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Development of ANN models using monthly rainfall for central Telangana region

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Abstract

In the present study, artificial neural network technique has been employed to predict monthly rainfall for Medak, Khammam and Warangal stations of Central Telangana, India. The eighty-five years (January, 1901 to December, 1985) of rainfall data were used for training of models and twenty-eight years (January, 1986 to December, 2014) of rainfall data were used for testing of models. Gamma test, autocorrelation function and cross correlation function were used for selection of appropriate input variables. The ANN models were trained using multilayer perceptron with two learning rules i.e. Levenberg-Marquardt and Delta-bar-delta and two transfer functions viz. Sigmoid axon and Tanh axon. It was observed that the better results of monthly rainfall prediction of developed models were observed when rainfall of adjoining stations was used as inputs variable as compared to lagged rainfall of the same station. suggest that the M-8 model, K-7 model and W-5 may be used to predict monthly rainfall of Medak, Khammam and Warangal stations respectively for Central Telangana region.

Keywords: Rainfall, neurons, runoff, networks and monsoon

Introduction

Changes in water quantity are occurring mainly as consequences of global and local changes actuated by environmental factors, climate change and human induced changes. Rapid population growth and increasing economic activity have brought new challenges to the management of available water resources. Although irrigation is the main water consumption, it is likely to continue in India at present and in the years to come, with demand from other sectors such as drinking and industry increasing significantly. Therefore, it is necessary to properly assess the capacity of water resources. Without a reliable assessment of resource availability, it is impossible to properly plan, design, build, maintain and manage water resources projects to meet competitive demands such as irrigation, drought and flood management, domestic and industrial water supply, and power generation., fisheries and navigation. Water resources (surface water and groundwater) are restored through a continuous cycle of evaporation, precipitation and runoff. The water cycle is driven by global and climatic forces that introduce variation in precipitation and evaporation, which define runoff patterns and water availability over space and time (modulated by natural and artificial storage). Observations made over the past decades and predictions from climate change examples indicate the severity of spatial and temporal variations of water cycle dynamics (IPCC, 2013) [6]. When data is not sufficient and getting accurate predictions is more important than conceiving the actual physics, empirical models remain a good alternative method, and can provide useful results without a costly calibration time. Soft Computing is an emerging field and its main ingredients are fuzzy logic, neural computing, evolutionary computation, machine learning and probabilistic reasoning. ANN model is a black box models with particular properties which is greatly suited to dynamic nonlinear system modeling. The artificial neural network (ANN) technique for rainfall prediction is adding a new dimension to the system theoretic modeling approach and it is applying in recent years, as a successful tool to solve various problems. Of the rainfall-runoff process. ANN is also a powerful tool in solving complex nonlinear river flow forecasting problems and in particular when the time required generating a forecast is very short. Mathematically, an ANN can be treated as a universal approximation technique having an ability to learn from examples without the need of explicit physics (ASCE, 2000a, b) [2].

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Telangana State is endeavoring to increase the productivity of agriculture sector while ensuring the profits of the farmer increases. 55.49% of the state population in Telangana is dependent on agriculture and allied sectors for their livelihood. Agriculture in Telangana depends on rainfall. The average annual rainfall in the state is 906 mm, of which 80 per cent comes from the south-west monsoon. Agriculture is one of the most critical areas for climate change. Climate change is considered to be a great challenge in terms of rainfall variability. Both climate change and change reduce yields and profitability on rainfed agriculture. Variations in the annual rainfall of the southwest monsoon directly affect the production and productivity of rainfed crops in Telangana. Crop productivity can also be significantly affected when thermal stress due to moisture stress or heat wave conditions caused by chronic dry spells occurs during the critical life stages of the crop. Telangana state is most vulnerable to cyclones, heavy rains, and floods including drought due to its widespread and peculiar geographic location. Drought is one of the most crippling hazards that impact the state. Keeping in view the above facts, an attempt has been made to estimate monthly rainfall of Central Telangana.

Review of literature on monthly rainfall

ANN models to estimate runoff over three different medium-sized watersheds found in Kansas. Performance of applied structures and repetitive neural networks can be determined by comparison with other empirical approaches. Established monthly rainfall and temperature inputs and selected the obtained monthly runoff as output. They explained that feed-forward neural networks have not provided significant improvements over other regression mechanisms without time delay. However, inclusion of feed forward with RNN resulted in better performance Annala *et al.* (2000.)^[1] Examined the role of ANN in various branches of hydrology and found that ANNs were robust tool for modeling many of nonlinear hydrologic processes such as rainfall-runoff, stream flow, ground water management, water quality simulation and precipitation. There were still some questions about the application of this emerging technique in engineering, which needs further study on some important aspects such as physical interpretation of ANN architecture, optimal training data set, adaptive learning, and extrapolation. The merits and limitations of ANN applications have been discussed, and potential research avenues have been explored briefly ASCE (2000)^[2] described the Artificial Neural Network (ANN) technology with error-back propagation algorithm to provide forecast of Indian summer monsoon rainfall on monthly and seasonal time scales. Based on the Parthasarathy dataset, ANN technology was applied to the five-time series of monthly routes and seasonal average (June + July + August + September) rainfall from June to July, August, September from 1871 to 1994. The values of the previous five years from all five-time series were used to train ANN to estimate for the next year. Various statistics were calculated to examine the performance of the model and it was found that it could be used as a tool to estimate the model on seasonal and monthly time scales. Various researchers have observed that the relationships between different predictors and Indian monsoons are changing over time, leading to changes in the predictive capacity of monsoons. This issue is discussed and it was found that the monsoon system inherently has a decadal scale variation in predictability. Sahai *et al.* (2000)^[15] studied and compared the accuracy of short-term rainfall forecasts obtained with time-series analysis methods using past rainfall

depths as a single input information. The proposed methods are linear random auto-regressive moving average (ARMA) models, artificial neural networks (ANN) and nonparametric near-neighbor method. The rainfall forecasts obtained using the considered methods were then redirected by the lumped, conceptual, rainfall-runoff model, thereby implementing a coupled rainfall-runoff forecasting approach for case study on the Apennine Mountains. The study analyzed and compared the relative advantages and limitations of each time-series analysis technique used to issue rainfall forecasts for lead-times ranging from 1 to 6 h.

The results also indicated how the considered time-series analysis techniques, and especially those based on the use of ANN, provide a significant improvement in the flood forecasting accuracy in comparison to the use of simple rainfall prediction approaches of heuristic type, which were often applied in hydrological practice Toth *et al.* (2000)^[18] developed three different types of ANN *viz.* multilayer feed forward neural networks, partial recurrent neural networks and time delay neural networks and found to provide reasonable predictions of the rainfall depth one time-step in advance Luk *et al.* (2001)^[8] studied the artificial neural network methodology for modeling daily flows during monsoon flood events for the large-scale catchment area of the Narmada River in Madhya Pradesh, India. The spatial variation of rainfall is calculated by subdividing the catchment area and by considering the average rainfall of each sub-catchment area parallel to the model and as a separate lump input. Compared to the linear and nonlinear MISO models, a linear multiple-input single-output (MISO) model with ANN provides better representation of rainfall-runoff relationships over such large watersheds. The model provides a systematic approach to runoff estimation and suggests an improvement in prediction accuracy over other models by Rajurkar *et al.* (2002)^[13].

General description of study area

Telangana state was isolated from north western part of Andhra Pradesh on 2 June 2014 as the recently formed 29th state of India with Hyderabad as its capital. The Godavari and Krishna are two major rivers basin spread in Telangana state. Based on agro-climatic zone, Telangana state is divided into three zones namely northern Telangana zone, central Telangana zone and southern Telangana zone. The study area is central Telangana zone and consists of Medak, Warangal and Khammam districts of Telangana state. This section deal with location, climate and soil attributes of the study area.

Location

The study was conducted in central Telangana region which includes three districts i.e., Medak. The details of rain gauge site and data length of rain gauge stations are given in Table 1.

Table 1: Detail of rain gauge site and data length

District	Latitude	Longitude	Altitude, (m)	Data
Medak	18.03°N	78.27° E	442	1901-2014
Warangal	18.00° N	79.58° E	302	1901-2014
Khammam	17.25° N	80.15° E	107	1901-2014

Climate

The area comes under semi-arid area and has a mainly dry and warm climate. The summer is beginning in March and has high temperature in the month of May with normal temperatures around the 420 C. The meteorological season for

the study area is divided into four distinct parts, i.e. monsoon (June to September), post monsoon (October to November), winter (December to February) and summer (March to May). The monsoon arrives in month of June and continues up to September with around 755 mm of average annual rainfall.

Soil characteristics

The characteristics of soil provides adequate information about natural vegetation, infiltration of soil, types of soil, land forms, as well as nature of soils which can be used for land and development. The central Telangana zone have different types of soils such as red soils (48%), black soils (25%), laterite soils (7%) which is mostly present in Medak, Warangal and Khammam districts of Telangana region. The water holding capacity varies from moderate to high. Soils have drainage behavior ranging from well drained to poorly drained state under low land situation. There is a wide range of variation in nitrogen and phosphorus status of the soils. Most of the soils belong to land use capability classes I-III of which some pockets are problematic due to erosion and flood.

Agriculture

The geographical area of the central Telangana, which is under agriculture (43%), forest (24%), current fallow lands (8%), Non-Agricultural uses (7.80%), barren and uncultivable land (5%) and falls under other fallows (6%) and under cultivable waste, Permanent pastures (5%). In central Telangana, 68% of the total gross cropped area occupied by Rice, Cotton, Maize, Soybean, Bengal gram, Maize, Green gram, Red gram, Black gram, Groundnut, Sunflower and Tobacco.

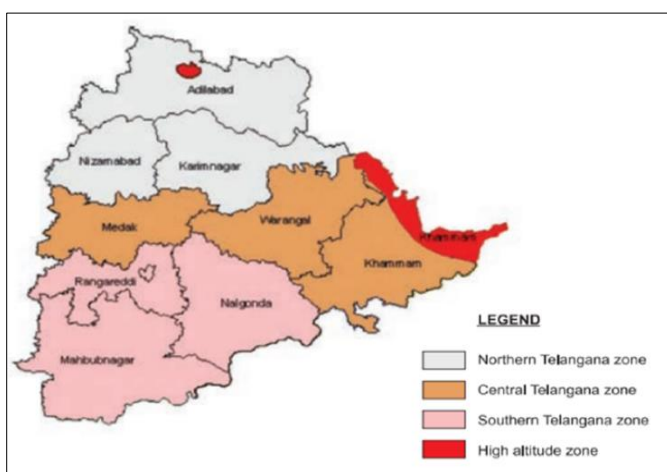


Fig 1: Agroclimatic zones in Telangana State

Data Acquisition

The monthly rainfall data for the period from January 1901 to December 2014 for Central Telangana region namely (Medak, Warangal, Khammam) were obtained from Indian Water Portal site from (1901 to 2002) and from Indian Meteorological Department (IMD) of respective districts (2003 to 2014).

The monthly data of rainfall for 113 years from January 2001 to December 2014 were divided into two phases. The first phase is used for training. The training phase used 85 years of data from January, 1901 to December, 1985, and the second phase 28 years data from January 1986, to December 2014 for validation of developed models.

Basic concept of artificial neural networks (ANNs)

Artificial neural network comprises of neurons (nodes), which are the vital unit of artificial neural network. Neuron, is able to acknowledge and pass on signals starting with one neuron then onto the next neuron. The essential idea of neuron display is double edge handling unit and was introduced by McCulloch and Pitts (1943) [9]. The most widely recognized structure of a neuron is shown in Fig. 2.

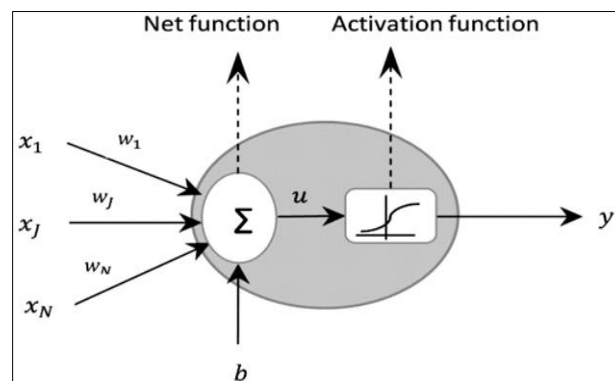


Fig 2: Basic structure of neural system

In neural system each neuron has a various information source. A neuron calculates an output by applying net and activation function on inputs. First, net function sum weighted inputs (u), then output is calculated based on activation function ($y = (u)$). The net function is usually linear, as follows:

$$u = \sum_{i=1}^N x_i W_i + b$$

Where x_i is an input vector, w_i is the association weight from the i^{th} neuron in the input layer and b is the threshold value or the inclination of the neuron.

The nodes can take input data information can perform basic activity on information on data. The information passed through different neurons. The output of each node is known as its activation or node value. Each link connection with weight. ANN learns by altering the association quality between the processing elements. This is done by adjusting the weights on introduction of a set of preparing utilizing learning guideline. Once the learning phase is complete, the weights are "frozen".

Artificial neural network architecture

An artificial neural network naturally consists of three different layers of neurons, the input layer, one or more hidden layers, and the output layer. The quality of the neurons in the input and output layer depends on the problem and the number of hidden layers and the number of neurons in the hidden layers must be accurate. In practice, having a single hidden layer with enough neurons usually leads to the exact estimate required. Having a large number of hidden neurons gives the network the flexibility to solve more complex problems, including a large number of neurons. May cause a tightening problem. Various mechanisms have been introduced to reach the optimal number of neurons. One of the most promising solutions to achieve this number is the trial and error approach.

Depending on the pattern of connections between layers, ANN can be generated in feed-forward or recursive form. Repetitive neural network is mainly used when there are temporary patterns in the data. Feed-forward neural networks are the most common neural networks when there is a static pattern in the data, so some users identify the phrase "neural networks" as the feed-forward network only. There are different types of feed-forward neural networks, such as multilayer perceptron (MLP) and radial base function (RBF). The most popular neural network model in hydrology is multilayer feed-forward neural networks (Fernando and Jayawardena, 1998; ASCE Task Committee, 2000a and Dawson and Wilby, 2001) [5, 1, 2].

Feed-forward multilayer perceptron

Feed-forward multilayer perceptron neural networks (MLP) are composed of several layers of neurons. The connections between neurons (information flow) are in one direction, from the input layer, through hidden layers and to the output layer. Fig. 3. Shows a single hidden layer feed-forward neural network.

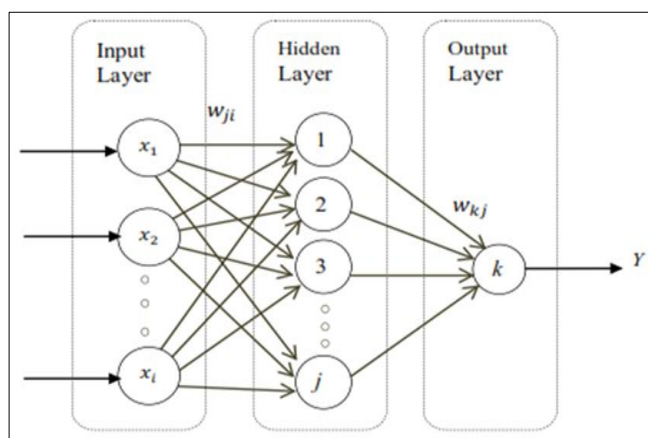


Fig 3: Single hidden layer feed-forward neural network

There are no connections between neurons or layers in a single layer and no feedback connections. The output of neurons in each layer is applied as inputs to the next layer. The final product of this network can be achieved by the following equation:

$$Y = f_o \left[\sum_j W_{kj} f_h \left(\sum_i W_{ji} x_i + b_j \right) + b_k \right]$$

Where x is an input vector, W_{ji} is the connection weight from the i^{th} neuron in the input layer to the j^{th} neuron in the hidden layer; b_j is the threshold value or bias of j^{th} hidden neuron; W_{kj} is the connection weight from the j^{th} neuron in the hidden layer to the k^{th} neuron in the output layer; b_k is bias of k^{th} output neuron and f_h and f_o are the activation function for hidden and output layer.

Learning algorithm

Learning algorithm is a basic feature of neural networks. During the learning process, the learning or training algorithm updates the network parameters to achieve the desired model performance based on the training data set. Learning the process of adjusting weights at the output layer in response to the training data provided at the input layer and depending on the practice rule. The learning process allows the network to

adapt its response over time to produce the desired output. Learning network parameters or training algorithm to achieve the desired model performance based on the training data set. There are three main classifications for ANN practice, supervised, supervised, and reinforced. The most commonly used learning model is, above all, supervised learning neural networks. Unsupervised practice does not train neural networks to reach target results and work primarily for sample classification purposes. However, supervised learning algorithms require both inputs and associated outputs to train the network and are very suitable for solving time series forecasting problems.

Back-propagation algorithm

The most commonly used learning algorithm for training neural networks is the back-propagation algorithm. The back-propagation algorithm (BP) operates the algorithm, which adjusts the association weights and bias in the backward direction. It is an optimization approach based on gradient descent to minimize the total error between desired and actual outputs. The information data is multiplied by the initial weights, and then the weighted information is added by summation to give a net input to each neuron.

$$Net = w_1 x_1 + w_2 x_2 + \dots + w_{ji} x_i$$

$$Net = \sum_{i=1}^N w_{ji} x_i$$

Where X_i is the input to any neuron, w_{ji} is the connection weighted between j^{th} layer to i^{th} layer, N is the number of inputs and Net is the net for j^{th} neuron. The output of k^{th} node of the hidden layer b_k is given as:

$$b_j = f(net)$$

where $f(net)$ is the activation function, example a tanh activation function. This can be represented as:

$$b_j = \frac{e^{(net)} - e^{(-net)}}{e^{(net)} + e^{(net)}}$$

The calculated error at the output layer is propagated to the hidden layers and then to the input layer to determine updates for the weights. The average sum of the square error E for a single input-output pair of data sets is as follows:

$$E = \frac{1}{2} \sum_{i=1}^N (c_i - d_i)^2$$

Where E is the Total error, c_i is the observed or calculated output at i^{th} node and d_i is the target or desired output at i^{th} node.

A set of pattern examples is used in the training process. Each example is paired with an input and a corresponding target output. Patterns are introduced to the network in a series of repetitive manner, with appropriate weight corrections being made in the process to adapt the network to the desired behavior. This repetition continues until the connection weight values allow the network to make the necessary mapping. Each performance of the entire pattern set was named an epoch. The term repetition after this refers to a

model epoch or a complete epoch depending on the situation. The generalized delta rule is used to calculate the values of local gradients. Each weight update is defined as:

$$\Delta w_{ji}(n) = \eta \delta_j a_i$$

and the equations of the generalized delta rule used to calculate the values are

$$\delta_j = a_j(1 - a_j)(t_j - a_j)$$

$$\delta_j = (1 - a_j) \sum_{k=1}^{N_{l+1}} \delta_k w_{jk}$$

The error measurement depends on the difference between the desired t_j and actual a_j values so the weight update of the output units can be calculated directly using the available values. However, that measure is not available for the hidden neurons. The solution is to back-propagate the j values layer by layer through the network.

The learning algorithm also called gradient search is used to calculate the adjusted weights and biases of the network to minimize the error between computed and observed output. In searching with the momentum component there are two parameters to be selected, the step size and the momentum. The Neural Builder provides a default value for the learning rates. In this study, Delta-Bar-Delta learning and Levenberg-Marquardt algorithms are used.

a. Delta Bar Delta

The Delta-Bar-Delta (DBD) algorithm is a meta- processing algorithm in the sense that it learns the learning-rate parameters of an underlying base learning system. The base learning system is the Least-Mean-Square (LMS) rule, also known as the delta rule. The Delta-Bar-Delta (DBD) network used the same architecture as a back-propagation network. The DBD is an exclusive algorithmic method of learning and recover the convergence rate of feed forward and back-propagation networks. The DBD get the information from previous weights.

The Delta Bar Delta is a custom step-by-step system for searching for a performance surface. Step size and momentum are modified according to the previous values of the error at the neurons. If both the current and past weight update are the same signs, it will simply increase the learning rate. The logic is that the error decreases if the weight moves individually in the same direction, and then it approaches faster with a larger step size. If the upgrades have different symbols, it is a sign that the weight has moved too far. When this happens, the learning rate decreases geometrically to avoid difference. It was urbanized for quadratic error functions;

$$\Delta w_{ji} = \alpha (t_3 - Y_3) g(h_3) x_i$$

where, α = Constant learning rate, $g(x)$ = neuron's activation function, t_3 = targeted output, h_3 = weighted sum of the neuron's inputs, y_3 = actual output, X_i = i^{th} input

b. Levenberg-Marquardt

The Levenberg-Marquardt Algorithm (LM) was adopted for neural network training by Hagan and Menhaj (1994). It is one of the most well-known high-order adaptive algorithms

known to reduce the mean square error (MSE) of a neural network. It is an associate of class learning algorithms called pseudo second-order methods. Standard gradient decent algorithms use only local estimation of the slope of the performance surface (error versus weights) to establish the best direction for weights to travel to reduce error. The main advantage of LM advance is that when the local twist of the presentation surface deviates from the parabola it defaults to gradient search, which can often occur in neural computing. In order to apply LM, the difficulty in training MLP should be designed as nonlinear optimization. The main drawback of this algorithm is the computational problem of calculating the matrix inverse with a few thousand variables.

$$W_{k+1} = W_k - (J^T J W_k + \mu I)^{-1} J^T e$$

Where μ = Parameter changed during the training process. If $\mu = 0$ Algorithm works as LM method and for large values of μ , algorithm works as steepest decent method.

Connection weights

Connection weights increase, decrease or change the symbol of the input signal 1. Zero weight indicates a lack of connection and a negative weight indicates a resistance relationship between the two nodes. In general, the input of node x_i is multiplied by the weight of the connection w_i between nodes x_i and produces the input signal to node. The connection weights therefore indicate the strength of the connection between the two nodes. Weights are stored in the nodes' local memory and also the network's long-term memory.

Threshold

The threshold is calculated by the set value based on the final output of the network. The entry value is used in the active function. A comparison is made between the calculated net input and the threshold to obtain the network output. For each and every application, there is a threshold limit. The activation function using threshold can be defined as

$$f(net) = \begin{cases} 1 & \text{if } net \geq \theta \\ -1 & \text{if } net < \theta \end{cases}$$

Activation function

Activation function also called transfer function is computational network that gives the output of a processing element as a function of input signal. Activation function uses the best processing element by using the trial and error method. There are various types of activation functions, which are commonly used in the hydrological models. The most commonly used activation functions in hydrology for the best applications are Sigmoid and hyperbolic tangent.

Hyperbolic tangent

In the present study hyperbolic tangent, activation function is used. The output range of hyperbolic tangent function is bounded into the range of -1 and 1, for inputs, which is considered as the desirable characteristics of this function. The hyperbolic tangent activation function is mathematically expressed as:

$$\text{Tanh}(x) = \frac{\sinh(x)}{\cosh(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

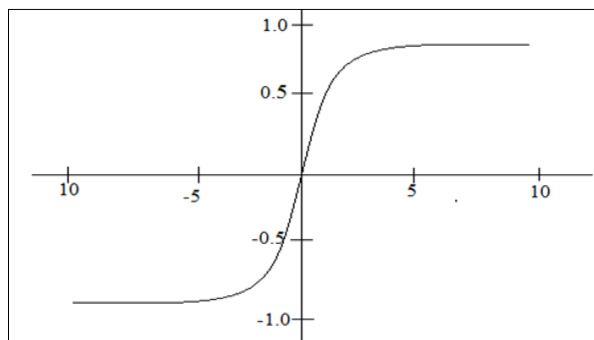


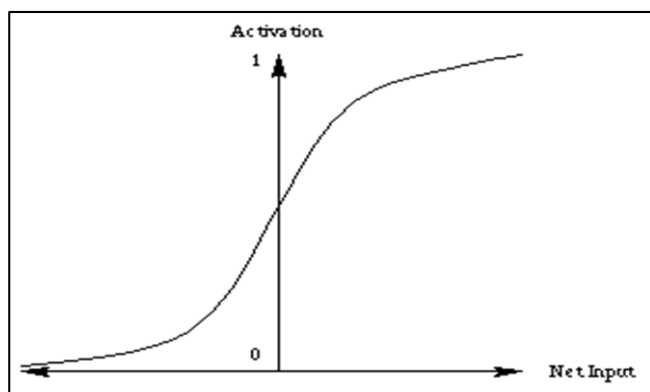
Fig 4: Hyperbolic tangent function

This function is defined as the ratio between hyperbolic sine and cosine, function as ratio of half difference and half-sum of exponential function in point x and $-x$, as shown in Fig 4. The hyperbolic tangent function is similar to sigmoid function with its outputs between -1 to 1.

Sigmoid Axon

A sigmoid Axon function is a numerical function having an S shape sigmoid curve). Sigmoid Axon function refers to the special case of the logistic function shown in figure and defined by the formula.

$$S(t) = \frac{1}{1+e^{-t}}$$



Gamma test

GT is one of the non-linear modeling tools that can research the appropriate input combination from the input variables to model the output data and additionally create a model sensitive path. GT calculates the minimum square errors that can be found on continuous non-linear models and unseen data. Assume that X_a and X_b are nearest to each other; then, Y_a and Y_b ought to likewise be near every other. In GT, it is attempted to make this view qualitative through mean difference between the closest neighbor limited arrangement of X_a and X_b and mean length between the comparing output purposes of Y_a and Y_b and accomplish estimation for error value. Let assume that there is a data set as follows:

$$\{(x_1 \dots x_m)y\} = (X, y) \quad \dots (3.13)$$

Where, $X = (x_1 \dots x_m)$ is the input vector in the output vector's areas of y and m is total number of input variables. If the relationship is established between the set members:

$$y = f(x_1 \dots x_m) + r \quad \dots (3.14)$$

Where f is smooth function and r is a random variable. GT is an estimated output variance of a non-smooth model. GT is based on the k^{th} ($1 \leq k \leq p$) nearest neighbors $X_{N[i,k]}$ for each vector X_i ($1 \leq i \leq M$). Delta function calculates the mean square distance of the k^{th} neighbor:

$$\delta_M(k) = \frac{1}{M} \sum_{i=1}^M |X_{N[i,k]} - X_i|^2 \quad \dots (3.15)$$

In which $/ /$ indicates Euclidean distance, corresponding gamma function is as follows:

$$\gamma_M(k) = \frac{1}{2M} \sum_{i=1}^M [Y_{N[i,k]} - Y_i]^2 \quad 1 \leq k \leq p \quad \dots (3.16)$$

Where, $Y_{N[i,k]}$ is value of y corresponding to the k^{th} neighbor of X_i in Eq. 3. In order to calculate gamma(Γ), the linear regression is fitted from P spot to values of $\delta_M(k)$ and $\gamma_M(k)$.

$$\gamma = A\delta + \Gamma \quad \dots (3.17)$$

The intercept of this line $\delta=0$ indicates the gamma value and $\gamma_M(k)$ is equal to the errors variance and it is provided that the combination $2^n - 1$ would be among them. Reviewing all the alternative combinations takes much time. Gamma test can determine the most efficient variable in modeling and the best input combination (Lafdani *et al.*, 2013)^[7].

Development for rainfall prediction models

The prediction of rainfall is enormously complex, vibrant, dynamic and nonlinear process, which is affected by many factors which are frequently inter-related. The methods used for rainfall forecasting range from completely black-box models to very detailed conceptual models. Historically, hydrologists and researchers have used two types of models: (a) deterministic/conceptual models that consider the dynamics of the principal process, or (b) systems theoretical/black-box models that do not consider the principal dynamics of the process. Moreover, a black box model is an input-output pattern of which there is no erstwhile information available and these models define the casual link between input-output patterns by alteration. One of the approaches for system theoretical modelling based on artificial neural networks has recently become very popular in the field of hydrological modelling and engineering due to their simplicity and adaptability to mug up and gather information from situation. In the present study, artificial neural network models with different activation functions have been developed for prediction rainfall on monthly basis. As the prediction of monthly rainfall is a complex and dynamic process and it needs a proper time lag for its prediction. Therefore, for development of rainfall prediction, different combinations of lag rainfall (i.e. rainfall of current month, previous one month, previous two month, previous three month and four month) as input and rainfall of current month as output were used in runoff prediction.

$$P_{ij} = f(P_{i,j-1}, P_{i,j-2}, P_{i,j-3}, P_{i,j-4} \dots P_{i,j-m}) \quad \dots (3.18)$$

Where, P_{ij} is the rainfall for j^{th} day, of the i^{th} year, and m standards for time lag which is taken as four in present study. The form of year wise data of rainfall data with time lag is shown in Table 2

Table 2: Input-output pairs in training and testing for rainfall prediction

Year (i)	Month (j)	Input for j_{th} months				Output
		X_1	X_2	X_3	X_4	Y
		$P_{i,j-1}$	$P_{i,j-2}$	$P_{i,j-3}$	$P_{i,j-4}$	$P_{i,j}$
1	1	$P_{1,2}$	$P_{1,3}$	$P_{1,4}$	$P_{1,5}$	$P_{1,1}$
	2	$P_{1,3}$	$P_{1,4}$	$P_{1,5}$	$P_{1,6}$	$P_{1,2}$
	3	$P_{1,4}$	$P_{1,5}$	$P_{1,6}$	$P_{1,7}$	$P_{1,3}$

	12	$P_{1,11}$	$P_{1,10}$	$P_{1,9}$	$P_{1,8}$	$P_{1,12}$
2	1	$P_{2,2}$	$P_{2,3}$	$P_{2,4}$	$P_{2,5}$	$P_{2,1}$
	2	$P_{2,3}$	$P_{2,4}$	$P_{2,5}$	$P_{2,6}$	$P_{2,2}$
	3	$P_{2,4}$	$P_{2,5}$	$P_{2,6}$	$P_{2,7}$	$P_{2,3}$

	12	$P_{2,11}$	$P_{2,10}$	$P_{2,9}$	$P_{2,8}$	$P_{2,12}$
...
114	1	$P_{114,1}$	$P_{114,2}$	$P_{114,3}$	$P_{114,4}$	$P_{114,1}$
	2	$P_{114,2}$	$P_{114,3}$	$P_{114,4}$	$P_{114,5}$	$P_{114,2}$
	3	$P_{114,3}$	$P_{114,4}$	$P_{114,5}$	$P_{114,6}$	$P_{114,3}$

	12	$P_{114,11}$	$P_{114,10}$	$P_{114,9}$	$P_{114,8}$	$P_{114,12}$

The rainfall of a station has also predicted using rainfall of adjoining two stations and different combinations of lag rainfall.

Results and Discussion

This chapter deals with selection of best input variables based on autocorrelation function, cross correlation function and Gamma test for development and applications of artificial neural networks model to predict monthly rainfall for Central Telangana districts Medak, Warangal, Khammam using monthly rainfall data of one hundred and thirteen years of period (January 1901 to December 20014). The data was divided into two sets *viz.* training data set (January, 1901 to December, 1985) and testing data set (January 1986, to December 2014) and were used for training and testing of developed models.

Development of Rainfall Models

Rainfall prediction models were developed for the study area using following techniques:

1. The selection of desired input and output pair was done through autocorrelation function, cross correlation function and Gamma test
2. Artificial neural network models were developed using sigmoid axon and Hyperbolic tangent axon activation function with two different learning rules *viz.* Levenberg–Marquardt and delta bar delta.

In this study three districts of central Telangana were mainly considered for prediction monthly rainfall. The five months lag rainfall was used to prepare the inputs parameter for present month rainfall prediction of each districts. The preparation of inputs and output combination was done by the autocorrelation and gamma test. The five months lag rainfall data (R_{M-1} , R_{M-2} , R_{M-3} , R_{M-4} , R_{M-5}) of Medak district were used as inputs and present month rainfall (R_M) as output and similarly, for Khammam district five months lag rainfall (R_{K-1} , R_{K-2} , R_{K-3} , R_{K-4} , R_{K-5}) were used as input and present month rainfall (R_K) as output. Also, the five months lag rainfall data (R_{W-1} , R_{W-2} , R_{W-3} , R_{W-4} , R_{W-5}) of Warangal district were used as inputs and present month rainfall (R_W) as output. Further present month rainfall (R_M) of Medak station was used as output and five months lag rainfall of Khammam (R_{K-1} , R_{K-2} , R_{K-3} , R_{K-4} , R_{K-5}) and Warangal station (R_{W-1} , R_{W-2} , R_{W-3} , R_{W-4} , R_{W-5}) as inputs and also the five months lag rainfall of Medak

(R_{M-1} , R_{M-2} , R_{M-3} , R_{M-4} , R_{M-5}) and Warangal station (R_{W-1} , R_{W-2} , R_{W-3} , R_{W-4} , R_{W-5}) were used as inputs and present month rainfall (R_K) of Khammam station as output. Similarly, present month rainfall (R_W) of Warangal was used as output and five months lag rainfall of Medak (R_{M-1} , R_{M-2} , R_{M-3} , R_{M-4} , R_{M-5}) and Khammam (R_{K-1} , R_{K-2} , R_{K-3} , R_{K-4} , R_{K-5}) were used as input.

Comparison of Gamma test, autocorrelation function and cross correlation function for inputs selection

The selection of precise input variables was one of process involved during the pre-processing of data in non-linear modeling system. There were few basic questions regarding input selection issue including inputs types, arrangement of input variable and exact quantity of the training data used for improvement of model (Noori *et al.*, 2011) [12]. After reviewing meteorological and hydrological modelling using artificial intelligence or data driven techniques have indicated that most of studies investigated with trial and error among the inadequate combinations and then suitable input variable will be selected. Similarly, over-fitting was one of major problems of artificial intelligence modeling during training period. If the network parameters were very less than number of training data, coincidental of over-fitting was near to zero. Inappropriately, estimation the large size of network was challenging before estimating of appropriate training data length. Recently, Gamma Test, autocorrelation function and cross correlation for inputs selection has been applied by meteorologists and hydrologists as a new approach to explain number of significant input models for training network to generate a plane model (Moghaddamnia *et al.*, 2009, Singh *et al.* 2016) [11, 16]. GT earliest was used by Stefansson *et al.* (1997) [17] and later was used in several studies (Remesan *et al.*, 2008; Moghaddamnia *et al.*, 2009; Lafdani *et al.*, 2013; Singh *et al.*, 2017) [14, 11, 7].

The gamma test was used for selection of input data. In this study, Gamma test was used for identification of input parameter for monthly rainfall prediction and remove those input parameters which has insignificant contribution to output. The large number of inputs and insignificant inputs variable has increased the complexity of model and it was main cause of the over fitting of model. The gamma test helps to take decisions about selection of input data or input which were actually affecting the result of developed models. Number of inputs was selected on the basis of gamma value

(Γ), standard error and V-ratio. The maximum variation in values of gamma and standard error were considered as the most influence model (Lafdani *et al.*, 2013)^[7]. The best input selection procedure, different combinations of input data were explored to assess their influence on the monthly rainfall prediction, from which meaningful combinations were given in Tables 3 through Table 6. Also, input parameters were selected using autocorrelation function and cross correlation. Based on comparison of results of gamma test and autocorrelation function and cross correlation common input parameter was taken as appropriate input variables. After the best input combinations were chosen and software of Neuro-Solutions was used for development of best ANN models.

It was observed from results of gamma test and autocorrelation function that the present month rainfall (R_M) of Medak station depends on the two lag months of rainfall. Similarly, for Khammam and Warangal station of present rainfall depend on the two months lag of rainfall as given in Table 3. Finally, different inputs were selected for three different stations were i.e. ($R_M = R_{M-1}, R_{M-2}$) for Medak station, ($R_M = R_{W-1}, R_{W-2}$) for Khammam station and ($R_K = R_{K-1}, R_{K-2}$) for Warangal station. In the same way, results of gamma test and cross correlation were used to select the best input variables of models as given in Table 4 to Table 6, Total

twelve input parameters were taken under consideration by correlating the adjacent districts. The present month rainfall (R_M) of Medak station correlated with five months lag rainfall ($R_W, R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}, R_K, R_{K-1}, R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$) of Warangal and Khammam stations. Further present month rainfall of Warangal station was correlated with five months lag rainfall ($R_M, R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}, R_K, R_{K-1}, R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$) of Medak and Khammam stations and present month lag rainfall of Khammam station was correlated with five months lag rainfall ($R_M, R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}, R_K, R_W, R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{K-5}$) of Medak and Warangal stations. Finally, the current month rainfall (R_M) of Medak station was found to be highly correlated with previous and present months rainfall (R_W, R_{W-1}) of Warangal and current month rainfall (R_K) of Khammam based on cross correlation and gamma test. Based on results of cross correlation and gamma test, the current month rainfall (R_M) of Medak station and current and previous months rainfall (R_W, R_{W-1}) of Warangal station were selected as inputs and current month rainfall (R_K) of Khammam station as output. Further present month rainfall (R_M, R_K) of Medak and Khammam station was selected as input variables and current month rainfall of Warangal station as output.

Table 3: Selection of most influence input parameters based on the Gamma test of Medak, Warangal and Khammam districts

Output	Input	Mask	Gamma	SE
R_M	$R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}$	11111	0.08710	0.00636
R_M	$R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}$	11110	0.09123	0.00513
R_M	$R_{M-1}, R_{M-2}, R_{M-3}, R_{M-5}$	11101	0.08800	0.00682
R_M	$R_{M-1}, R_{M-2}, R_{M-4}, R_{M-5}$	11011	0.09195	0.00687
R_M	$R_{M-1}, R_{M-3}, R_{M-4}, R_{M-5}$	10111	0.09890	0.00382
R_M	$R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}$	01111	0.09408	0.00387
R_K	$R_{K-1}, R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$	11111	0.008334	0.003348
R_K	$R_{K-1}, R_{K-2}, R_{K-3}, R_{K-4}$	11110	0.08493	0.00315
R_K	$R_{K-1}, R_{K-2}, R_{K-3}, R_{K-5}$	11101	0.083359	0.003403
R_K	$R_{K-1}, R_{K-2}, R_{K-4}, R_{K-5}$	11011	0.08228	0.00347
R_K	$R_{K-1}, R_{K-3}, R_{K-4}, R_{K-5}$	10111	0.08518	0.00279
R_K	$R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$	01111	0.08098	0.00238
R_W	$R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}$	11111	0.10428	0.004829
R_W	$R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}$	11110	0.10443	0.004437
R_W	$R_{W-1}, R_{W-2}, R_{W-3}, R_{W-5}$	11101	0.10507	0.004576
R_W	$R_{W-1}, R_{W-2}, R_{W-4}, R_{W-5}$	11011	0.10167	0.0056844
R_W	$R_{W-1}, R_{W-3}, R_{W-4}, R_{W-5}$	10111	0.099683	0.00356
R_W	$R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}$	01111	0.19014	0.003105

Table 4: Selection of best input parameters based on the Gamma test for rainfall prediction of Medak district

Output	Input	Mask	Gamma	SE
R_M	$R_W, R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}, R_K,$ $R_{K-1}, R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$	111111111111	0.02785	0.00061
R_M	$R_W, R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_K, R_{K-1},$ $R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$	111110111111	0.02467	0.00209
R_M	$R_W, R_{W-1}, R_{W-2}, R_{W-3}, R_{W-5}, R_K, R_{K-1},$ $R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$	111110111111	0.02468	0.00207
R_M	$R_W, R_{W-1}, R_{W-2}, R_{W-4}, R_{W-5}, R_K, R_{K-1},$ $R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$	111011111111	0.02579	0.00179
R_M	$R_W, R_{W-1}, R_{W-3}, R_{W-4}, R_{W-5}, R_K, R_{K-1},$ $R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$	110111111111	0.02500	0.00223
R_M	$R_W, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}, R_K, R_{K-1},$ $R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$	101111111111	0.03558	0.00147
R_M	$R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}, R_K, R_{K-1},$ $R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$	011111111111	0.04199	0.00021
R_M	$R_W, R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}, R_{K-1},$ $R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$	111111011111	0.03090	0.00014
R_M	$R_W, R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}, R_K,$ $R_{K-2}, R_{K-3}, R_{K-4}, R_{K-5}$	111111101111	0.02756	0.00126
R_M	$R_W, R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}, R_K,$ $R_{K-1}, R_{K-3}, R_{K-4}, R_{K-5}$	111111110111	0.00229	0.00228
R_M	$R_W, R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}, R_K,$ $R_{K-1}, R_{K-2}, R_{K-4}, R_{K-5}$	111111111011	0.02791	0.00178
R_M	$R_W, R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}, R_K,$ $R_{K-1}, R_{K-2}, R_{K-3}, R_{K-5}$	111111111101	0.02628	0.00178
R_M	$R_W, R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}, R_K,$ $R_{K-1}, R_{K-2}, R_{K-3}, R_{K-4}$	111111111110	0.00282	0.00169

Table 5: Selection of best input parameters based on the Gamma test for rainfall prediction of Khammam district

Output	Input	Mask	Gamma	SE
R_K	$R_M, R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}, R_W,$ $R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}$	111111111111	0.01686	0.00085
R_K	$R_M, R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_W, R_{W-1},$ $R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}$	111110111111	0.01626	0.00074
R_K	$R_M, R_{M-1}, R_{M-2}, R_{M-3}, R_{M-5}, R_W, R_{W-1},$ $R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}$	111101111111	0.01665	0.00153
R_K	$R_M, R_{M-1}, R_{M-2}, R_{M-4}, R_{M-5}, R_W, R_{W-1},$ $R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}$	111011111111	0.01772	0.00019
R_K	$R_M, R_{M-1}, R_{M-3}, R_{M-4}, R_{M-5}, R_W, R_{W-1},$ $R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}$	110111111111	0.01673	0.00190
R_K	$R_M, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}, R_W, R_{W-1},$ $R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}$	101111111111	0.01787	0.00184
R_K	$R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}, R_W, R_{W-1},$ $R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}$	011111111111	0.02682	0.00155
R_K	$R_M, R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}, R_{W-1},$ $R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}$	111111011111	0.04710	0.00085
R_K	$R_M, R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}, R_W,$ $R_{W-2}, R_{W-3}, R_{W-4}, R_{W-5}$	111111101111	0.01852	0.00164
R_K	$R_M, R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}, R_W,$ $R_{W-1}, R_{W-3}, R_{W-4}, R_{W-5}$	111111110111	0.01742	0.00115
R_K	$R_M, R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}, R_W,$ $R_{W-1}, R_{W-2}, R_{W-4}, R_{W-5}$	111111111011	0.01629	0.00070
R_K	$R_M, R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}, R_W,$ $R_{W-1}, R_{W-2}, R_{W-3}, R_{W-5}$	111111111101	0.01536	0.00139
R_K	$R_M, R_{M-1}, R_{M-2}, R_{M-3}, R_{M-4}, R_{M-5}, R_W,$ $R_{W-1}, R_{W-2}, R_{W-3}, R_{W-4}$	111111111110	0.01691	0.00115

Table 6: Selection of most influence input parameters based on the Gamma test for rainfall prediction of Warangal district

Output	Input	Mask	Gamma	SE
R _w	R _M , R _{M-1} , R _{M-2} , R _{M-3} , R _{M-4} , R _{M-5} , R _K , R _{K-1} , R _{K-2} , R _{K-3} , R _{K-4} , R _{K-5}	111111111111	0.00706	0.00066
R _w	R _M , R _{M-1} , R _{M-2} , R _{M-3} , R _{M-4} , R _K , R _{K-1} , R _{K-2} , R _{K-3} , R _{K-4} , R _{K-5}	111110111111	0.00743	0.00064
R _w	R _M , R _{M-1} , R _{M-2} , R _{M-3} , R _{M-5} , R _K , R _{K-1} , R _{K-2} , R _{K-3} , R _{K-4} , R _{K-5}	111101111111	0.00831	0.00051
R _w	R _M , R _{M-1} , R _{M-2} , R _{M-4} , R _{M-5} , R _K , R _{K-1} , R _{K-2} , R _{K-3} , R _{K-4} , R _{K-5}	111011111111	0.00786	0.00014
R _w	R _M , R _{M-1} , R _{M-3} , R _{M-4} , R _{M-5} , R _K , R _{K-1} , R _{K-2} , R _{K-3} , R _{K-4} , R _{K-5}	110111111111	0.00949	0.00094
R _w	R _M , R _{M-2} , R _{M-3} , R _{M-4} , R _{M-5} , R _K , R _{K-1} , R _{K-2} , R _{K-3} , R _{K-4} , R _{K-5}	101111111111	0.007064	0.00099
R _w	R _{M-1} , R _{M-2} , R _{M-3} , R _{M-4} , R _{M-5} , R _K , R _K - 1, R _{K-2} , R _{K-3} , R _{K-4} , R _{K-5}	011111111111	0.01170	0.00138
R _w	R _M , R _{M-1} , R _{M-2} , R _{M-3} , R _{M-4} , R _{M-5} , R _K - 1, R _{K-2} , R _{K-3} , R _{K-4} , R _{K-5}	111111011111	0.02274	0.00116
R _w	R _M , R _{M-1} , R _{M-2} , R _{M-3} , R _{M-4} , R _{M-5} , R _K , R _{K-2} , R _{K-3} , R _{K-4} , R _{K-5}	111111101111	0.00620	0.00920
R _w	R _M , R _{M-1} , R _{M-2} , R _{M-3} , R _{M-4} , R _{M-5} , R _K , R _{K-1} , R _{K-3} , R _{K-4} , R _{K-5}	111111110111	0.01061	0.00011
R _w	R _M , R _{M-1} , R _{M-2} , R _{M-3} , R _{M-4} , R _{M-5} , R _K , R _{K-1} , R _{K-2} , R _{K-4} , R _{K-5}	111111111011	0.00906	0.00095
R _w	R _M , R _{M-1} , R _{M-2} , R _{M-3} , R _{M-4} , R _{M-5} , R _K , R _{K-1} , R _{K-2} , R _{K-3} , R _{K-5}	111111111101	0.01005	0.00087
R _w	R _M , R _{M-1} , R _{M-2} , R _{M-3} , R _{M-4} , R _{M-5} , R _K , R _{K-1} , R _{K-2} , R _{K-3} , R _{K-4}	111111111110	0.00688	0.00097

4.3 Artificial neural network-based rainfall prediction

“Multilayer perceptron was used to train the models for monthly rainfall prediction, Single hidden layer networks with two learning rules i.e. Levenberg-Marquardt and Delta-bar-delta and two transfer functions viz. Sigmoid axon and Tanh axon were used for the development of ANN models. Table 7 show different models with different combinations of learning rule and transfer functions for ANN models of Medak, Khammam and Warangal district. The appropriate architecture selection has been one of most essential challenge for multilayer perceptron neural network. The total node of inputs was basically determined based on number of input variables to be linked with an output variable. The different

feature of input design was parallel with weight input vector. Correspondingly, total neuron present in the output layer was equally connected with weight input vector. The number of hidden layer in architecture has been very important issue while resolving the actual problems based on the MLP neural network. The very common and very popular way for chosen accurate number of hidden layer was trial and error technique. Basically, in field of hydrology and meteorology modelling the use of single hidden layer is common. Also, the number of neurons in architecture of model was generally chosen using the trial and error technique. In the present study, model was trained with number of neurons in architecture vary from 1 to 20, maximum 1000 iteration and 0.001 threshold.

Table 7: ANN models of Medak, Khammam and Warangal district for monthly rainfall prediction

Model	Input variables	Learning algorithm	Transfer function	Learning rule	Hidden Layer
M-1	R_{M-1}, R_{M-2}	MLP	Sigmoid axon	LM	Single
M-2	R_{M-1}, R_{M-2}	MLP	Sigmoid axon	DBD	Single
M-3	R_{M-1}, R_{M-2}	MLP	Tanh axon	LM	Single
M-4	R_{M-1}, R_{M-2}	MLP	Tanh axon	DBD	Single
M-5	R_W, R_{W-1}, R_K	MLP	Sigmoid axon	LM	Single
M-6	R_W, R_{W-1}, R_K	MLP	Sigmoid axon	DBD	Single
M-7	R_W, R_{W-1}, R_K	MLP	Tanh axon	LM	Single
M-8	R_W, R_{W-1}, R_K	MLP	Tanh axon	DBD	Single
K-1	R_{K-1}, R_{K-2}	MLP	Sigmoid axon	LM	Single
K-2	R_{K-1}, R_{K-2}	MLP	Sigmoid axon	DBD	Single
K-3	R_{K-1}, R_{K-2}	MLP	Tanh axon	LM	Single
K-4	R_{K-1}, R_{K-2}	MLP	Tanh axon	DBD	Single
K-5	R_M, R_W, R_{W-1}	MLP	Sigmoid axon	LM	Single
K-6	R_M, R_W, R_{W-1}	MLP	Sigmoid axon	DBD	Single
K-7	R_M, R_W, R_{W-1}	MLP	Tanh axon	LM	Single
K-8	R_M, R_W, R_{W-1}	MLP	Tanh axon	DBD	Single
W-1	R_{W-1}, R_{W-2}	MLP	Sigmoid axon	LM	Single
W-2	R_{W-1}, R_{W-2}	MLP	Sigmoid axon	DBD	Single
W-3	R_{W-1}, R_{W-2}	MLP	Tanh axon	LM	Single
W-4	R_{W-1}, R_{W-2}	MLP	Tanh axon	DBD	Single

Model	Input variables	Learning algorithm	Transfer function	Learning rule	Hidden Layer
M-1	R_{M-1}, R_{M-2}	MLP	Sigmoid axon	LM	Single
M-2	R_{M-1}, R_{M-2}	MLP	Sigmoid axon	DBD	Single
M-3	R_{M-1}, R_{M-2}	MLP	Tanh axon	LM	Single
M-4	R_{M-1}, R_{M-2}	MLP	Tanh axon	DBD	Single
M-5	R_W, R_{W-1}, R_K	MLP	Sigmoid axon	LM	Single
M-6	R_W, R_{W-1}, R_K	MLP	Sigmoid axon	DBD	Single
M-7	R_W, R_{W-1}, R_K	MLP	Tanh axon	LM	Single
M-8	R_W, R_{W-1}, R_K	MLP	Tanh axon	DBD	Single
K-1	R_{K-1}, R_{K-2}	MLP	Sigmoid axon	LM	Single
K-2	R_{K-1}, R_{K-2}	MLP	Sigmoid axon	DBD	Single
K-3	R_{K-1}, R_{K-2}	MLP	Tanh axon	LM	Single
K-4	R_{K-1}, R_{K-2}	MLP	Tanh axon	DBD	Single
K-5	R_M, R_W, R_{W-1}	MLP	Sigmoid axon	LM	Single
K-6	R_M, R_W, R_{W-1}	MLP	Sigmoid axon	DBD	Single
K-7	R_M, R_W, R_{W-1}	MLP	Tanh axon	LM	Single
K-8	R_M, R_W, R_{W-1}	MLP	Tanh axon	DBD	Single
W-1	R_{W-1}, R_{W-2}	MLP	Sigmoid axon	LM	Single
W-2	R_{W-1}, R_{W-2}	MLP	Sigmoid axon	DBD	Single
W-3	R_{W-1}, R_{W-2}	MLP	Tanh axon	LM	Single
W-4	R_{W-1}, R_{W-2}	MLP	Tanh axon	DBD	Single

Conclusion

Artificial neural networks have been proven to be the most successful tool in dealing with highly complicated problems due to their powerful capability to model non-linear systems without the need to make any assumptions. The task here was more complicated because in the field for meteorological observations all decisions were taken in the visage of uncertainty. Artificial neural network software was used to train multilayer feed-forward neural network with back propagation algorithm. The transfer functions Tanh Axon and Sigmoid Axon with learning algorithm (Levenberg-Marquardt and Delta Bar Delta) were used in this study for monthly

rainfall prediction. The appropriate architecture selection was one of most essential challenge for multilayer perceptron neural network. The total node of inputs was basically determined based on number of input variables to be linked with an output variable. The different feature of input design was parallel with weight input vector. Correspondingly, total neuron present in the output layer was equally connected with weight input vector. The number of hidden layers in architecture was very important issue while resolving the actual problems based on the MLP neural network. The very common and very popular way for choosing accurate number of hidden layers i.e. trial and error technique was used.

Basically, in field of hydrology and meteorology modelling with single hidden layer was used. Also, the number of neurons in architecture of model were chosen using the trial and error technique. In the present study, model was trained with number of neurons in architecture vary from 1 to 20, maximum 1000 iteration and 0.001 threshold.

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