PREDICTION OF SEASONAL AND ANNUAL RAINFALL USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Prediction of seasonal and annual rainfall for a river basin is of utmost importance for planning and design of irrigation and drainage systems as also for command area development. Assessment of rainfall can be carried out by different approaches like deterministic, stochastic, conceptual and soft computing. This paper illustrates the use of artificial neural network (ANN) for prediction of rainfall for Krishna and Godavari river basins. ANN models such as Multi-Layer Perceptron (MLPN), cascade correlation and conjugate gradient 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 ANN models. The study showed that MLPN is better suited for prediction of seasonal and annual rainfall for Krishna and Godavari river basins.

Keywords: Correlation; Mean square error; Model efficiency; Neural network; Rainfall; Multi Layer Perceptron

INTRODUCTION

Prediction of seasonal and annual rainfall for a river basin is of utmost importance for planning and design of irrigation and drainage systems as also for command area development. Since the distribution of rainfall varies over space and time, it is required to analyze the data covering long periods and recorded 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. For example, analysis of consecutive days of rainfall is more relevant for drainage design of agricultural lands, whereas analysis of weekly rainfall data is relevant for planning of cropping pattern. Likewise, analysis of monthly, seasonal and annual data is more useful for water management practices. 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 (Jain et al, 2009). In this context, ANN is considered an effective tool for prediction of hydrometeorological variables such as rainfall, runoff, temperature, 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. Figure 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 also called 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, polynomial, and sinusoid in ANN. 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 (Kaltech, 2008).

$$f(S) = \left[1 + \exp\left(-S_i\right)\right]^{-1} \text{ and } S_i = \sum_{i=1}^{N} I_i W_{ij} + O_i, \text{ j=1,2,3,.....M} \quad (1)$$

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 input and hidden layers, N is the number of observations and M is the number of neurons of 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.

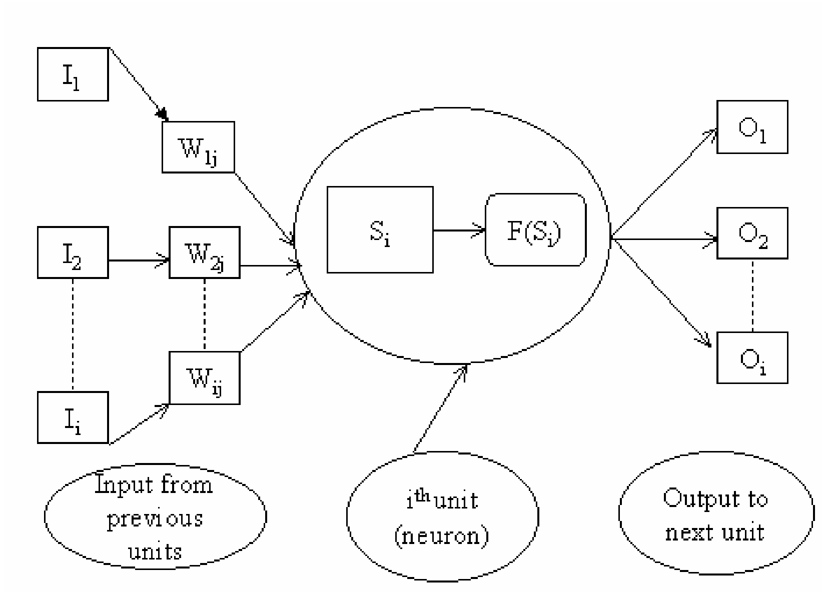


Figure1: Architecture of ANN

Number of network models such as Multi Layer Perceptron (MLPN), Cascade Correlation (CCN), Conjugate Gradient (CGN), Radial basis function, Bayesian, etc are commonly used for training the network data. The objective in training the network is to reduce the global error between the predicted and targeted outputs. From the research reports on ANN, it is understood that number of researchers have applied different networks for prediction of rainfall for various regions (Carriere et al., 1996; Shamseldin et al, 1997; Tokar and Markus, 2000; Rajurkar et al, 2004; Sarangi et al, 2005; Wang et al, 2007; See et al, 2008; Jain et al, 2009; Amr et al , 2011; El-Shafie et al, 2011). 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 the present study, an attempt has been made to predict the seasonal and annual rainfall using MLPN, CCN and CGN models for Krishna and Godavari river basins. 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 ANN model for rainfall prediction. The methodology adopted in prediction of rainfall using three network models and MPIs are briefly described in the ensuing sections.

METHODOLOGY

Multi-Layer Perceptron Network

MLPN is the most widely used for rainfall prediction and its architecture with single hidden layer is shown in Figure 1. Gradient descent is the most commonly used supervised training algorithm in MLPN (Kaltech, 2008). 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. (2). This error is propagated backward through the network to each neuron, and the connection weights are adjusted based on Eq. (3).

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

where P_i is the recorded rainfall for i^{th} year and P_i^* is the predicted rainfall for i^{th} year.

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

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.

Cascade Correlation Network

In MLPN, all weights change simultaneously while responding to a new training pattern. This process results in an unnecessary motion of the network leading to more efforts and time. This can be avoided in the CCN by training only one layer of weights and keeping the rest of the weights unchanged. In CCN, hidden nodes are added one by one starting from zero during the training until the training termination criterion is reached. The CCN does not involve learning by descending down the error gradient, but by maximizing the effect (or correlation) of the new hidden unit output on the residual error. It also does not involve transmission of the error as detailed in MLPN (Jain et al, 2009). The training procedure of CCN is as follows:

i) Consider only the input and output units.
ii) Train direct the input-output weights over the entire training set using delta rule. This process does not require back propagation through the hidden units.
iii) Add one hidden unit by following the separate procedure. Then freeze its input weights and train all output weights once again by using the delta rule.

    (a) Consider the new hidden unit; (b) Connect it to all input units as well as to all other existing hidden units; and (c) Take all training data sets one by one and adjust the input weights of this new hidden unit after each training set. This adjustment is done so as to maximize the overall correlation between the new hidden unit value and the residual error.

iv) Repeat step (iii) until minimum error is reached or a specified maximum number of iterations are over.

Conjugate Gradient Network

CGN differs from MLPN is gradient calculations and subsequent corrections to weights and bias. In CGN, a search direction d_k is computed at each training iteration 'k' and the error function f(S) is minimized along it with the use of a line search. The gradient descendent does not move down the error gradient as in the foregoing back propagation method but along a direction that is conjugate to the previous step. The change is gradient is thus taken as orthogonal to the previous step with the advantage that the function minimization carried out in each step, is fully preserved because of the lack of any interference from the subsequent steps (Thirumalaiah and Deo, 2000). The five-step iteration process is as follows:

i) Initialize weight vector P by using uniform random numbers from the interval (-0.5, 0.5). Calculate error gradient $\overline{g_o}$ by using back propagation at this point. Select intial search direction $\overline{d_o}$ using $\overline{d_o} = -\overline{g_o}$.
ii) For each iteration 'j', determine constant α_j, which minimizes the error function $f(P_j + \alpha_j \overline{d_j})$ by line search. Here $\overline{d_j}$ is the search direction at iteration 'j'. Update the weight factor P_{j+1} to P_j using $P_{j+1} = P_j + \alpha_j d_j$.
iii) If the error at this iteration, 'j+1' is acceptable or if a specified number of computations of the function and gradients is reached, terminates the algorithm.
iv) Otherwise, get the new director vector $\overline{d_{j+1}}$ by using the error gradient $\overline{g_{j+1}}$ at the iteration 'j+1' such that $\overline{d_{j+1}} = -\overline{g_{j+1}}$.If 'j+1' is an integral multiple of N (where N is the dimension of P); otherwise, $\overline{d_{j+1}} = -\overline{g_{j+1}} + \beta_j d_j$ with

$$\beta_j = \frac{\left(\overline{g_j g_j^T}\right)}{\left(\overline{g_o g_o^T}\right)} \qquad \text{Here, } \overline{g}_j \text{ is the error gradient at iteration 'j'.} \tag{4}$$

v) Repeat the above steps for the next iteration.

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. (5) 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.

$$NOR(P_i) = \frac{P_i - Min(P_i)}{Max(P_i) - Min(P_i)} \tag{5}$$

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

Model Performance

Following Chen and Adams (2006), the performance of predicted seasonal and annual rainfall using MLPN, CCN and CGN models is analyzed by CC, MEF and RMSE, and are:

$$CC = \frac{\sum_{i=1}^{N}\left(P_i - \overline{P}\right)\left(P_i^* - \overline{P^*}\right)}{\sqrt{\left(\sum_{i=1}^{N}\left(P_i - \overline{P}\right)^2\right)\left(\sum_{i=1}^{N}\left(P_i^* - \overline{P^*}\right)^2\right)}} \tag{6}$$

$$MEF\ (\%) = \left(1 - \frac{\sum_{i=1}^{N}\left(P_i - P_i^*\right)^2}{\sum_{i=1}^{N}\left(P_i - \overline{P}\right)^2}\right) * 100 \tag{7}$$

$$RMSE = \left((1/N)\sum_{i=1}^{N}\left(P_i - P_i^*\right)^2\right)^{1/2} \tag{8}$$

where $\overline{P}$ is the average recorded rainfall and $\overline{P^*}$ is the average predicted rainfall.

APPLICATION

An attempt has been made to predict the seasonal and annual rainfall for Krishna and Godavari river basins using MLPN, CCN and CGN models. The drainage area of Krishna and Godavari basins are 2,95,650 km^2 and 3,30,628 km^2. The average annual rainfall for Krishna and Godavari basins are 825.7 mm and 1068.3 mm respectively. Seasonal and annual rainfall data recorded at the river basins for the period 1901-2005 are used. The data for the period 1901-1965 are used for training (TRG), data for the period 1966-1985 for validation (VAL) and data for the period 1986-2005 for cross-validation (CVL). From the analysis of historical rainfall data, it is observed that the percentages of rainfall received during monsoon (June-September), post-monsoon (October-December), winter (January-February) and summer (March-May) seasons, with reference to annual rainfall are 70.4%, 18.9%, 1.2% and 9.5% respectively for Krishna basin. Similarly, the percentages of rainfall received during monsoon, post-monsoon, winter and summer seasons are noted to be 84.4%, 8.8%, 2.1% and 4.7% respectively for Godavari basin (IITM, 2007).

RESULTS AND DISCUSSIONS

Statistical software, namely, SPSS Neural Connection was used to train the network data and to predict the seasonal and annual rainfall for Krishna and Godavari basins. For the model development, the rainfall of i-1^{th} year is considered as the input and the predicted rainfall in i^{th} year as the output for MLPN, CCN and CGN models that are used for prediction of monsoon, post-monsoon, summer and annual rainfall. For winter season, the rainfall of i-1^{th} and i-2^{th} years are considered as the input and the predicted rainfall in i^{th} year as the output for MLPN, CCN and CGN models. By using SPSS, network data is trained with different combinations of parameters to determine optimum network architecture of MLPN, CCN and CGN models for Krishna and Godavari river basins.

Prediction of rainfall for Krishna basin

For Krishna basin, the factors α=0.7 and ε=0.05 were used in optimizing the network architecture of MLPN. The optimum network architecture with model parameters was used to predict the seasonal and annual rainfall for Krishna basin. Tables 1 and 2 give the values of MPIs on the predicted seasonal and annual rainfall using MLPN, CCN and CGN models for Krishna basin.

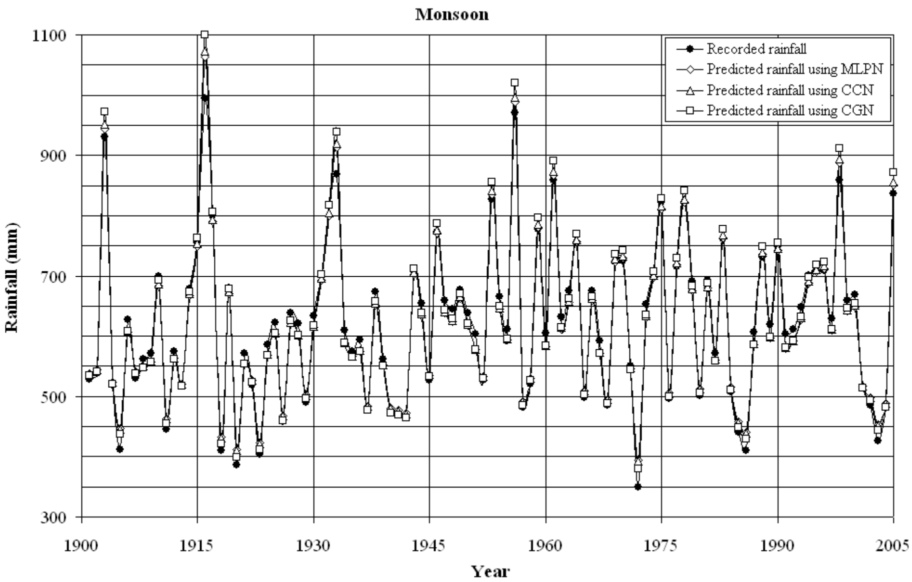
Table 1: Comparison on RMSE values using MLPN, CCN and CGN models for seasonal and annual rainfall patterns of Krishna basin

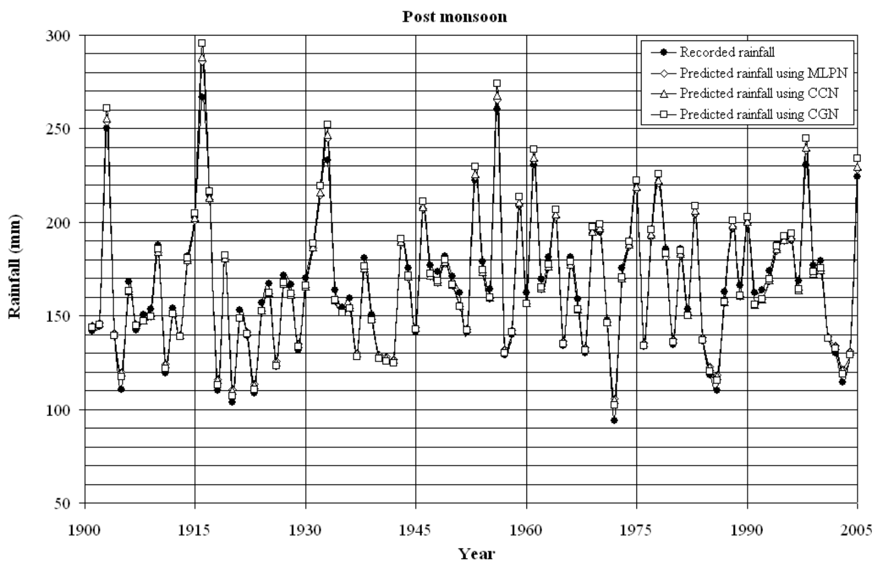
Seasonal/ Annual	Network architecture			RMSE (mm)								
				MLPN			CCN			CGN		
	MLPN	CCN	CGN	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Monsoon	1-15-1	1-12-1	1-20-1	13.9	10.3	11.3	16.4	11.8	25.0	17.4	13.6	37.9
Post Monsoon	1-12-1	1-10-1	1-15-1	3.7	2.8	5.7	4.4	2.9	7.6	4.7	3.7	10.2
Winter	2-12-1	2-10-1	2-15-1	0.3	0.2	0.4	0.3	0.2	0.4	0.5	0.4	0.6
Summer	1-12-1	1-10-1	1-15-1	1.9	1.4	2.6	2.2	1.6	3.5	2.4	1.8	5.1
Annual	1-15-1	1-12-1	1-20-1	19.8	14.7	20.0	23.3	16.5	36.5	25.0	19.5	53.8

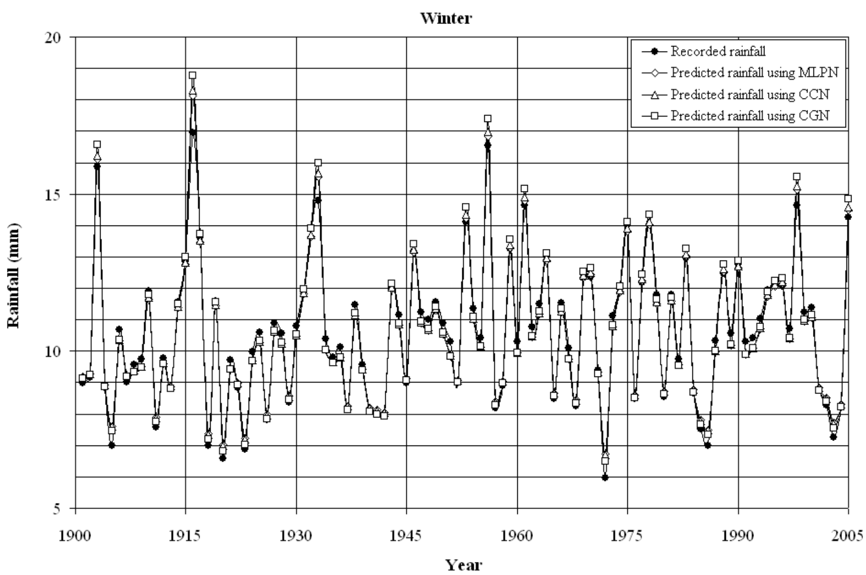
Table 2: Comparison on CC and MEF values using MLPN, CCN and CGN models for seasonal and annual rainfall patterns of Krishna basin

Seasonal/ Annual	MEF (%)									CC		
	MLPN			CCN			CGN					
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL	MLPN	CCN	CGN
Monsoon	97.4	96.9	97.0	95.3	95.2	95.4	94.6	94.7	90.1	0.996	0.991	0.990
Post Monsoon	97.3	96.5	97.2	95.1	95.0	95.3	94.7	95.0	90.0	0.996	0.990	0.989
Winter	97.1	96.6	97.1	95.4	95.1	95.1	94.5	94.8	90.3	0.996	0.991	0.988
Summer	97.2	96.7	97.4	95.2	95.0	95.2	94.7	94.6	90.0	0.996	0.990	0.990
Annual	97.3	96.7	97.2	95.3	95.1	95.3	94.6	94.8	90.1	0.996	0.991	0.989

From the values of MPIs obtained during TRG, VAL and CVL periods, as given in Tables 1 and 2, it is noticed that: (i) RMSE on the predicted rainfall using MLPN is less than the corresponding values given by CCN and CGN models and the architecture of MLPN is better suited to train the network data; (ii) There is generally good correlation coefficient between the recorded and predicted rainfall using MLPN, CCN and CGN models, with the values varying from 0.988 to 0.996; (iii) The RMSE on the predicted rainfall using MLPN, with reference to recorded rainfall, varied from about 0.2 mm to 14 mm for seasonal pattern; and 15 mm to 20 mm for annual pattern; (iv) The MEF values obtained from MLPN and CCN models are about 97% and 95% respectively. (v) MEF on prediction of seasonal and annual rainfall using CGN at TRG and VAL, and CVL periods is computed as 95% and 90% respectively. Figures 2 and 3 show the plot of recorded and predicted seasonal and annual rainfall using MLPN, CCN and CGN models for Krishna basin.


Monsoon
Recorded rainfall
Predicted rainfall using MLPN
Predicted rainfall using CCN
Predicted rainfall using CGN
Rainfall (mm)
Year
1100
900
700
500
300
1900
1915
1930
1945
1960
1975
1990
2005


Post monsoon
Recorded rainfall
Predicted rainfall using MLPN
Predicted rainfall using CCN
Predicted rainfall using CGN
Rainfall (mm)
Year
300
250
200
150
100
50
1900
1915
1930
1945
1960
1975
1990
2005


Winter
Recorded rainfall
Predicted rainfall using MLPN
Predicted rainfall using CCN
Predicted rainfall using CGN
Rainfall (mm)
Year
20
15
10
5
1900
1915
1930
1945
1960
1975
1990
2005

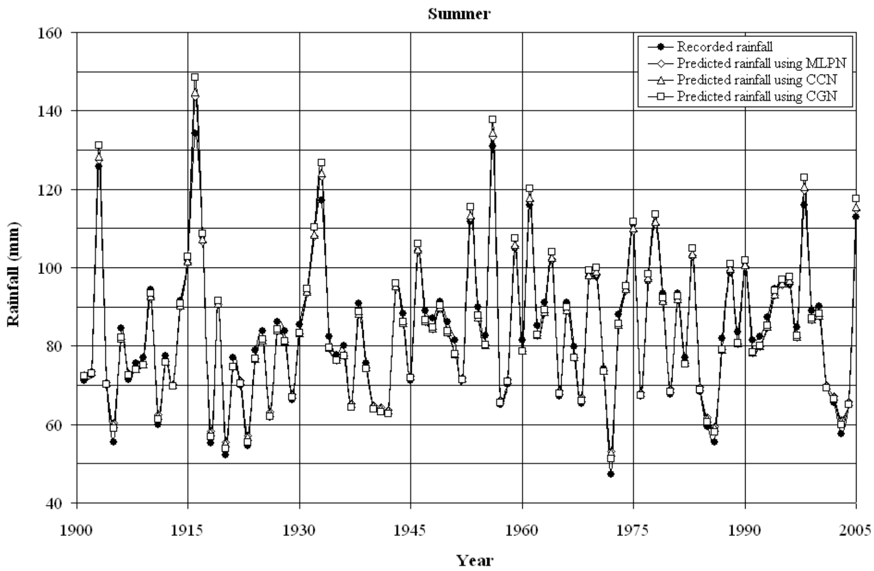


Figure 2: Plot of recorded and predicted seasonal rainfall using MLPN, CCN and CGN for Krishna basin

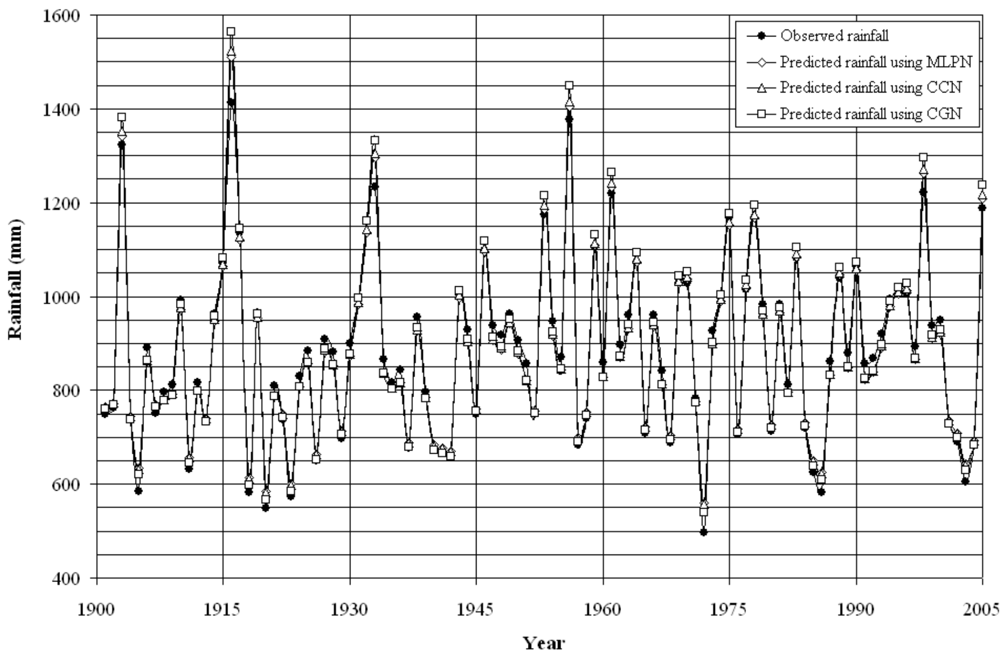


Figure 3: Plot of recorded and predicted annual rainfall using MLPN, CCN and CGN models for Krishna basin

Prediction of rainfall for Godavari basin

For Godavari basin, the factors α=0.8 and ε=0.12 were used in optimizing the network architecture of MLPN. The optimum network architecture with model parameters was used to predict the seasonal and annual rainfall for Godavari basin. Tables 3 and 4 give the values of MPIs on the predicted seasonal and annual rainfall using MLPN, CCN and CGN models for Godavari basin.

Table 3: Comparison on RMSE values using MLPN, CCN and CGN models for seasonal and annual rainfall patterns of Godavari basin

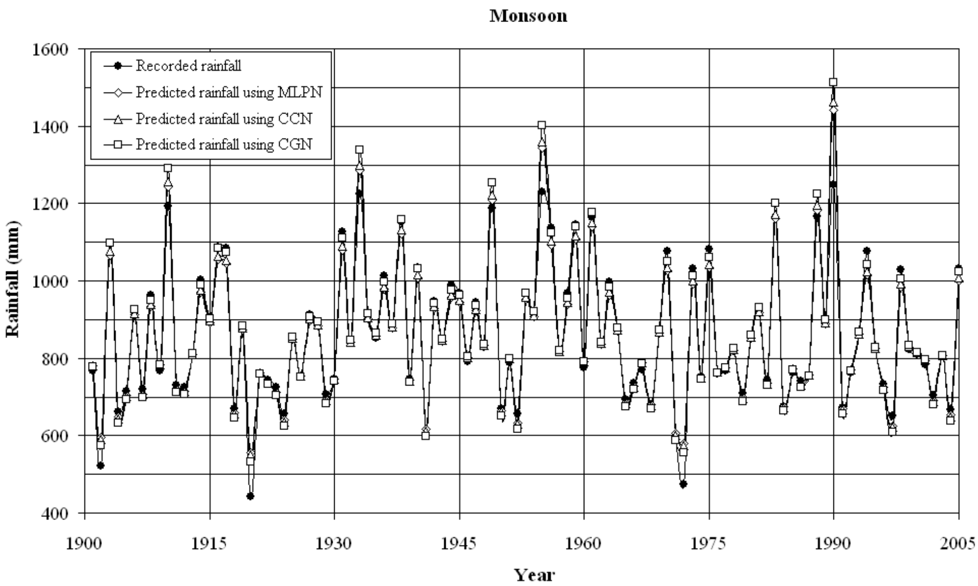
Seasonal/ Annual	Network architecture	RMSE (mm)		
		MLPN	CCN	CGN

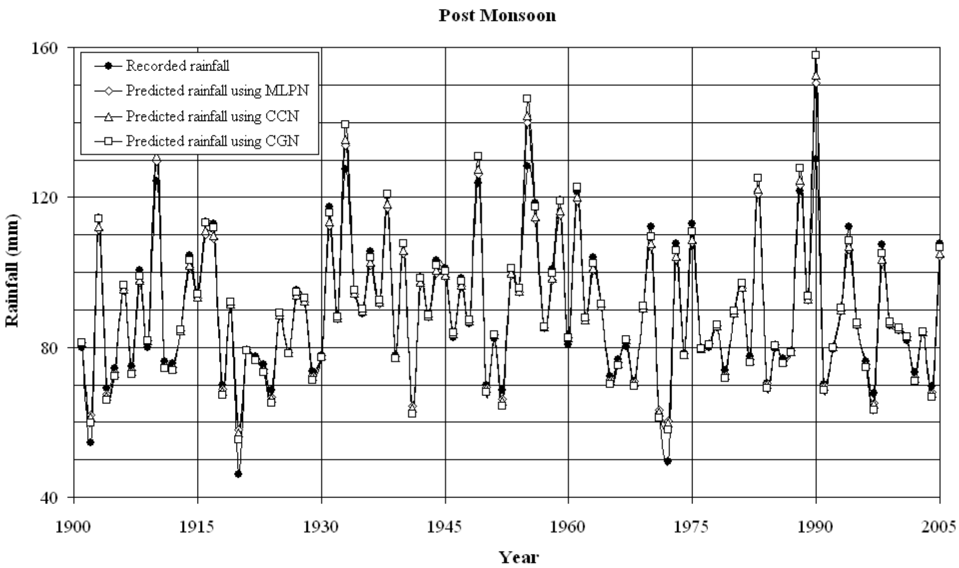
	MLPN	CCN	CGN	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Monsoon	1-20-1	1-15-1	1-25-1	22.4	10.7	15.9	22.7	20.1	16.4	23.2	24.6	22.2
Post Monsoon	1-15-1	1-12-1	1-20-1	2.3	1.1	6.5	2.4	2.1	6.9	2.6	2.6	8.6
Winter	2-15-1	2-12-1	2-20-1	0.6	0.3	1.5	0.7	0.5	1.9	0.9	0.6	2.0
Summer	1-15-1	1-12-1	1-20-1	1.6	0.5	3.5	1.7	0.8	3.9	1.9	1.0	5.0
Annual	1-20-1	1-15-1	1-25-1	26.9	12.6	27.4	27.5	23.5	29.1	28.6	28.8	37.8

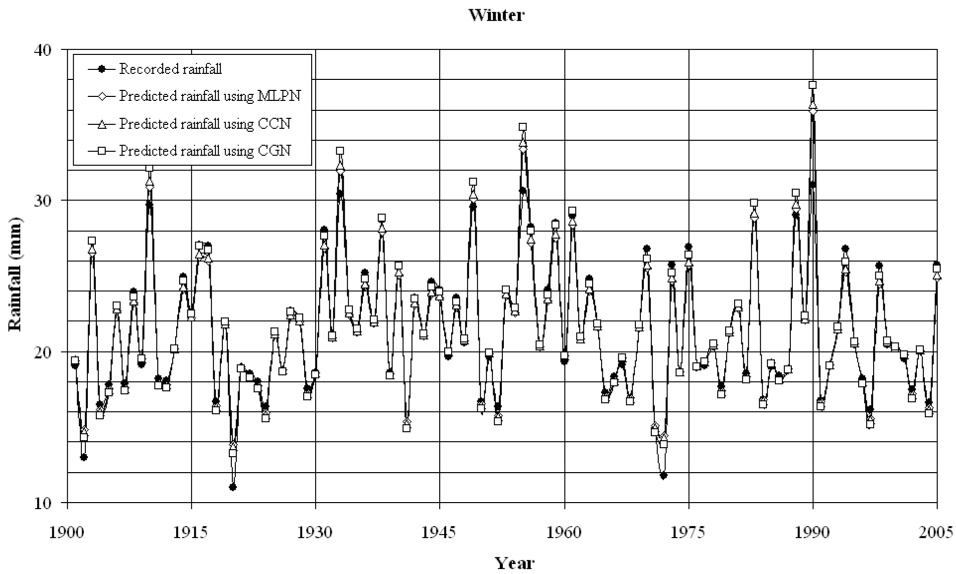
Table 4: Comparison on CC and MEF values using MLPN, CCN and CGN models for seasonal and annual rainfall patterns of Godavari basin

Seasonal/ Annual	MEF (%)									CC		
	MLPN			CCN			CGN					
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL	MLPN	CCN	CGN
Monsoon	96.4	95.9	85.9	95.3	95.2	84.4	94.6	93.7	85.4	0.980	0.971	0.963
Post Monsoon	96.3	95.5	86.2	95.1	95.0	83.9	94.7	93.0	85.4	0.980	0.973	0.969
Winter	96.1	95.6	86.1	95.4	95.1	84.2	94.5	93.8	85.4	0.980	0.974	0.968
Summer	96.2	95.7	86.4	95.2	95.0	83.8	94.7	93.6	85.2	0.980	0.976	0.965
Annual	96.3	95.7	86.2	95.3	95.1	84.1	94.6	93.5	85.4	0.980	0.974	0.966

Figures 4 and 5 show the plot of recorded and predicted seasonal and annual rainfall using MLPN, CCN and CGN models for Godavari basin.


Monsoon
1600
1400
1200
1000
800
600
400
Rainfall (mm)
1900
1915
1930
1945
1960
1975
1990
2005
Year
Recorded rainfall
Predicted rainfall using MLPN
Predicted rainfall using CCN
Predicted rainfall using CGN


Post Monsoon
160
120
80
40
Rainfall (mm)
1900
1915
1930
1945
1960
1975
1990
2005
Year
Recorded rainfall
Predicted rainfall using MLPN
Predicted rainfall using CCN
Predicted rainfall using CGN


Winter
40
30
20
10
Rainfall (mm)
1900
1915
1930
1945
1960
1975
1990
2005
Year
Recorded rainfall
Predicted rainfall using MLPN
Predicted rainfall using CCN
Predicted rainfall using CGN

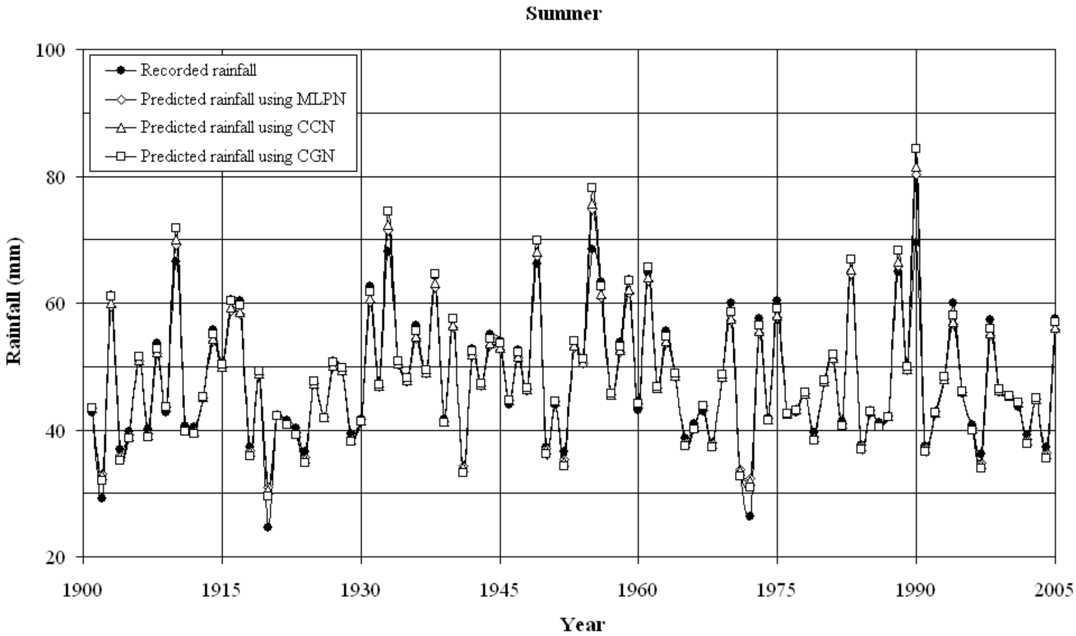


Figure 4: Plot of recorded and predicted seasonal rainfall using MLPN, CCN and CGN for Godavari basin

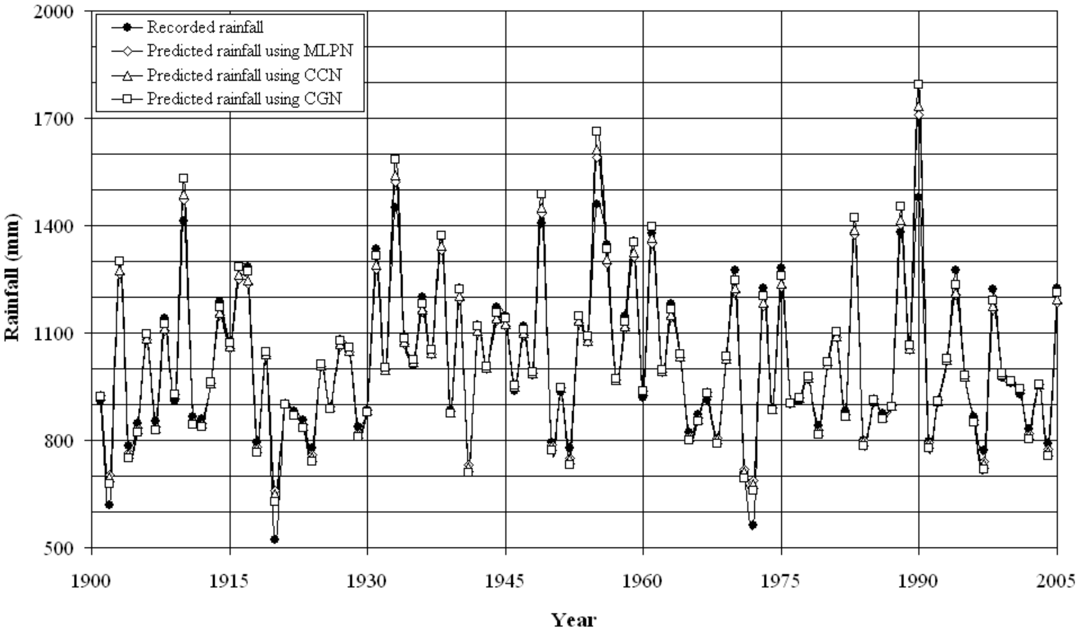


Figure 5: Plot of recorded and predicted annual rainfall using MLPN, CCN and CGN models for Godavari basin

From the values of MPIs obtained during TRG, VAL and CVL periods, as given in Tables 3 and 4, it is noticed that: (i) RMSE on the predicted rainfall using MLPN showed that the architecture of MLPN is found to be suitable to train the network data; (ii) There is generally good correlation coefficient between the recorded and predicted rainfall using MLPN, CCN and CGN models, with the values varying from 0.963 to 0.980; (iii) The RMSE on the predicted rainfall using MLPN, with reference to recorded rainfall, varied from about 0.3 mm to 22 mm for seasonal pattern; and 13 mm to 27 mm for annual pattern; (iv) The MEF obtained from MLPN, CCN and CGN models at TRG and VAL periods varied from about 93% to 96% for seasonal and annual rainfall; (v) The MEF on prediction of seasonal and annual rainfall at CVL using MLPN, CCN and CGN models are about 86%, 84% and 85% respectively.

Analysis based on MLPN using statistical parameters

The statistical parameters such as mean, standard deviation (SD), skewness and kurtosis for the recorded and predicted seasonal and annual rainfall using MLPN for Krishna and Godavari basins were computed and given in Tables 5-7.

Table 5 (a). Statistical parameters of recorded and predicted rainfall using MLPN for monsoon and post monsoon seasons of Krishna basin

Statistical parameters	Monsoon						Post monsoon					
	Recorded			MLPN			Recorded			MLPN		
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Mean (mm)	619.6	623.9	632.7	617.7	623.4	630.2	166.3	167.5	169.9	165.8	167.4	169.2
SD (mm)	137.1	131.1	123.1	138.3	122.3	121.5	36.8	35.2	33.1	37.1	32.8	32.6
Skewness	0.714	-0.344	-0.138	1.185	-0.092	0.400	0.712	-0.345	-0.136	1.183	-0.090	0.405
Kurtosis	0.340	-0.693	-0.321	1.390	-1.004	-0.119	0.343	-0.695	-0.323	1.393	-1.007	-0.121

Table 5 (b). Statistical parameters of recorded and predicted rainfall using MLPN for winter and summer seasons of Krishna basin

Statistical parameters	Winter						Summer					
	Recorded			MLPN			Recorded			MLPN		
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Mean (mm)	10.6	10.6	10.8	10.5	10.6	10.7	83.6	84.2	85.4	83.3	84.1	85.0
SD (mm)	2.3	2.2	2.1	2.4	2.1	2.1	18.5	17.7	16.6	18.7	16.5	16.4
Skewness	0.710	-0.340	-0.136	1.180	-0.092	0.400	0.714	-0.344	-0.138	1.185	-0.094	0.403
Kurtosis	0.340	-0.691	-0.321	1.392	-1.005	-0.120	0.341	-0.694	-0.324	1.394	-1.006	-0.123

Table 6 (a). Statistical parameters of recorded and predicted rainfall using MLPN for monsoon and post monsoon seasons of Godavari basin

Statistical parameters	Monsoon						Post monsoon					
	Recorded			MLPN			Recorded			MLPN		
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Mean (mm)	875.7	811.9	851.9	871.5	811.4	853.4	91.3	84.7	88.8	90.9	84.6	89.0
SD (mm)	177.7	172.1	171.2	173.2	150.9	196.2	18.5	17.9	17.9	18.1	15.7	20.4
Skewness	0.155	0.440	1.017	0.591	0.718	1.659	0.157	0.442	1.018	0.595	0.720	1.669
Kurtosis	-0.417	0.092	0.147	0.107	0.115	3.322	-0.419	0.095	0.149	0.109	0.118	3.325

Table 6 (b). Statistical parameters of recorded and predicted rainfall using MLPN for winter and summer seasons of Godavari basin

Statistical parameters	Winter						Summer					
	Recorded			MLPN			Recorded			MLPN		
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Mean(mm)	21.8	20.2	21.2	21.7	20.2	21.2	48.8	45.2	47.4	48.5	45.2	47.5
SD (mm)	4.4	4.3	4.3	4.3	3.8	4.9	9.9	9.6	9.5	9.6	8.4	10.9
Skewness	0.153	0.443	1.019	0.593	0.719	1.660	0.155	0.440	1.017	0.591	0.718	1.659
Kurtosis	-0.415	0.090	0.145	0.109	0.117	3.320	-0.417	0.092	0.147	0.107	0.115	3.322

Table 7. Statistical parameters of recorded and predicted annual rainfall using MLPN for Krishna and Godavari basins

Statistical parameters	Krishna						Godavari					
	Recorded			MLPN			Recorded			MLPN		
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Mean (mm)	880.1	886.3	898.7	877.4	885.6	895.1	1037.5	962.0	1009.3	1032.6	961.4	1011.1
SD (mm)	194.7	186.2	174.9	196.4	173.7	172.6	210.6	203.9	202.8	205.2	178.8	232.4
Skewness	0.715	-0.344	-0.139	1.187	-0.094	0.402	0.157	0.443	1.019	0.593	0.719	1.665
Kurtosis	0.343	-0.693	-0.323	1.393	-1.005	-0.120	-0.419	0.094	0.149	0.109	0.117	3.324

From Tables 5-7, it may be noted that the variation on the average predicted rainfall using MLPN with reference to average recorded rainfall is considered to be minimum for seasonal and annual rainfall patterns of Krishna and Godavari basins. From the analysis of the results based on MPIs and statistical parameters, it is suggested that MLPN could be used for prediction of seasonal and annual rainfall for Krishna and Godavari river basins.

CONCLUSIONS

The paper described the procedures involved in prediction of seasonal and annual rainfall for using MLPN, CCN and CGN models for Krishna and Godavari river basins. The study showed that the seasonal and annual rainfall prediction using MLPN network is comparatively better than CCN and CGN models for both the river basins. The results indicated that the RMSE on the predicted rainfall using MLPN, with reference to recorded rainfall, varied from about 0.2 mm to 14 mm for seasonal pattern; and 15 mm to 20 mm for annual pattern for Krishna basin. The results also indicated that the RMSE values varied from about 0.3 mm to 22 mm for seasonal; and 13 mm to 27 mm for annual pattern for Godavari basin. The paper presented that the MEF in rainfall prediction using MLPN for Krishna basin is about 97%. For Godavari basin, MEF in rainfall prediction at training and validation periods is computed as about 96% and 86% at cross-validation. The paper also presented that the CC in rainfall prediction using MLPN is computed as 0.996 for Krishna basin and 0.980 for Godavari basin. From the results of the data analysis, it is suggested that MLPN is better suited for prediction of seasonal and annual rainfall for the river basins under study. The plot of recorded and predicted rainfalls using MLPN, CCN and CGN models for Krishna and Godavari basins are developed and presented in the paper.

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