BEST: Journal of Management, Information
Technology and Engineering (BEST: JMITE)
Vol. 2, Issue 2, Dec 2016, 13-22

MODELLING OF ANNUAL EXTREME RAINFALL USING MLP AND RBF NETWORKS

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ABSTRACT

Assessment of rainfall is of utmost important for planning, design and management of water resources projects such as irrigation and drainage systems, flood protection measures, drought assessment and command area development. As rainfall distribution varies over space and time, the data covering long periods observed at various locations are needed to be analyzed for arriving at reliable information for decision support. Since the ancient methods of astrological and observational are very empirical and unverifiable, the approaches like deterministic, conceptual, stochastic and Artificial Neural Network (ANN) are generally used for rainfall prediction. In this paper, a study on modelling the Annual Extreme Rainfall (AER) of Joshimath and Tohana rain-gauge stations is carried out by applying ANN based Multi Layer Perceptron (MLP) and Radial Basis Function (RBF) networks. The performance of the MLP and RBF networks used in modelling the AER is evaluated by model performance analysis using correlation coefficient, model efficiency and mean absolute percentage error. The paper shows the MLP is better suited network for modelling the AER of Joshimath and RBF network for Tohana.

KEYWORDS: Correlation, Mean Absolute Percentage Error, Model Efficiency, Multi Layer Perceptron, Neural Network, Radial Basis Function, Rainfall

INTRODUCTION

Rainfall is the main factor that controls the hydrological cycle. Much of the ecology, geography and land use of region depends on functions of the hydrological cycle, and therefore rainfall provides both constraints and opportunities in land and water resources management. The rainfall prediction plays an important role in flood protection and drought reduction and thus has economic benefits for water resources management (Cannon and Mckendry, 1999). In earlier time periods, ancient methods of astrological and observational are commonly used for prediction of rainfall. The astrological method consists of computation of planetary position and conjunctions of planets and stars or study of solar ingress and particular dates of months. The observational method consists of changes in atmospheric, chemical and physical factors, cloud forms and other sky features. The ancient methods are very empirical and unverifiable (Enireddy et al., 2010). Under these circumstances, various methods such as statistical, mathematical, deterministic, conceptual, stochastic and Artificial Neural Network (ANN) models are generally used for prediction of rainfall (Dubey, 2015). However, past research experience shows that there is an abundance of literature on development of deterministic, conceptual and stochastic models (ASCE, 2000a) and therefore ANN is used in the present study.

In ANN, number of training algorithms such as Multi Layer Perceptron (MLP), Cascade Correlation (CCN), Conjugate Gradient, Genetic (GNT), Radial Basis Function (RBF), Bayesian, etc., are generally applied for training the network data (Jeong and Kim, 2005; Nanda et al., 2013). The objective in training the network is to minimize the error between the predicted and targeted outputs. From the research reports on ANN, it is understood that the number of researchers have applied different networks for modelling the rainfall data for various regions (Kannan et al., 2010; Amr et al., 2011; Jalal et al., 2012; Pallavi et al., 2012). Thirumalaiah and Deo (2000) studied the application of CCN and MLP networks to real-time forecasting of hourly flood runoff and daily river stage for major river basins in India. Rajurkar et al. (2004) applied the ANN for modelling daily flows during monsoon flood events for a catchment in India using daily rainfall data as input vector of the network model. Jain and Srinivasulu (2004) expressed that the ANN model trained with GNT network was able to overcome the problems associated with the modelling of low-flows. Sarangi et al. (2005) developed the ANN and regression models using watershed scale geomorphologic parameters to predict surface runoff and sediment losses of St. Espirit watershed, Canada and found that ANN model performed better than the regression model. Jothiprakash et al. (2006) expressed that the stream flow prediction with ANN model was more satisfactorily than the HEC-4 model in case of multi-site stream flow generation. See et al. (2008) applied the graphical and statistical methods to visualize hidden neuron behaviour in a trained neural network rainfall-runoff model developed for the river Ouse catchment in northern England.

Wang et al. (2011) studied the three-layer feed forward time delay neural network combined with a GNT network to predict runoff level of Linsham Watershed, Sinchuan, China. Wang et al. (2012) employed a hybrid genetic algorithm to optimize parameter values for Xinanjiang model for flood forecasting in Shuangpai reservoir. They have established the ANN models to predict flow with 6 hours lead time for Amber and Mole rivers. Chen et al. (2013) applied the Feed Forward Back Propagation (FFBP) and Conventional Regression (CR) methods to develop the rainfall-runoff relationships for Linbien River in southern Taiwan and found that the FFBP performs better than the CR method. Farajzadeh et al. (2014) compared the feed-forward neural network and time series analysis using ARIMA model for modelling the monthly rainfall and runoff of Urmia lake basin. They found that the ARIMA model is better suited for prediction of runoff. Mislan et al. (2015) applied BPN model to predict the rainfall in Tenggarong, East Kalimantan - Indonesia. Sundara Kumar et al. (2016) applied ANN model for prediction of runoff for Sarada river basin. But, there is a general agreement in applying the MLP and RBF networks for modelling the rainfall data for a region though different networks are available for training the network data. In this paper, a study on modelling the Annual Extreme Rainfall (AER) of Joshimath and Tohana rain-gauge stations is carried out by applying ANN based MLP and RBF networks. The performance of the MLP and RBF networks used in modelling the AER is evaluated by Model Performance Indicators (MPIs) such as Correlation Coefficient (CC), Model Efficiency (MEF) and Mean Absolute Percentage Error (MAPE) (Vivekanandan, 2014). The theoretical descriptions of MLP and RBF networks applied in training the network data and computation of MPIs is briefly described in the ensuing sections.

METHODOLOGY

The objective of the study is to identify the most suitable network for modelling the AER. The various steps involved in the study comprises of (i) derive the series of AER from daily rainfall data; (ii) train the network data using MLP and RBF networks; (iii) evaluate the model performance of MLP and RBF networks applied in modelling the AER; and (iv) conduct the study and analyse the results obtained thereof.

Multi Layer Perceptron Network

In MLP, as shown in Figure 1, gradient descent algorithm is used for training the network data. Each input unit of the training data set is passed through the network from input layer to output layer. The network output is compared with the desired target output and output error (E) is computed using Eq. (1). This error is propagated backward through the network to each neuron, and the connection weights are adjusted based on Eq. (2).

$$E = \frac{1}{2}\sum_{i=1}^{N}\left(X_i - X_i^*\right)^2 \tag{1}$$

Where, X_i is the observed AER for i^{th} event and X_i^* is the predicted AER for i^{th} event (Tokar and Markus, 2000).

$$\Delta W_{ij}(M) = -\varepsilon\frac{\partial E}{\partial W_{ij}} + \alpha\Delta W_{ij}(M-1) \tag{2}$$

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 MLP network, 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 (Mustafa et al., 2013).

Radial Basis Function Network

RBF network is supervised and three-layered feed forward neural network and presented in Figure 2. The hidden layer of RBF network consists of a number of nodes and a parameter vector called a ‘center’, 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 center. The design of neural networks is a curve-fitting problem in a high dimensional space in RBF (Hsu et al., 1995).

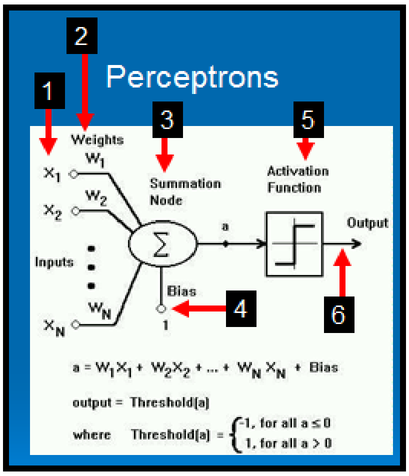

Figure 1: Structure of MLP Network

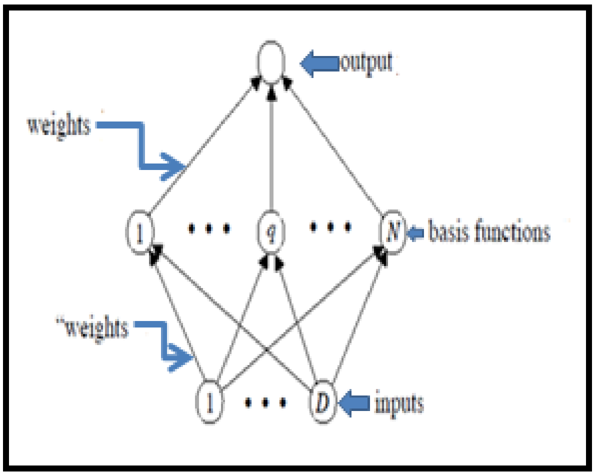

Figure 2: Structure of RBF Network

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 (Kaltech, 2008). 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 center. The transfer function of a RBF is mostly built up of Gaussian rather than sigmoid. The Gaussian function decrease with distance from the center. The transfer function of the nodes is 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 $\underline{X}(X_1, X_2, \ldots X_M)$ and the radial center $\underline{X}^{(j)} = (W_{1j}, W_{2j}, \ldots W_{Mj})$ can be written as:

$$r_j = \left\| \underline{X} - \underline{X^{(j)}} \right\| = \left[\sum_{i=1}^{M} \left(X_i - W_{ij} \right)^2 \right]^{1/2} \quad (3)$$

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

$$X^{(k)} = W_0 + \sum_{j=1}^{N} c_j^{(k)} \Phi(r_j) = W_0 + \sum_{j=1}^{N} c_j^{(k)} \Phi\left(\left\| \underline{X} - \underline{X^{(j)}} \right\| \right) \quad (4)$$

Where, c_j is the centre of the neuron in the hidden layer and $\Phi(r_j)$ is the response of the jth hidden unit and W_0 is the bias term (Ozgur, 2009). For both MLP and RBF networks, the units (or) neurons in the hidden layer are initially computed by Eq. (5) and further optimized to reduce the error between the predicted and targeted outputs.

$$H_M = \frac{I_P + O_P}{2} + \sqrt{S_N} \quad (5)$$

where, H_M is the number of neurons (M) in hidden layer (H), S_N is the number of data samples (N) used in MLP and RBF networks, I_P is the number of input units (P) in input layer (I) and O_P is the number of output units (P) in output layer (O).

Normalization of Data

By considering the nature of activation function adopted in ANN, the training data set values are normalized between 0 and 1 by Eq. (6) and passed into the network (Sudheer et al., 2008). After the completion of training, the output values are denormalized to provide the results in original domain.

$$NOR(X_i) = \frac{X_i - Min(X_i)}{Max(X_i) - Min(X_i)} \quad (6)$$

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.

Model Performance Analysis

The performance of the MLP and RBF networks appied in prediction of AER are evaluated by MPIs, which is as follows:

$$CC = \frac{\sum_{i=1}^{N} \left(X_i - \overline{X} \right)\left(X_i^* - \overline{X^*} \right)}{\sqrt{\left(\sum_{i=1}^{N} \left(X_i - \overline{X} \right)^2 \right)\left(\sum_{i=1}^{N} \left(X_i^* - \overline{X^*} \right)^2 \right)}} \quad (7)$$

$$MEF(\%) = \left(1 - \frac{\sum_{i=1}^{N} \left(X_i - X_i^* \right)^2}{\sum_{i=1}^{N} \left(X_i - \overline{X} \right)^2} \right) * 100 \quad (8)$$

$$\mathrm{MAPE} = \left((1/N) \sum_{i=1}^{N} \left| \frac{X_i - X_i^*}{X_i} \right| \right) * 100 \quad (9)$$

Where, $\overline{X}$ is the average value of observed AER and $\overline{X^*}$ is the average value of predicted AER (Chow et al., 2012).

APPLICATION

In this paper, a study on modelling the AER of Joshimath and Tohana using MLP and RBF networks was carried out. Joshimath rain-gauge station is located between the latitude 30^o 34′ N and longitude 79^o 33′ E in Chamoli district of Uttarakhand. Similarly, Tohana rain-gauge station is located between the latitude 29^o 42′ N and longitude 75^o 55′ E in Tohana Tehsil of Fatehabad district, Haryana. The series of AER was extracted from the daily rainfall data and used in the study. For Joshimath, the AER data for the period 1978 to 2005 was used for training the network whereas the data for the period 2006 to 2010 was used for validation and data for the period 2011 to 2015 was used for cross-validation. Similarly, for Tohana, the AER data for the period 1951 to 1991 was used for training the network whereas the data for the period 1992 to 2001 was used for validation and data for the period 2002 to 2011 was used for cross-validation.

RESULTS AND DISCUSSIONS

In this paper, SPSS Neural Connection software was used to train the network data with MLP and RBF networks for modelling the AER. For determining the optimum network architecture of MLP network, the network data was trained with different combinations of values of momentum factor (α) and learning rate (ε). Similarly, the network data was trained with RBF network by different combinations of number of nodes and weight factors to determine the optimum network architecture of RBF.

Modelling of AER using MLP and RBF Networks

In this paper, the input units were initially normalized by using Eq. (6) and trained with MLP and RBF networks. For Joshimath, the momentum factor (α) and learning rate (ε) were fixed as 0.8 and 0.05 while optimizing the network architecture of MLP. Similarly, for Tohana, the values of α=0.5 and ε=0.07 were used for determination of optimum network architecture of MLP. For Joshimath and Tohana, the network data was trained with the optimum network architectures of MLP and RBF, as given in Table 1. The trained networks with model parameters were used for prediction of rainfall. The output units were denormalized by using Eq. (6) to obtain the predicted value of rainfall. The MPIs of MLP and RBF networks were computed using Eqs. (7 to 9) and also given in Table 1. Figures 3 and 4 give the plots of observed and predicted AER (using MLP and RBF networks) for Joshimath and Tohana respectively.

Table 1: Network Architectures with MPIs of MLP and RBF Networks for Joshimath and Tohana

Network Architecture and MPIs	Joshimath						Tohana					
	MLP			RBF			MLP			RBF		
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Network Architecture	1-7-1			1-10-1			1-9-1			1-12-1		
CC	0.994	0.999	0.987	0.968	0.996	0.962	0.984	0.991	0.950	0.990	0.990	0.990
MEF (%)	97.2	94.6	97.0	92.6	92.7	86.7	93.9	98.2	88.3	95.8	97.8	96.7
MAPE (%)	5.4	3.4	4.8	6.1	6.1	8.1	6.6	6.3	10.8	8.9	4.8	8.9
TRG: Training; VAL: Validation; CVL: Cross-validation												

From Table 1, it is noticed that: (i) The MAPE obtained from MLP network is comparatively less than the corresponding values of RBF network during training, validation and cross-validation and therefore the MLP network model is identified as better suited network for modelling the AER of Joshimath; (ii) The MAPE obtained from RBF network is comparatively less than the corresponding values of MLP network during validation and cross-validation and therefore the RBF network is found to be suitable for modelling the AER of Tohana; (iii) For Joshimath, the percentage of MEF is computed as about 95% while validating the network data with MLP network whereas 97% during cross-validation; (iv) The percentage of MEF is computed as about 98% while validating the network data with RBF network whereas 97% during cross-validation for Tohana; (v) For both Joshimath and Tohana, the values of CC indicates there is generally a good correlation between the observed and predicted AER using MLP and RBF networks; and (vi) The CC value is computed as 0.990 for Tohana while validating the network data with RBF network.

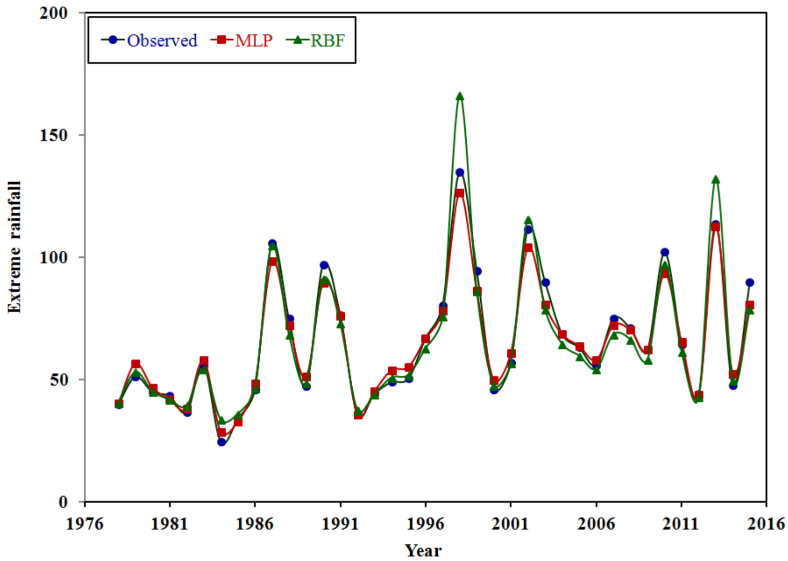

Figure 3: Observed and Predicted AER using MLP and RBF Networks for Joshimath

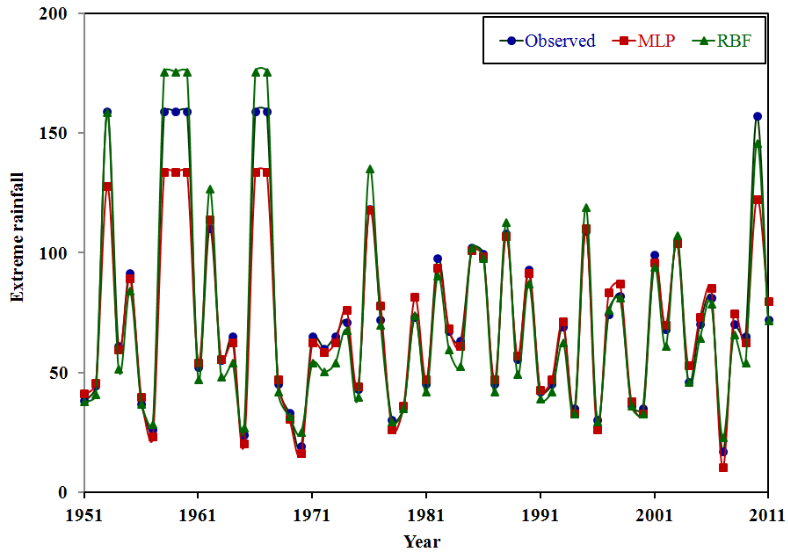

Figure 4: Observed and Predicted AER using MLP and RBF Networks for Tohana

Analysis Based on Descriptive Statistics

The performance of the MLP and RBF networks used in modelling the AER was also analysed by descriptive statistics such as average, Standard Deviation (SD), Coefficient of Variance (CV) Coefficient of Skewness (CS) and Coefficient of Kurtosis (CK). The results of descriptive statistics were presented in Tables 2 and 3.

Table 2: Descriptive statistics of Observed and Predicted AER for Joshimath

Descriptive Statistics	Observed AER			Predicted AER using					
				MLP			RBF		
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Average (mm)	63.2	73.3	71.9	62.7	71.3	71.0	63.3	68.8	72.9
SD (mm)	27.0	17.8	29.6	23.4	13.7	27.1	29.0	16.8	35.9
CV (%)	42.7	24.2	41.2	37.4	19.3	38.2	45.9	24.4	49.2
CS	0.971	1.308	0.680	0.882	1.288	0.958	1.983	1.591	1.518
CK	0.395	2.053	-1.278	0.610	1.975	0.471	4.916	2.853	2.244

Table 3: Descriptive Statistics of Observed and Predicted AER for Tohana

Descriptive Statistics	Observed AER			Predicted AER using					
				MLP			RBF		
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Average (mm)	75.7	61.4	75.0	71.9	62.3	73.3	75.6	60.6	71.7
SD (mm)	42.7	29.1	36.5	35.7	30.6	29.8	48.6	31.0	33.9
CV (%)	56.4	47.4	48.7	49.6	49.2	40.7	64.3	51.2	47.3
CS	0.882	0.472	1.011	0.452	0.253	-0.585	1.112	0.725	1.098
CK	-0.292	-1.359	2.760	-0.930	-1.674	1.851	-0.072	-0.614	1.901

CONCLUSIONS

The paper presented the study on modelling the AER observed at Joshimath and Tohana rain-gauge stations adopting MLP and RBF networks. The selection of best suitable network for modelling the AER was made by model performance analysis using MPIs and statistical analysis based on descriptive statistics. From the results, the following conclusions were drawn from the study:

- The network architectures viz., 1-7-1 of MLP (for Joshimath) and 1-12-1 of RBF (for Tohana) obtained from training period was used for validating the network data.
- For Joshimath, the MAPE on the predicted rainfall using MLP and RBF networks, with reference to observed rainfall, was found to be 3.4% and 6.1% respectively while validating the network data. For Tohana, the MAPE was computed as 6.3% for MLP network whereas 4.8% for RBF.
- The model performance analysis using MPIs confirmed the suitability of MLP (for Joshimath) and RBF (for Tohana) networks used in modelling the AER.
- During cross-validation, the MEF in modelling the AER using MLP and RBF networks was computed as about 97%. The CC values indicated there is generally perfect line of agreement between the observed and predicted AER values for both Joshimath and Tohana.
- The percentage of variation on the average predicted AER using MLP network, with reference to average observed AER, was found to be 2.7% during validation whereas 1.4% during cross-validation for Joshimath.

- The percentage of variation on the average predicted AER using RBF network, with reference to average observed AER, was found to be 1.3% during validation whereas 4.4% during cross-validation for Tohana.
- The results presented in the paper would be helpful to the stakeholders for planning, design and management of water resources projects such as irrigation and drainage systems, flood protection measures, drought assessment and command area development in Joshimath and Tohana regions.

ACKNOWLEDGEMENTS

The author is grateful to Dr. M. K. Sinha, Director, Central Water and Power Research Station, Pune, for providing the research facilities to carry out the study. The author is thankful to India Meteorological Department, Pune, for supply of rainfall data used in the study.

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