(i)) is the series maximum value of X(i).

IV. RESULTS AND DISCUSSION

By applying the procedures of MLP and RBF, prediction of AMR for Gaganbawada, Lanja and Radhanagari sites with the aid of SPSS (Software Package for Social Science) software, was carried out. For this purpose, the AMS of meteorological data considered in the study was trained with MLP and RBF networks. Table 1 presents the details of number of data points pertaining to input and output variables considered in rainfall prediction. In addition, the details of Optimum Network Architecture (ONA), parameters of MLP and RBF adopted in training the network data, and variables used in rainfall prediction are presented in Table 1.

Prediction of AMR using MLP and RBF Networks

By using the parameters, as given in Table 1, the network data was trained with MLP and RBF networks for prediction of AMR. The descriptive statistics of the observed and predicted values of AMR using MLP and RBF networks for Gaganbawada, Lanja and Radhanagari are given in Table 2 while the time series plots are presented in Figure 3.

Table 1. Parameters and variables used in prediction of AMR using MLP and RBF networks

Parameters/ Variables	Gaganbawada				Lanja				Radhanagari			
	MLP		RBF		MLP		RBF		MLP		RBF	
	TRG	TES	TRG	TES	TRG	TES	TRG	TES	TRG	TES	TRG	TES
Type of data series	Annual				Annual				Annual			
Input variable (i^{th} year)	RFL, Tmin, Tmax, AWS				RFL, Tmin, Tmax, AWS				RFL, Tmin, Tmax, AWS			
Output variable ($i+1^{th}$ year)	AMR				AMR				AMR			
ONA	4-12-1		4-15-1		4-18-1		4-21-1		4-18-1		4-24-1	
Learning rate (ε)	0.8		-		0.7		-		0.6		-	
Momentum factor (α)	0.7		-		0.6		-		0.5		-	
Number of data points (Data set used)	54	17	54	17	54	18	54	18	54	18	54	18
	(1950 to 2003 for training and 2004 to 2020 for testing)				(1950 to 2003 for training and 2004 to 2021 for testing)				(1950 to 2003 for training and 2004 to 2021 for testing)			

Table 2. Descriptive statistics of observed and predicted AMR using MLP and RBF networks

Descriptive statistics	Observed		MLP		RBF	
	Training	Testing	Training	Testing	Training	Testing
Gaganbawada						
Average (mm)	248.0	260.1	247.9	255.4	246.7	255.0
SD (mm)	62.3	78.7	59.2	70.8	53.6	67.1
CV (%)	25.1	30.3	23.9	27.7	21.7	26.3
C_s	0.977	1.242	0.751	0.964	1.525	1.310
C_k	4.130	1.334	0.897	0.067	3.907	0.846
Lanja						
Average (mm)	191.3	188.2	190.6	187.5	190.1	187.1
SD (mm)	41.8	37.1	38.4	36.7	36.1	34.3
CV (%)	21.9	19.7	20.1	19.6	19.0	18.3
C_s	0.659	0.473	0.793	1.003	1.309	1.586
C_k	0.816	-0.277	0.496	1.681	2.164	3.648
Radhanagari						
Average (mm)	190.8	194.8	189.2	195.5	186.6	199.2
SD (mm)	45.7	87.5	44.2	78.8	38.4	73.3
CV (%)	24.0	45.0	23.4	40.3	20.6	36.8
C_s	1.648	0.742	0.784	0.630	1.414	1.124
C_k	5.729	0.142	0.664	-0.689	2.932	0.623
SD: Standard Deviation; CV: Coefficient of Variation; C_s: Coefficient of Skewness; C_k: Coefficient of Kurtosis						

From Table 2, for Gaganbawada, it was noted that the percentage of variation in average predicted AMR using MLP and RBF networks with reference to average observed AMR during testing period is 1.8% and 2.0% respectively. Likewise, for Lanja, these values were computed as 0.4% for MLP and 0.6% for RBF. For Radhanagari, the percentage of variation in average AMR using MLP and RBF networks with reference to average observed AMR during testing period was computed 0.4% and 2.3% respectively. From these results, it was witnessed that the performance of MLP network in rainfall prediction is better than RBF for all three sites. Also, from Table 2, it was found that the CVs of the predicted AMR of Gaganbawada, Lanja and Radhanagari during testing period are 27.7%, 19.6% and 40.3% respectively. The scatter plots between the observed and predicted AMR using MLP and RBF networks for all three sites are shown in Figure 4.

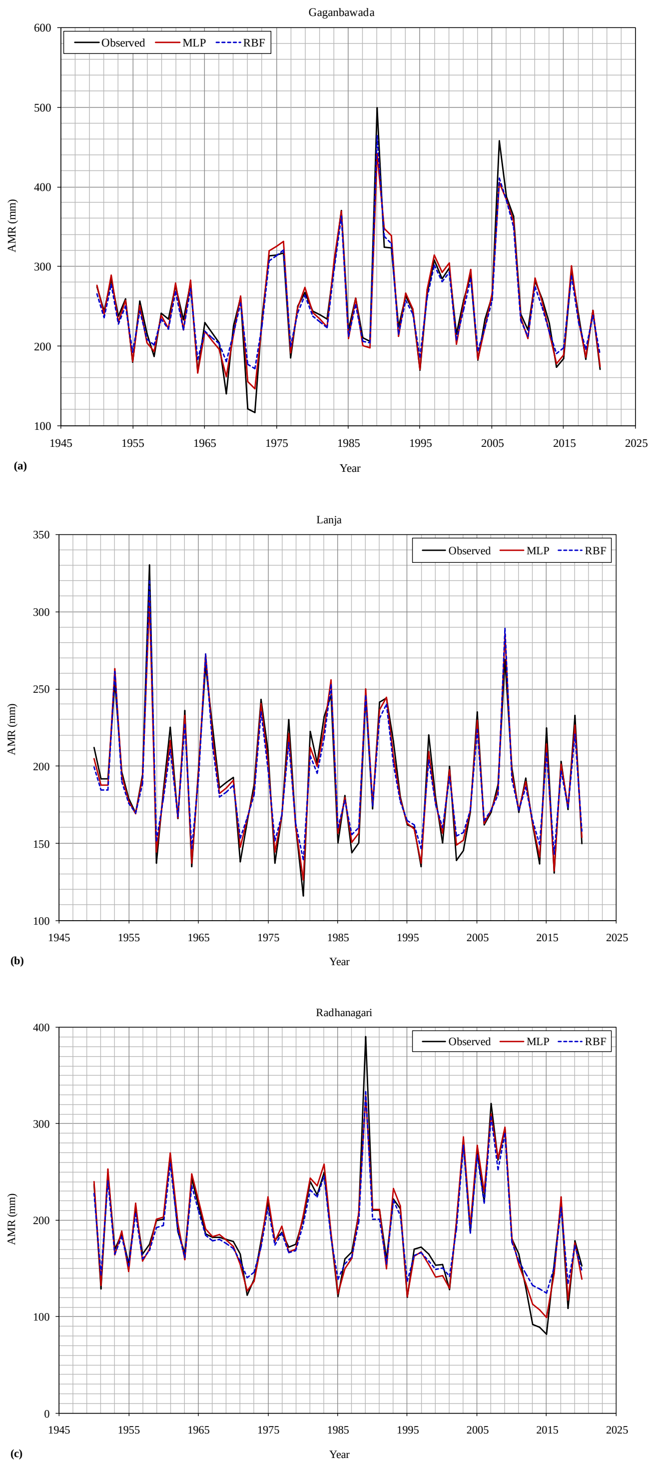

Figure 3. Time series plots of observed and predicted AMR using MLP and RBF for Gaganbawada, Lanja and Radhanagari

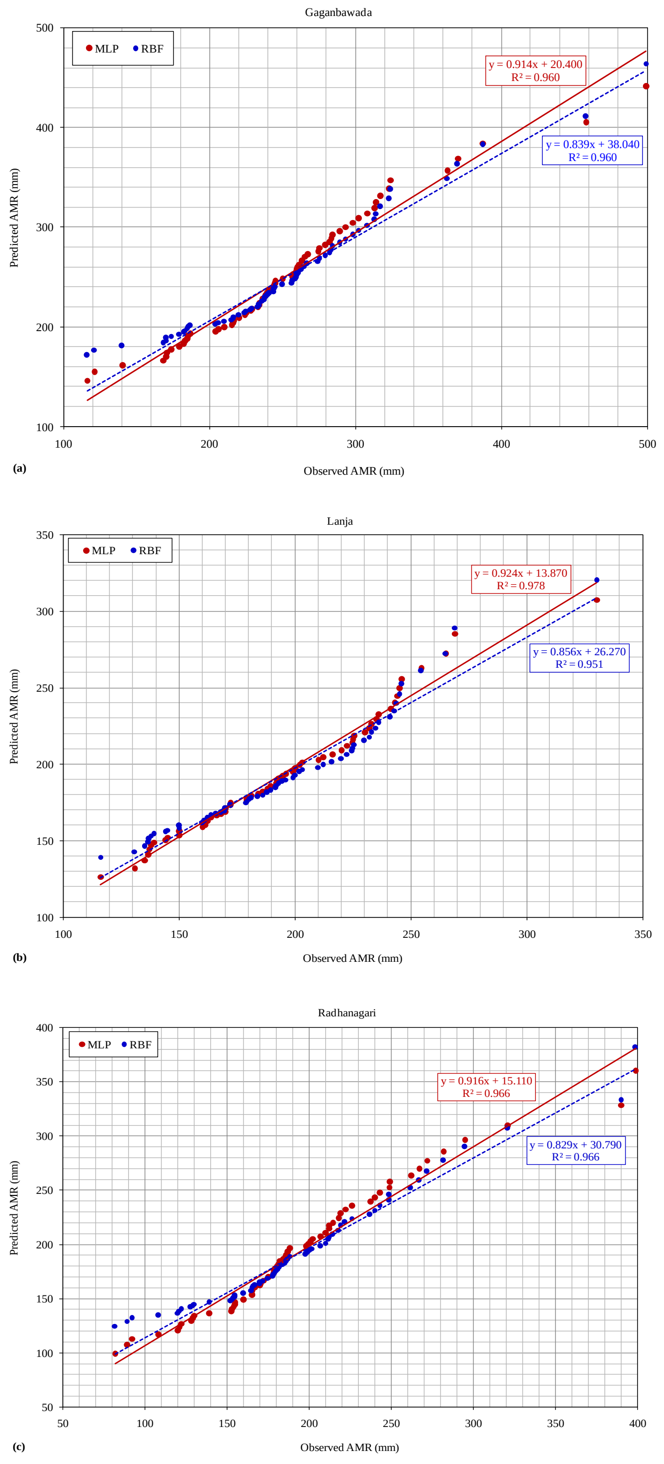

Figure 4. Scatter plots of observed and predicted AMR using MLP and RBF for Gaganbawada, Lanja and Radhanagari

Table 3. Computed values of model performance indicators of MLP and RBF networks

Model Performance Indicators	Gaganbawada				Lanja				Radhanagari			
	MLP		RBF		MLP		RBF		MLP		RBF	
	TRG	TES	TRG	TES	TRG	TES	TRG	TES	TRG	TES	TRG	TES
CC	0.978	0.991	0.975	0.989	0.990	0.986	0.979	0.963	0.975	0.991	0.987	0.987
MEF (%)	95.5	96.6	93.7	95.8	97.5	97.2	94.4	92.4	94.9	97.4	94.3	94.8
RMSE (mm)	13.1	14.1	15.5	15.6	6.5	6.0	9.8	9.9	10.3	13.8	10.8	19.4

Analysis of Results Based on MPIs

The performance of MLP and RBF networks adopted in prediction of AMR for Gaganbawada, Lanja and Radhanagari was evaluated through MPIs viz., CC, MEF and RMSE, and the results are given in Table 3. Based on the MPIs of MLP and RBF networks in the testing period, the following observations were drawn from the study:

i) The fitted lines of the predicted AMR (Figure 3) indicated that the predicted AMR using MLP is very closure to the observed AMR.
ii) The scatter plots (Figure 4) showed that there is a good line of agreement between observed and predicted AMR.
iii) The correlation between the observed and predicted AMR using MLP and RBF networks was found to be very good, and the CC values vary from 0.975 to 0.991 for Gaganbawada while 0.963 to 0.990 for Lanja and 0.975 to 0.991 for Radhanagari.
iv) The RMSE values of MLP were found as minimum when compared with those values of RBF during training and testing periods.
v) The model efficiency in rainfall prediction using MLP and RBF networks varied between 93.7% and 96.6% for Gaganbawada while 92.4% to 97.5% for Lanja and 94.3% to 97.4% for Radhanagari.

Based on the evaluation of the results using MPIs, the study showed that MLP is better suited network for prediction of AMR for all sites considered in the study**.**

V. CONCLUSION

The paper presented a study on prediction of AMR using MLP and RBF networks for Gaganbawada, Lanja and Radhanagari sites located within Panchganga catchment. The annual maximum series of rainfall, minimum and maximum temperature, and average wind were used as input variables to predict the AMR. The performance of the MLP and RBF networks adopted in prediction of AMR was evaluated through MPA using MPIs viz., CC, MEF and RMSE. Based on the analysis of results obtained from MLP and RBF networks, some of the conclusions drawn from the study were summarized and are given as below:

- The optimum network architecture with network parameters of MLP and RBF, as given in Table 1, was used for training the network data.
- The MPIs showed that MLP gave better results than RBF in rainfall prediction during training and testing.
- The CC values indicated that there was generally a good correlation between the observed and predicted rainfall using MLP and RBF networks and these values vary 0.975 to 0.991 for Gaganbawada while 0.963 to 0.990 for Lanja and 0.975 to 0.991 for Radhanagari.
- The model efficiency on rainfall prediction using MLP for Gaganbawada in testing period was computed as 96.6% while 97.2 for Lanja and 97.4 for Radhanagari.
- During testing period, the RMSE in rainfall prediction using MLP was computed as 14.1 mm for Gaganbawada, 6.0 mm for Lanja and 13.8 mm for Radhanagari.
- The percentage of variation on the average of predicted rainfall using MLP with reference to average of observed rainfall in testing period was computed as 1.8% for Gaganbawada while 0.4% for Lanja and Radhanagari.
- The selection of best suitable network was adjudged on the basis of fitted regression lines together with MPIs and accordingly MLP is better suited network for prediction of AMR though the variation between the observed and predicted rainfall using MLP and RBF are found as minimum.

The outcomes of the study would be useful for stakeholders for planning of irrigation and drainage system as also for command area development in Gaganbawada, Lanja and Radhanagari sites.

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