RAINFALL FORECASTING USING

ARTIFICIAL NEURAL NETWORK

A dissertation submitted for the partial fulfillment of the requirements

for the degree of

MASTERS OF TECHNOLOGY

IN

HYDRAULICS & WATER RESOURCES ENGINEERING

BY

ASHISH KUMAR SINGH
(2K14/HFE/04)

Under the Guidance of

Dr. K.C. TIWARI
Professor
Department of Civil Engineering
Delhi Technological University
Delhi

DELHI TECHNOLOGICAL UNIVERSITY
(FORMERLY DELHI COLLEGE OF ENGINEERING)
DELHI - 110042
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CANDIDATE'S DECLARATION

I do hereby certify that the work presented is the report entitled "**Rainfall Forcasting using Artificial Neural Network**" in the partial fulfillment of the requirements for the award of the degree of "Master of Technology" in Hydraulics & Water Resources engineering submitted in the Department of Civil Engineering, Delhi Technological University, is an authentic record of my own work carried out from January 2016 to July 2016 under the supervision of Dr. K. C. Tiwari (Professor), Department of Civil Engineering.

I have not submitted the matter embodied in the report for the award of any other degree or diploma.

Ashish Kumar Singh

Date: /7/16 (2K14/HFE/04)

CERTIFICATE

This is to certify that above statement made by the candidate is correct to best of my knowledge.

Dr. K. C. Tiwari
(Professor)
Department of Civil Engineering
Delhi Technological University

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ABSTRACT

Rainfall forecasting is the application of science and technology to predict the state of rainfall for a given location. This is done by collecting the quantitative data of the rainfall and using scientific understanding of the rainfall process to forecast the future conditions. In India, Rainfall forecasting is done by Indian Meteorological Department (IMD), New Delhi which provides the real-time monitoring and statistical analysis of district-wise daily rainfall. Several research works have been done using different methodologies of which the ANN technique is the fastest and provides reliable solutions. In this dissertation, ANN methodology is applied for forecasting of rainfall in Delhi region. Here, ANN methodology is used to forecast rainfall using various configuration of the models. This configuration depend on the various structural parameters, such as, number of hidden layers, number of neurons in each layer, activation functions and training backpropagation algorithms. These models are categorized according to the training algorithms, namely Levenberg-Marqurdt backpropagation algorithm (LM), Bayesian regularization backpropagation (BR) algorithm and Scaled Conjugate backpropagation (SC) algorithm. Seven models are there in each category. These models have been trained and tested. The results give two models with least value of performance parameter, '*mse*', one from LM and BR each with three hidden layers with 10 number of neurons in each layer. Then, the forecast of the selected models have been checked for validation which give the satisfactory results for ANN based forecasting of rainfall in Delhi region.

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CHAPTER – 1

INTRODUCTION

1.1 General

The term precipitation denotes all forms of water that reach the earth surface from the atmosphere. The usual forms of precipitation are rainfall, snowfall, hail, frost and dew. Of all these, only first two contribute significant amounts of water. The precipitation at a place and its form depend on a number of meteorological factors, such as the weather elements like wind, temperature, humidity and pressure in the volume region enclosing the clouds and the ground surface at a given place (K. Subramanya, Engineering hydrology (third edition)).

In India, Rainfall being predominant form of precipitation causing stream flow, especially the flood flow in a majority of rivers. The magnitude of rainfall varies with time and space. These differences in the magnitude of rainfall in various part of the country at a given time and variation of rainfall at a place in various season of the year are obvious and need no further discussion. It is this variation that is responsible for many hydrological problems such as floods and droughts.

1.1.1 Seasonal Characteristics of rainfall in India – From the point of view of climate the Indian subcontinent can be considered to have two major seasons and two transitional periods, (K. Subramanya, Engineering hydrology (third edition)), as

1. South west monsoon (June – September) – 80% of the Average Annual Rainfall occurs in this season.
2. Transition-I, post monsoon (October – November)
3. Winter season (December – February)
4. Transition-II, summer (March – May)

1.1.2Regional Characteristics of rainfall in India – The rainfall in different regions in the country is not uniform varies from place to place due to different geological and climatic factors. These variations can be easily observed from Fig. 1 (K. Subramanya, Engineering hydrology (third edition))

1. Areas of Heavy Rainfall (Over 200cm) - occurs in west coasts, on the Western Ghats as well as the Sub-Himalayan areas in North East and Meghalaya Hills. Assam, West Bengal, West Coast and Southern slopes of eastern Himalayas.

2. Areas of Moderately Heavy Rainfall (100-200 cm) - This rainfall occurs in Southern Parts of Gujarat, East Tamil Nadu, North-eastern Peninsular, Western Ghats, eastern Maharashtra, Madhya Pradesh, Odisha, the middle Ganga valley.
3. Areas of Less Rainfall (50-100 cm) - Upper Ganga valley, eastern Rajasthan, Punjab, Southern Plateau of Karnataka, Andhra Pradesh and Tamil Nadu.
4. Areas of Scanty Rainfall (Less than 50 cm) - Northern part of Kashmir, Western Rajasthan, Punjab and Deccan Plateau.

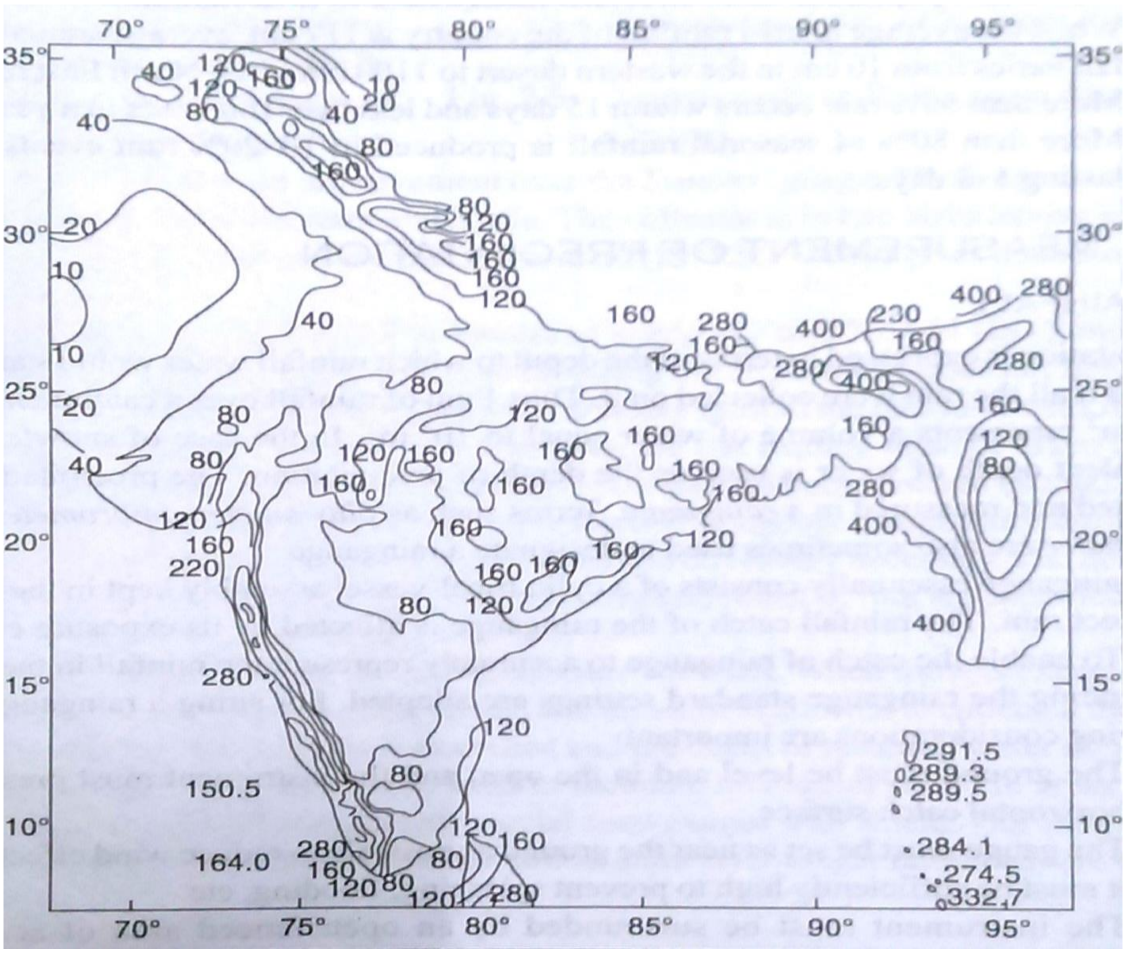

Fig. 1 Regional Characteristics of rainfall in India and neighborhood (Natural Resource of Humid Tropical Asia-Natural Resources Research, XII. UNESCO, 1974)

1.2 Rainfall Forecasting & Its Necessity

Rainfall forecasting is the application of science and technology to predict the state of the atmosphere for a given location. Rainfall forecasts are made by collecting quantitative data about the current state of the atmosphere and using scientific understanding of atmospheric processes to project how the atmosphere will evolve (Kumar et al., 2011). Due to chaotic nature of the atmosphere, the massive computational power required to solve the equations that describe the atmosphere, error involved in measuring the initial conditions, and an incomplete understanding of atmospheric processes mean that forecasts become less accurate as the difference in current time and the time for which the forecast is being made increases.

Rainfall is one of the most complex and difficult elements of the hydrological cycle to understand and to model due to the complexity of the atmospheric processes that generate rainfall and the tremendous range of variation over a wide range of scales both in space and time (Hung et al., 2009). Thus, accurate rainfall forecasting is one of the greatest challenges in operational hydrology, despite many advances in weather forecasting in recent decades.

There are a variety of end uses to rainfall forecasts. Rainfall warnings are important forecasts because they are used to protect life and property. Forecasts based on temperature and rainfall are important to agriculture, and therefore to traders within commodity markets. Temperature forecasts are used by utility companies to estimate demand over coming days. On an everyday basis, people use weather forecasts to determine what to wear on a given day. Since outdoor activities are severely curtailed by heavy rain, snow and the wind chill, forecasts can be used to plan activities around these events, and to plan ahead and survive them.

Rainfall is of great interest as much for its climatic and meteorological relevance, as well for its direct importance to productive sectors of the society. Rainfall provide suitable conditions for many types of ecosystem as well as water for hydroelectric power plants and crop irrigation. The occurrence of extreme rainfall in a short time causes serious damage to economy and sometimes even loss of lives due to flood. Sometimes, insufficient rainfall for long period causes drought. This can effect to economic growth of the country. Thus, rainfall forecasting is very important because of its effects on human life, water resources and water usage.

1.3 Rainfall Forecasting In India

In India, Rainfall forecasting is done by Indian Meteorological Department (IMD), New Delhi. The information regarding rainfall forecasting in India is, summarily, provided on the official website of Indian Meteorological Department (www.imd.gov.in). India receives 80 per cent of its annual rainfall during the southwest monsoon season of June to September. Rainfall over the country during this season shows a wide range of spatial variation due to orographic influences and preferential occurrence of rain-bearing systems in certain regions. India has a very extensive rain-gauge network for rainfall monitoring.

The real-time monitoring and statistical analysis of district-wise daily rainfall is one of the important functions of the Hydro-meteorological Division of IMD at New Delhi. Based on the real time daily rainfall data, weekly district-wise, sub-division-wise and state-wise rainfall distribution summaries are prepared regularly by the Rainfall Monitoring Units. Maps showing weekly and cumulative rainfall figures in 36 meteorological subdivisions of the country are prepared. This information is very important to many user agencies, particularly for agricultural planning.

IMD has an important and active role of providing technical guidance to concerned states/central agencies in procurement and installation of standardized equipment, inspection of existing and new rain-gauge stations, and imparting specialized training to personnel at various levels in the states/agencies. IMD renders assistance and advice on the meteorological aspects of hydrology, water management and multipurpose river valley projects management. These services are utilized by the Central Water Commission, Ministry of Agriculture, Ministry of Water Resources, Railways, Damodar Valley Corporation Flood Control Authorities and the State Governments. These special units of the Hydrometeorology Division cater to the needs of specific interests.

1.4 Rainfall Forecasting Techniques

Forecasting is the process of making predictions of the future based on past and present data and analysis of trends, i.e., estimation of some variable of interest at some specified future date. Prediction is a similar, but more general term. In hydrology the terms "forecast" and "forecasting" are sometimes reserved for estimates of values at certain specific future times, while the term "prediction" is used for more general estimates, such as rainfall occurrence over a long period.

Rainfall forecasting is the application of different forecasting techniques to the previous rainfall records. These techniques are classified as –

1. Neural network based method – Non-linear method
2. Regression based methods – Linear method

The neural network based methods have gained attention due to their very high computational capacity. These methods can be used over regression based methods to achieve better and faster results. Also, these methods are more robust under noisy environment. Neural network based methods are more flexible in terms of solving different problems simultaneously and are highly adaptive to newer environments.

1.5 Artificial Neural Networks and Their Application

An Artificial neural network (ANN) is a computational approach inspired by studies of the brain and nervous systems in living organisms. ANN draws an analogy between the functioning of human brain and attempts to incorporate the same mechanism in the processing of digital data.

With proper architecture, an ANN has proven to be a powerful mathematical model which excels at function approximation and pattern recognition. Most attracting feature of ANN is the ability to extract relation between input and output with being involved in the physics of the process

Already there are several areas where ANN techniques are being tried out to obtain better and improved results. For example ANN techniques have found application in banking industries for document checking and credit application evaluation etc., in defence industries for weapon steering and target recognition etc., in manufacturing industries for manufacturing process control and product design and analysis etc., in hydrology for rainfall forecasting and determining the relation between runoff and precipitation etc. Though there are several such application that can be found in the literature, however this work addresses the application of ANN in the field of hydrology, particularly, the rainfall forecasting.

1.6 Statement of the Problem

Artificial neural network (ANN) have gained popularity amongst hydrologist. The practicing hydrologic community is becoming aware of the potential of ANN as an alternative modeling tool. From hydrological point of view, the application of ANN in rainfall forecasting have been found to be producing great results as compared to the other counterpart methods.

The objective of this dissertation is to –

1. **Study rainfall forecasting and its necessity** – for this, the study for the concept of rainfall forecasting has to be studied and a study has to be done for requirement of the rainfall forecasting as rainfall forecast is directly or indirectly related to the country's economy and is used to protect life and property.

2. **Study ANN model in rainfall forecasting** – For getting higher accuracy of the neural network forecasting, several factors are responsible. These factors are number of hidden layers, number of hidden neurons in each layer, transfer function etc. Improper selection of any of these factors may result in inaccurate forecasting. Therefore, there is need to study the effect of various neural network parameter and their interdependency in order to make suitable recommendation for the proper selection of the model.

3. **Validation check of ANN model** – After application of the technique, the output should be analyzed for the validation of the model selected for rainfall forecasting.

1.7 Organisation of the Dissertation

The work presented in this dissertation has been organized into seven chapters.

This chapter gives a brief introduction to the various aspects of rainfall forecasting and the ANN technique. Besides, it also enumerates the objectives of the study and outlines the scope of the present work with justification. In Chapter 2, the motivation for the present study and the literature review of the present study are described. It also discuss the relation between motivation and literature review for rainfall forecasting using ANN.

Chapter 3 depicts the study area, details of the data acquisition and used in the present study and details of the software applied to the methodology of this dissertation.

Chapter 4 represents the theoretical background of the study which includes concept of ANN, ANN parameters affecting forecasting, application of ANN in hydrology and procedure for ANN modelling.

Chapter 5 describes the complete methodology applied to the study of the objectives mentioned in chapter 1 in this dissertation.

Then in Chapter 6, the results obtained from the study are discussed and analyzed in details. Finally, the conclusion have been reported in Chapter 7.

CHAPTER - 2

LITERATURE REVIEW

2.1 Motivation

A variety of research work have been done in context of rainfall forecasting using different methodologies. As discussed in chapter1, these methodologies are broadly classified as Regression based methods and Neural Network based methods. Also, the neural network based methods are better forecasting methods than regression based methods. Some works related to succession of neural network based methods over regression based methods are as follows –

Nanda et al. (2013) studied the ARIMA (1, 1, 1) model and Artificial Neural Network (ANN) models like Multi-Layer Perceptron (MLP), Functional-link Artificial Neural Network (FLANN) and Legendre Polynomial Equation (LPE) to predict the time series data. MLP, FLANN and LPE gave very accurate results for complex time series model. All the Artificial Neural Network model results matched closely with the ARIMA (1, 1, 1) model with minimum Absolute Average Percentage Error (AAPE). Comparing the different ANN models for time series analysis, it was found that FLANN gives better prediction results as compared to ARIMA model with less Absolute Average Percentage Error (AAPE) for the measured rainfall data. Similar work has been done by **El-shafie et al. (2011**). He applied two rainfall prediction models in Alexandria, Egypt. These models are Artificial Neural Network (ANN) model and Multi Regression (MLR) model. A Feed Forward Neural Network FFNN model was developed and implemented to predict the rainfall on yearly and monthly basis. In order to evaluate the incomes of both models, statistical parameters, such as, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient Of Correlation (R) and BIAS were used to make the comparison between the two models. The data set that has been used in this study includes daily measurements for the rainfall and temperature and cover the period from 1957 to 2009. The FFNN model has shown better performance than the MLR model. Therefore, the ANN model is a nonlinear mapping tool, which potentially is more suitable for rainfall forecasts.

Another work has been done by **Babu et al. (2014)** which includes the suitable combination of linear and nonlinear models providing a more accurate prediction model than an individual linear or nonlinear model for forecasting time series data. This hybrid ARIMA–ANN model apply an ARIMA model to given time series data, consider the error between the original and the ARIMA predicted data as a nonlinear component, and model it using an ANN in different ways. These models give predictions with higher accuracy than the individual models, but still, there is scope for further improvement in the accuracy if the nature of the given time series is taken into account before applying the models.

2.2 Literature Review for ANN Based Methods

From the above works by various researchers, neural network technique for forecasting has gained attention of many hydrologists and other researchers for few past decade. Some popular works in this regards are as follows –

Some researchers implemented the different ANN modelling technique, such as, **Luk et al. [2001]** studied the alternative technique, namely pattern recognition, of artificial neural network for developing the rainfall forecasting model. Three alternative types of ANN, such as multilayer feed forward neural networks, partial recurrent neural networks, and time delay neural networks, were identified, developed and found to provide reasonable predictions of the rainfall depth one time-step in advance. **Khodashenas et al. [2010]** carried out the study for rainfall prediction in Mashhad synoptic Centre, Iran. From the total 636 monthly precipitation data (from 1958 to 2008), 580 data has been used for training networks and the rest selected randomly has been used for validation of the models. To forecast the precipitation data of this station by ANN, a new approach of three-layer feed-forward perceptron network with back propagation algorithm was used. The sensitivity of the prediction accuracy to the content and length of input layer was investigated. Based on the most suitable parameters, two structures M531 and M741 have been selected. Statistical properties were calculated to examine the performance of the models and it was found that in the best model of monthly prediction, the correlation coefficient (R), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) are 0.93, 0.99 mm, 6.02 mm, respectively. **Olson et al. [2004]** carried out the study for rainfall prediction in the Chikugo River basin, Kyushu Island, southern Japan. He used this technique to improve results by using two approaches. One is couple two NNs in series, the first to determine rainfall occurrence, and the second to determine rainfall intensity during rainy periods; and the second is to categorize rainfall into intensity categories and train the NN to reproduce these rather than the actual intensities. The experiments focused on estimating 12-h mean rainfall in the form of large-scale values of wind speeds at 850 hPa and precipitable water. The results indicated that two NNs in series may greatly improve the reproduction of intermittency; longer data series are required to reproduce variability; intensity categorization may be useful for probabilistic forecasting; and overall performance in this region is better during winter and spring than during summer and autumn. **Nasseri et al. [2008]** carried out studies in Upper Parramatta catchment in the western suburbs of Sydney, Australia. In this study, feed-forward type networks will be developed to simulate the rainfall field and back propagation (BP) algorithm coupled with genetic algorithm (GA) will be used to train and optimize the networks. The technique will be implemented to forecast rainfall for a number of times using rainfall hyetograph of recording rain gauges. Results of the study showed the structuring of ANN network with the input parameter selection, when coupled with

GA, performed better compared to similar work of using ANN alone. **Hayati et al. [2007]** described a short term temperature forecasting model with three layer MLP network with 6 hidden neurons, a sigmoid transfer function for the hidden layer and a pure linear function for the output layer was found to yield the best performance. The scaled conjugate gradient algorithm was used for training. The following input parameters were measured every three hours: wind speed, wind direction, dry bulb, temperature, wet bulb temperature, relative humidity, dew point, pressure, visibility, amount of cloud. The other input parameters were measured daily: gust wind, mean temperature, maximum temperature, minimum temperature, precipitation, mean humidity, mean pressure, sunshine, radiation, evaporation. **Zhang et al. [1997]** proposed that ANNs need to be employed in groups when the transformation from the input to the output space is complex. This group theory treats the input-output mapping as being piecewise continuous. The idea is that each network predicts only in the range where the transformation is continuous, while a reasoning network determines the appropriate summation of responses. The authors were successful in making half-hourly rainfall estimates. **Hung et al. [2009]** analyzed the technique of ANN for rainfall forecasting and flood management in Bangkok, Thailand. In this study, 4 years of hourly data from 75 rain gauge stations in the area were used to develop the ANN model and Different network types were tested with different kinds of input information. Preliminary tests showed that a generalized feed forward ANN model using hyperbolic tangent transfer function achieved the best generalization of rainfall. And, forecasts by ANN model were compared to the convenient approach namely simple persistent method. Results show that ANN forecasts have superiority over the ones obtained by the persistent model. Rainfall forecasts for Bangkok from 1 to 3 h ahead were highly satisfactory.

This chapter concludes that there are various techniques for rainfall forecasting, but the neural network based techniques are found to show better results than the conventional methods. Also, research on neural network based methods is in nascent stage and yet to be studied further for getting higher accuracy in the results.

CHAPTER - 3
DATA AND SOFTWARE USED

3.1 Study Area

In this dissertation, rainfall forecasting is done for Delhi-NCT area. National Capital Territory of Delhi occupies an area of 1483 Sq. Km. and lies between 28^0 24' 15'' and 28^0 53' 00'' N latitudes and 76^0 50'24" and 77^0 20' 30" E longitudes. About 81% of the annual rainfall in Delhi-NCT is received during the monsoon months July, August and September. The rest of the annual rainfall is received in the form of winter rain.

3.2 Data Used

For the forecasting of the rainfall using ANN modelling technique, time series of rainfall of previous years is required. These data are made available by IMD (Indian Meteorological Department). The average monthly time series for rainfall occurrence of 102 years from 1901 to 2002 of Delhi-NCT is available on the website provided by IMD (www.imd.gov.in). For calculation of normal rainfall of NCT Delhi, rainfall records from 1901-2002 for various rain-gauge stations, namely, Alipur, Badli, Keshopur, Delhi Sadar, Palam, etc. were considered. These stations shown in **Fig. 2**. The normal annual rainfall of NCT Delhi is 611.8 mm. The rainfall increases from the South-West to the North-West. These data is represented in the end of the dissertation (**Appendix 1**).

The data available is used as input for ANN model for rainfall forecasting. Here the data available and the target or output data may be of different unit. So this input data is first normalized to convert it into the standard form.

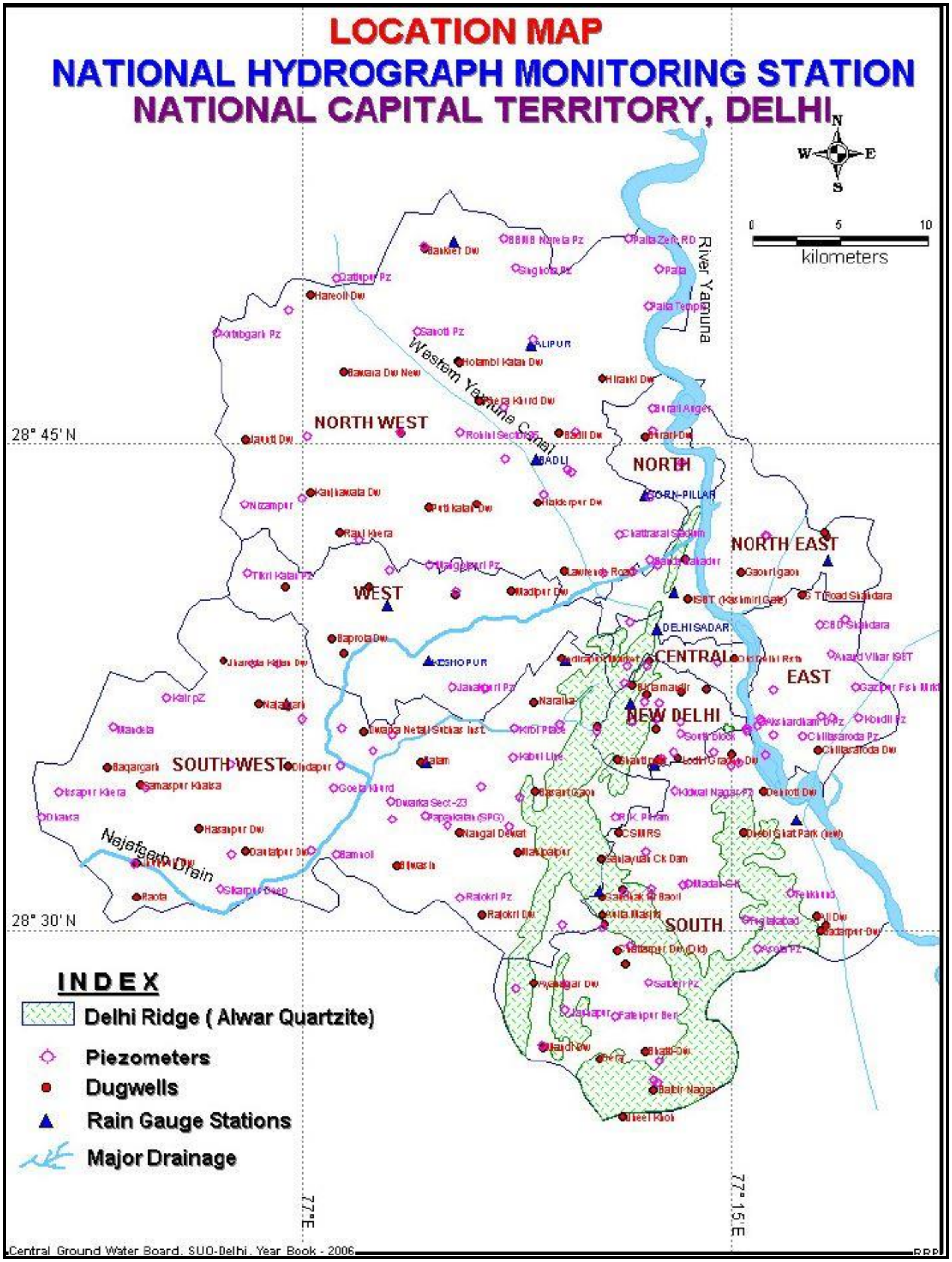

Fig. 2 Rain-Gauge stations in Delhi-NCT (Central Ground Water board CGWB, year book, 2006)

3.3 Software Used

The above methodology is carried out with the help of high end applicable software known as MATLAB.

The name MATLAB stands for matrix laboratory. MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time.

The Neural Network Fitting Tool GUI nntool available in MATLAB (R2015a) is used to carry out the analysis on the rainfall data using Artificial Feed-Forward Neural Network with back-propagation principles. The input dataset consists of samples corresponding to respective year arranged column-wise in an MS Excel sheet which is later imported into the MATLAB workspace.

CHAPTER 4

THEORETICAL BACKGROUND

4.1 What is ANN?

An artificial neural network (ANN) is an interconnected group of artificial neurons that has a natural property for storing experiential knowledge and making it available for use. Artificial neural networks (ANNs) are a family of models inspired by biological neural networks (the central nervous systems of animals, in particular the brain) which are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown (Luk et al., 2001). In other words, 'artificial neural network' refers to the massively parallel distributed processor made up of simple processing units, known as neurons, which has natural tendency for storing experimental knowledge and make it available for use (American Society for Civil Engineering (ASCE) Committee, 2011).

Their development is based on the following rules (ASCE Committee, 2011):

1. Information processing occurs at many single elements called nodes, also referred to as units, cells, or neurons
2. Signals are passed between nodes through connection links.
3. Each connection link has an associated weight that represents its connection strength.
4. Each node typically applies a nonlinear transformation called an activation function to its net input to determine its output signal.

A typical ANN consists of number of neurons that are organized according to particular arrangement. ANN can be categorized on the basis of direction of flow and processing (D. Nagesh Kumar, *'ANN Applicaton in Hydrology'*). In a feed-forward network, nodes are generally arranged in layers starting at the first input layer and ending at the final output layer. There can be several hidden layers, with each having one or more number of neurons. The neurons in one layer are connected to other neurons on the next layer, but not to those in the same layer. Thus, the output of a neuron in a layer is only dependent on the inputs it receives from the previous layer and the corresponding weights. On the other hand, in the recurrent network, information flows through the network in both the direction, i.e., from input to output and vice-versa.

General form of Artificial neural network (**Multi-layer Feed-forward network (MLFN)**) of 3 layers and its architecture is shown as in **Fig. 3**. The first layer has input neurons which send data via synapses to the second layer of hidden neurons, and then via more synapses to the third layer of output neurons with the application of the appropriate activation function. These synapses store parameters called "synaptic weights" that manipulate the data in the calculations.

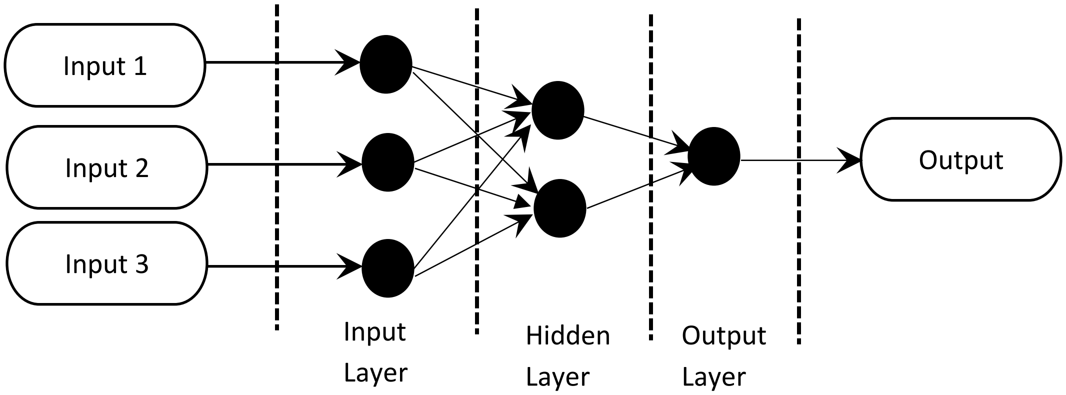

Fig. 3 Architecture of Multilayered Feed Forward Network (Nanda et al., 2013)

Mathematically, Activation function is defined as a composition of other functions $f_i(x)$, which can further be defined as a composition of other functions. This can be conveniently represented as a network structure, with arrows depicting the dependencies between variables and **Fig. 4** represent the working of activation employed to the network.

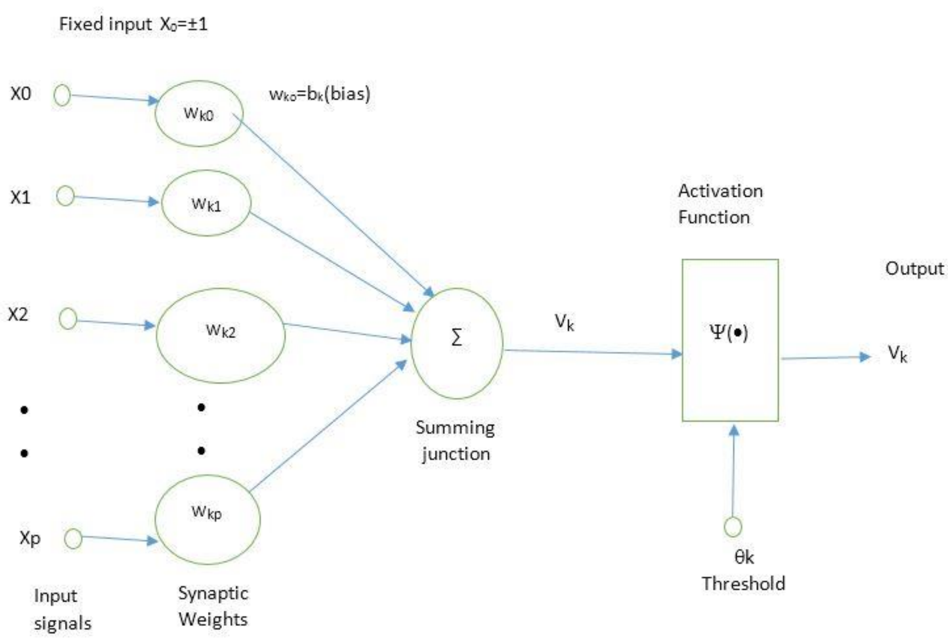

Fig. 4 Working principle of ANN activation function (Nanda et al., 2013)

In fig. 3 shown above, for k^{th} node the working of activation function f(x) is as follows,

$$Y_k = f\left(\sum_{i=1}^{p} w_{ki} x_i + b_k \right) \quad \textbf{... (Eq. 4.1)}$$

4.2 ANN Parameters Affecting Forecasting

ANN methodology, though effective in so far as forecasting is concerned, has not always been able to produce accurate results. The accuracy of forecasting depends upon various neural network parameters. There are a range of neural network parameters which influences the overall accuracy of the results.

4.2.1 Number of hidden layers –

Only one layer of hidden nodes is sufficient to approximate any function with finitely many discontinuities to arbitrary precision, provided the activation functions are non-linear, e.g., signed functions. However, multiple layers may provide greater flexibility necessary to model complex shaped solutions and the exact number hidden layers need to be found experimentally.

4.2.2 Number of hidden nodes –

In general, higher number of neurons may provide greater potential for developing a solution that fits closely to that implied by training process because each neuron combining two nodes is associated with a weight. When training is carried out, all these weights get adjusted to provide an optimal solution and each neuron get its share of weight correction. Thus, higher number of neurons signifies higher number of neuron weights adjustments. A near perfect solution may be generated if number of neurons is sufficiently high but this also means higher training time. Therefore, best solutions lies in choosing those many number of hidden neurons which may produce near accurate results without taking long for training.

4.2.3 Training algorithm –

The algorithm used for training the model is 'backpropagation'. Backpropagation is a common method of training artificial neural networks so as to minimize the objective function. It is a supervised learning method, and is a generalization of the delta rule. It requires a dataset of the desired output for many inputs, making up the training set. It is most useful for feed forward networks. The term is an abbreviation for "backward propagation of errors". Backpropagation requires that the activation function used by the artificial neurons be differentiable.

Training is composed of two major phases (Tokar et al., 1999), namely forward pass and reverse pass. In the forward pass, first the input data are multiplied by the initial weights, then the weighted inputs are added by simply summation to yield the net to each neuron. The net of a neuron is passed through an activation or transfer function to produce the output of a neuron. In the backpropagation networks, the modification of the network weights is accomplished with the derivative of the activation function. The log-sigmoid and hyperbolic-tangent functions are the most commonly used continuous-transfer functions in the backpropagation networks. After the output of the neuron is transmitted to the next layer as an input, this procedure is repeated until the output layer is reached. The error between the output of the network and the target outputs are computed at the end of each forward pass. If an error is higher than a selected value, the procedure continues with a reverse pass; otherwise, training is stopped. In the reverse pass, the weights in the network are modified by using the error value. The modification of weights in the output layer is different from the modification of weights in the hidden layers. In the output layer, the target outputs are provided, whereas in the intermediate layers, target values do not exist. Therefore, backpropagation uses the derivatives of the objective function with respect to the weights in the entire network to distribute the error to neurons in each layer in the entire network (**Fig. 5**).

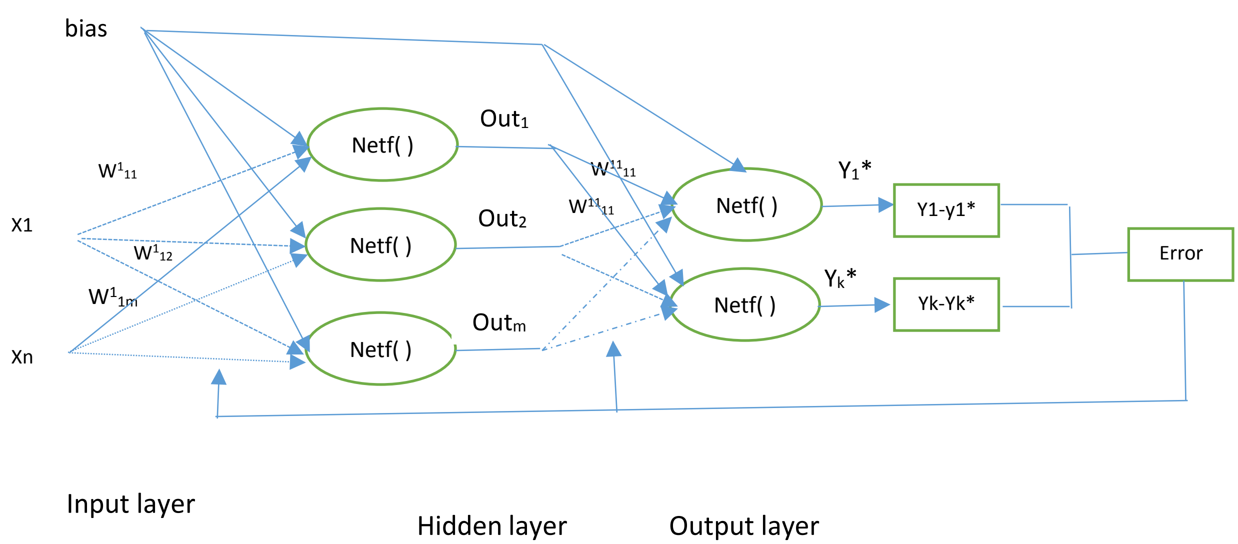

Fig. 5 Schematic of Back-Propagation Network (Tokar et al., 1999)

In the above diagram, X_n is the n^{th} input; W'_{1m} is the Weight from I^{th} Input to M^{th} Neuron in I^{th} Layer; $f(\,)$ is the transfer function; Y_m is the Output of Neuron m in Hidden Layer; and y^*_k is the K^{th} Network Output.

The mathematical process involved in backpropagation algorithm consists of three steps (Martin T. Hagan, '*Neural Network Design', 2nd edition, 2003*). These steps are as follows,

1. **First step** – propagate the input forward through the network,

$$a^0 = p$$

$$a^{m+1} = f^{m+1}\left(w^{m+1} a^m + b^{m+1}\right) \qquad \text{for } m = 0, 1, \ldots, M-1$$

$$a = a^M$$

2. **Second step** – propagate sensitivities back through the network,

$$s^M = -2F^M (n^M)(t-a)$$

$$s^m = F^m (n^m)(w^{m+1})^T s^{m+1} \qquad \text{for } m = M-1, \ldots, 2, 1$$

3. **Third step** – updated weights and biases are calculated as follows,

$$W^m (k+1) = W^m(k+1) - \alpha s^m (a^{m-1})^T$$

$$B^m (k+1) = b^m (k) - \alpha s^m$$

There is a variety of backpropagation algorithm is available. The concerned three types of backpropagation algorithms are –

1. **Levenberg-Marquardt backpropagation –** This backpropagation is used to update the weights and biases of the network according to Levenberg-marquardt optimization. This is the fastest supervised algorithm for training of the network. The Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix.
   The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following equation –

   $$X_{k+1} = X_k - [J^TJ + \mu I]^{-1} J^Te$$

   Where, $H = J^TJ$, is the hessian matrix; $g = J^Te$, is the gradient; J is the jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix.

2. **Bayesian regularization backpropagation –** This also update the weights and biases of the network according to Levenberg-marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. Bayesian regularization minimizes a linear combination of squared errors and weights. It also modifies the linear combination so that at the end of training the resulting network has good generalization qualities. Due to this, this algorithm is very time consuming.

3. **Scaled conjugate gradient backpropagation –** This updates weight and bias values according to the scaled conjugate gradient method. This algorithm, despite showing less accuracy, is quite faster as compared to Bayesian regularization backpropagation algorithm.

4.3 Neural Network Application in Hydrology

The goal of an ANN is to generalize relation of the form

$$Y = f(X)$$

Where, X is an n dimensional input vector consisting of variables $x_1, x_2, \ldots, x_i, \ldots, x_n$ and Y is the m dimensional output vector consisting of resulting variables of interest $y_1, y_2, \ldots, y_i, \ldots, y_m$ (American Society for Civil Engineering (ASCE) Committee, 2011).

In hydrology, the values of x_i can be variables such as rainfall, temperature, previous flows, water levels, spatial location, basin area, evaporation, elevation, slope, and meteorological data and so on. The values of y_i can be hydrological responses such as predicted rainfall, run-off, stream flows, ordinates of the hydrographs, rain fields and others. A firm understanding of hydrologic process under consideration is an important pre-requisite for the successful application of ANNs.

ANNs are able to extract relation between inputs and outputs without being involved in the physics of the process. Their ability to provide mapping from one multi-variate space to another, given a set of data representing that mapping. Even, if the data is noisy and contaminated with errors, ANN have been known to identify the underlying rule. These properties suggest that ANN may be well suited for the problem of estimation and prediction in hydrology.

ANN have been used by various researchers for rainfall-runoff modelling, precipitation forecasting, stream-flow forecasting, ground water modelling, water quality, water management, reservoir operations and other hydrologic application. Although, there are number of research work is available in the literature.

The problem of rainfall forecasting lends itself admirably to ANN application. The non-linear nature of the relationship, availability of the long historical records and complexity of physical-based model in this regard, are some of the factors that leads researchers to neural network based approach. ANN models provide higher training and testing accuracy when compared with other regression and simple conceptual model. The procedure for ANN modelling is discussed in detail in the following section.

4.4 Procedure for ANN Modelling

For forecasting process, ANN modelling technique has to follow the procedure which involved the following steps (American Society for Civil Engineering (ASCE) Committee, 2011) –

1. Data pre-processing
2. Modelling of the ANN architecture.

3. Training of the ANN model
4. Testing of the ANN model
5. Comparison of results

4.4.1 Data Pre-Processing –

Neural network training can be more efficient if you perform certain pre-processing steps on the network inputs and targets. This process is also known as normalization. The normalization step is applied to both the input vectors and the target vectors in the data set. In this way, the network output always falls into a normalized range. The network output can then be reverse transformed back into the units of the original target data when the network is put to use in the field. In most cases, this may not need to be use directly, since the preprocessing steps become part of the network object.

It is important that the data cover the range of inputs for which the network will be used. Multilayer networks can be trained to generalize well within the range of inputs for which they have been trained. However, they do not have the ability to accurately extrapolate beyond this range, so it is important that the training data span the full range of the input space.
Main functions used in forecasting problem (MATLAB helpdesk, pre-processing functions) are 'mapminmax' (which normalize inputs/targets to fall in the range [−1, 1]) and 'removeconstantrows' (which remove inputs/targets that are constant).

After the data have been collected, there are two steps that need to be performed before the data are used to train the network: the data need to be preprocessed, and they need to be divided into subsets.

4.4.2 Modelling of the ANN Architecture –

After pre-processing of data, the architecture of ANN model for rainfall forecasting has to be defined. The selection of the architecture of ANN model is completely dependent on the problem specification (Martin T. Hagan, '*Neural Network Design', 2nd edition, 2003*).

Rainfall forecasting is mostly done by using multi-layered feed forward network with same or different number of neurons in each layer. The number of hidden layers and number of neurons in each layer are the architectural parameters on which accuracy of the output depends and hence affecting the performance of the network.

Problem specifications help define the network in the following ways:

1. Number of network inputs = number of problem inputs

2. Number of neurons in output layer = number of problem outputs
3. Output layer transfer function choice at least partly determined by problem specification of the outputs

ANN provides a flexible network object type that allows many kinds of networks to be created and then used with different functions. This flexibility is possible because networks have an object-oriented representation. The representation allows you to define various architectures and assign various algorithms to those architectures.

For rainfall forecasting, the first thing is an array containing the number of neurons in each hidden layer. One hidden layer generally produces excellent results, but more than one hidden layer can be applied, if the results with one are not adequate. Increasing the number of neurons in the hidden layer increases the power of the network, but requires more computation and is more likely to produce over-fitting. The second thing is the name of the training function to be used.

4.4.3 Training of ANN Model –

The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance, as defined by the network performance function. The default performance function for feed forward networks is mean square error (mse) which is the average squared error between the network outputs 'a' and the target output 't'. It is defined as follows:

$$\text{mse} = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \qquad \text{... (\textbf{Eq. 4.2})}$$

For training multilayer feed-forward networks, any standard numerical optimization algorithm can be used to optimize the performance function, but there are a few that have shown excellent performance for neural network training. These optimization methods use either the gradient of the network performance with respect to the network weights, or the Jacobian of the network errors with respect to the weights. The gradient and the Jacobian are calculated using a technique called the backpropagation algorithm, which involves performing computations backward through the network. Such algorithms are already have been discussed in previous sections.

4.4.4 Testing of ANN Model –

When the training process is completed, network performance can be checked to determine if any changes need to be made to the training process, the network architecture or the data sets. The next step in validating the network is to generate some plots for the network performance. These plots are as follows,

1. **Error Autocorrelation Plot** – This plot describes how the prediction errors are related in time. For a perfect prediction model, there should only be one nonzero value of the autocorrelation function, and it should occur at zero lag, which is the mean square error. This would mean that the prediction errors were completely uncorrelated with each other. If there was significant correlation in the prediction errors, then it should be possible to improve the prediction, perhaps by increasing the number of delays in the tapped delay lines.

2. **Input-Error Cross-Correlation Plot** – This input-error cross-correlation function illustrates how the errors are correlated with the input sequence $x(t)$. For a perfect prediction model, all of the correlations should be zero. If the input is correlated with the error, then it should be possible to improve the prediction, perhaps by increasing the number of delays in the tapped delay lines.

3. **Regression Plots** – Regression plots display the network outputs with respect to targets for training, validation, and test sets. For a perfect fit, the data should fall along a 45 degree line, where the network outputs are equal to the targets. Here the value of correlation coefficient is always less than 1 and for perfect fit it must be close to 1.

If the training were perfect, the network outputs and the targets would be exactly equal, but the relationship is rarely perfect in practice.

The performance of the ANN model for forecasting of rainfall is measured in terms of mean squared errors (mse).

4.4.5 Comparison of Results –

The 'mse' of the target & output is obtained and compared with standard deviation (the 'mse' obtained should be less than the Standard deviation).The analysis of all Neural network with different Neuron in hidden layer is done. The best network that has least RMSE and more correlation b/w target & output is considered for testing purpose. The best network is used for testing new data set.

CHAPTER - 5

METHODOLOGY

Rainfall forecasting can be made possible by collecting quantitative data about the current state of the atmosphere and using scientific understanding of atmospheric processes to project how the atmosphere will evolve. For this, ANN has found to be most appropriate due to the various reasons already discussed in the previous chapters. Rainfall warnings are important forecasts as they are used to protect life and property.

For the forecasting process, the typical type of ANN is used, i.e., multi-layered feed forward network. This network performs according to the flow diagram as shown below –

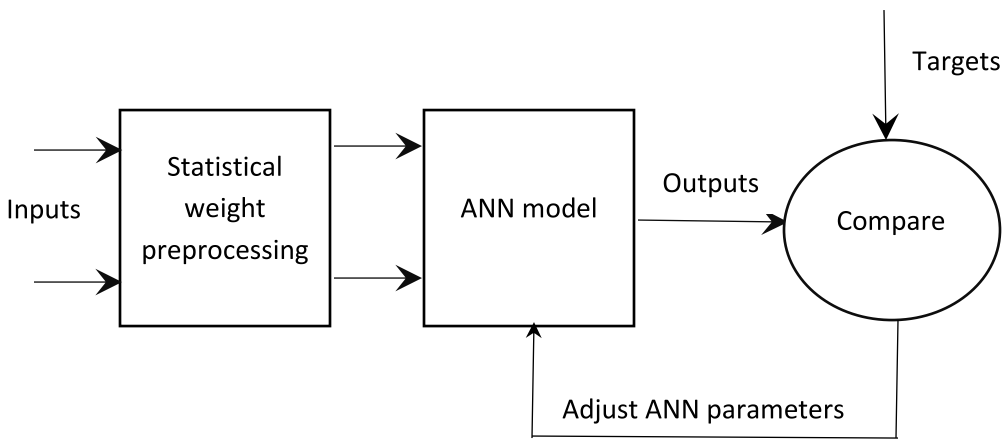

Fig. 6 Flow diagram of ANN modelling (Nanda et al., 2013)

5.1 Methodology for Present Study

From hydrological point of view, the application of ANN in rainfall forecasting have been found to be producing great results as compared to the other counterpart methods. Hence, the objective of present study is to –

4. Study rainfall forecasting and its necessity
5. Study ANN model in rainfall forecasting
6. Validation check of ANN model

5.1.1 Study Rainfall Forecasting and Its Necessity

As already discussed in chapter 1 (section 1.2), the process of application of science and technology to predict the state of the atmosphere in future, especially rainfall for a given location is known as Rainfall forecasting. These forecasts are made by collecting quantitative records, as in case here, previous records of rainfall which are provided by the various official agencies, about the current state of the atmosphere and using scientific understanding of atmospheric processes to check that how the atmosphere will change.

For the study of process of rainfall forecasting, a variety of literature has been reviewed to study the various methods of rainfall forecasting presently implemented by various researchers and by various official agencies. In India, particularly in the study area of this dissertation, the gathering of the information is done from the various official agencies monitoring the rainfall forecasting process. Mainly, these agencies are Indian Meteorological department (IMD), Delhi; Central Ground Water Board (CGWB), Delhi; and Central Water Commission (CWC), Delhi.

Rainfall is of great interest as much for its climatic and meteorological relevance, as well for its direct importance to the productive sector of the society. In India, especially in our study area, i.e., Delhi-NCT, The average annual rainfall is approximately 611.8 mm (Indian Meteorological department (IMD)), most of which falls during the monsoon in July and August. As Delhi-NCT is known for various industries, rainfall forecasts are very important for the productive growth of the industries. Therefore, rainfall forecasting is very important because of its effects on human life, water resources and water usage.

5.1.2 Study ANN Model in Rainfall Forecasting

As the name suggest, ANN is a neural network based technique which is suitable for modeling over a very wide range of applications. The neural-network architecture bears a high similarity to the network of neurons in the brain of human. This can also be abbreviated as artificial intelligence. It is more flexible in terms of architecture. In this network architecture, there may be two or more layers. For example, a three-layer ANN has three layers, namely an input layer, a hidden layer, and an output layer. The number of neurons in the hidden layer is flexible. The neurons are processing units which are acyclically linked. Three-layer ANNs are widely used for time series forecasting.

This characteristic flexibility of ANN models can be used for getting high accuracy in the output results of forecasting of rainfall time series. Other than flexibility in number of neuron in the hidden layer, there are other parameters of ANN which are flexible in terms of getting the best output. These parameters are –

1. Training algorithm
2. Number of hidden layers

3. Number of hidden neurons in each layer
4. Activation function

The effect of these parameters are already discussed in the chapter 4 (section 4.2).

In the present study, various architectures are studied with different training algorithm and activation function. The training of different ANN models are done by using various backpropagation techniques. There are three training algorithm (backpropagation techniques) available which are mainly used for forecasting of the time series, namely, Levenberg-Marquardt backpropagation algorithm, Bayesian-regularization backpropagation algorithm and Scaled-conjugate backpropagation algorithm.

For the present study, according to the input data available, there are 12 neurons for input layer and 12 neurons for the output layer. Using above algorithms, seven models are created for each training algorithm with different number of hidden layers and number of neurons in each hidden layer. These models consists of 20, 20, 30, 50, 80, 40 and 100 neurons present in different combinations in each layer of the model. Of these model, two model consists of 20 neurons in one hidden layer with activation functions described in chapter 4 (section 4.2), i.e., one with hyperbolic-tangent function ('tansig' function) and other with log-sigmoid function ('logsig' function). Hence, there are twenty one model created for forecasting of rainfall using rainfall time series. The specifications of these twenty one models is shown in **table 1**.

From chapter 4 (section 4.4), The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance, as defined by the network performance function. This default network performance function for feed-forward networks is mean square error (*mse*) which is the average squared error between the network outputs and the target output. For each model created above, this network performance parameter 'mse' is calculated. On the basis of this parameter, different models are compared.

5.1.3 Validation Check of ANN Model

In this study, twenty one model using different architecture of number of neurons, number of hidden layers and activation function are synthesized and analyzed. From all the models, model with maximum performance is selected by comparing the values of network performance parameter, i.e., mean squared error '*mse*'. The model with minimum values of *mse* is selected. Then, the output of the selected model is checked.

For the validation check of the model, the input rainfall time series is divided into two parts. First part includes the 100 year data from 1901 – 2000 which is used in training and testing process, and second part includes the rainfall of 2001 and 2002 which will be used to validate the model.

S. No.	MODEL NAME	ACTIVATION FUNCTION	NEURON ARCH. *Input Neurons = 12 and Output Neurons = 12
1	**lm20_tan**	hyperbolic-tangent	12-20-12
2	**lm20_log**	log-sigmoid	12-20-12
3	**lm10_3**	hyperbolic-tangent	12-10-10-10-12
4	**lm10_5**	hyperbolic-tangent	12-10-10-10-10-10-12
5	**lm10_8**	hyperbolic-tangent	12-10-10-10-10-10-10-10-10-12
6	**lm10_20_10**	hyperbolic-tangent	12-10-20-10-12
7	**lm10_20_40_20_10**	hyperbolic-tangent	12-10-20-40-20-10-12
8	**br20_tan**	hyperbolic-tangent	12-20-12
9	**br20_log**	log-sigmoid	12-20-12
10	**br10_3**	hyperbolic-tangent	12-10-10-10-12
11	**br10_5**	hyperbolic-tangent	12-10-10-10-10-10-12
12	**br10_8**	hyperbolic-tangent	12-10-10-10-10-10-10-10-10-12
13	**br10_20_10**	hyperbolic-tangent	12-10-20-10-12
14	**br10_20_40_20_10**	hyperbolic-tangent	12-10-20-40-20-10-12
15	**scg20_tan**	hyperbolic-tangent	12-20-12
16	**scg20_log**	log-sigmoid	12-20-12
17	**scg10_3**	hyperbolic-tangent	12-10-10-10-12
18	**scg10_5**	hyperbolic-tangent	12-10-10-10-10-10-12
19	**scg10_8**	hyperbolic-tangent	12-10-10-10-10-10-10-10-10-12
20	**scg10_20_10**	hyperbolic-tangent	12-10-20-10-12
21	**scg10_20_40_20_10**	hyperbolic-tangent	12-10-20-40-20-10-12

Table. 1 Architecture of 21 ANN models

CHAPTER-6
RESULTS AND DISCUSSIONS

In the present study, models created for rainfall forecasting using different architecture are analyzed. For the purpose of rainfall forecasting, ANN models, even with single hidden layer and minimum number of neurons, are able to produce highly satisfactory results with minimum value of network performance parameter '*mse*'. These model, generally, shows high value of correlation between output and target rainfall data set.

6.1 Results

Results for the study carried out in this dissertation are given in detail in the following sections as per objectives of the study –

6.1.1 Study Rainfall Forecasting and Its Necessity

Rainfall forecasting has become an important field of research in the last few decades. This is the application of various science & technologies and understanding of rainfall process in order to predict the atmospheric changes and take the necessary action required to overcome the effect of these atmospheric changes. There are various application to rainfall forecasting.

A variety of research work by various researchers is studied in order to complete the objective of '*study rainfall forecasting and its necessity'.* This study shows that there are several methods of rainfall forecasting such as regression based methods, ANN based methods, etc. From these methods, ANN based methods show very high accuracy than the other methods.

The study of various rainfall monitoring agencies and their functions is also done. These organizations are Indian Meteorological Department (IMD), Central Ground Water Board (CGWB) and Central Water Commission (CWC).

1. **Indian Meteorological Department** – IMD is an agency of the Ministry of Earth Sciences of the Government of India. It is the principal agency responsible for meteorological observations, weather forecasting and seismology. IMD is headquartered in New Delhi and operates hundreds of observation stations across India and Antarctica.

   IMD undertakes observations, communications, forecasting and weather services. In collaboration with the Indian Space Research Organization, the IMD also uses the Indian

Remote Sensing satellite series (IRS) and the Indian National Satellite System (INSAT) for weather monitoring of the Indian subcontinent. IMD was the first weather bureau of a developing country to develop and maintain its own satellite system.

2. **Central Ground Water Board** – CGWB, is a subordinate office of the Ministry of Water Resources, Government of India, is national apex agency with the responsibility of providing scientific inputs for management, exploration monitoring, assessment, augmentation and regulation of ground water resources of the country.

   Major activities of CGWB includes macro/micro-level ground water management techniques, monitoring of ground water levels and water quality through a network of rain gauges and observation wells. The data generated by various studies taken up by CGWB provide a scientific base for water resource planning.

3. **Central Water Commission** – Central Water Commission is a technical organization in the field of water resources development and is a major agency of Government of India. CWC is charged with the general responsibility of initiating, coordinating and furthering in consultation with the State Governments concerned, schemes for the control, conservation and utilization of water resources in the respective state for the purpose of flood management, irrigation, navigation, drinking water supply and water power generation.

Forecasting rainfall helps the agricultural sector. Forecasting disasters aids in taking necessary precautions and helps mankind to be prepared. Rainfall forecast are important because they are used to protect life and property, and are directly or indirectly related to the country's economy. Hence, rainfall forecasting is very important to human being for their survival and economic growth of the mankind.

6.1.2 Study ANN Model for Rainfall Forecasting

In the present study, different architectures are studied with different training algorithm and different activation function. Basically, the training of different ANN models are done by using various backpropagation techniques, i.e., Levenberg-Marquardt algorithm, Bayesian-regularization algorithm and Scaled-conjugate algorithm. Using these algorithms, seven models are created for each training algorithm with different number of neurons in each hidden layer, number of hidden layers and activation functions as shown in chapter 5 (Table. 1)

The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance, as defined by the network performance function, i.e., '*mse*'. For each model created above, '*mse*' is calculated as shown in the following table –

S. No.	MODEL NAME	NEURON ARCH. *Input Neurons = 12 and Output Neurons = 12	MSE
1	**lm20_tan**	12-20-12	2.1997E+03
2	**lm20_log**	12-20-12	2.1982E+03
3	**lm10_3**	12-10-10-10-12	1.1374E+03
4	**lm10_5**	12-10-10-10-10-10-12	1.9957E+03
5	**lm10_8**	12-10-10-10-10-10-10-10-10-12	1.7513E+03
6	**lm10_20_10**	12-10-20-10-12	1.9112E+03
7	**lm10_20_40_20_10**	12-10-20-40-20-10-12	1.2494E+03
8	**br20_tan**	12-20-12	1.3963E+03
9	**br20_log**	12-20-12	1.5965E+03
10	**br10_3**	12-10-10-10-12	1.0375E+03
11	**br10_5**	12-10-10-10-10-10-12	2.5032E+03
12	**br10_8**	12-10-10-10-10-10-10-10-10-12	1.7582E+03
13	**br10_20_10**	12-10-20-10-12	1.1341E+03
14	**br10_20_40_20_10**	12-10-20-40-20-10-12	2.5268E+03
15	**scg20_tan**	12-20-12	2.3057E+03
16	**scg20_log**	12-20-12	2.3872E+03
17	**scg10_3**	12-10-10-10-12	2.2289E+03
18	**scg10_5**	12-10-10-10-10-10-12	2.3895E+03
19	**scg10_8**	12-10-10-10-10-10-10-10-10-12	2.3801E+03
20	**scg10_20_10**	12-10-20-10-12	2.1781E+03
21	**scg10_20_40_20_10**	12-10-20-40-20-10-12	2.3705E+03

Table. 2 value of '*mse*' for ANN models

On the basis of the values of '*mse*', two models are selected with the minimum values of '*mse*'. These models are **lm10_3** and **br10_3.**

Lm10_3 – In this model, the training algorithm is Levenberg-Marquardt backpropagation algorithm with three hidden layers containing 10 number of neurons in each layer. The activation function is hyperbolic-tangent ('tansig'). This model is found to be better model in rainfall forecasting. The characteristics regression plot, input-error cross correlation and error auto-correlation are shown below-

1. **Regression plot –** The value of overall correlation coefficient is found to be 0.91025, which is near to 1. Therefore, for this problem, the fit is reasonably good for all data sets, with R values in each case of 0.90 or above.

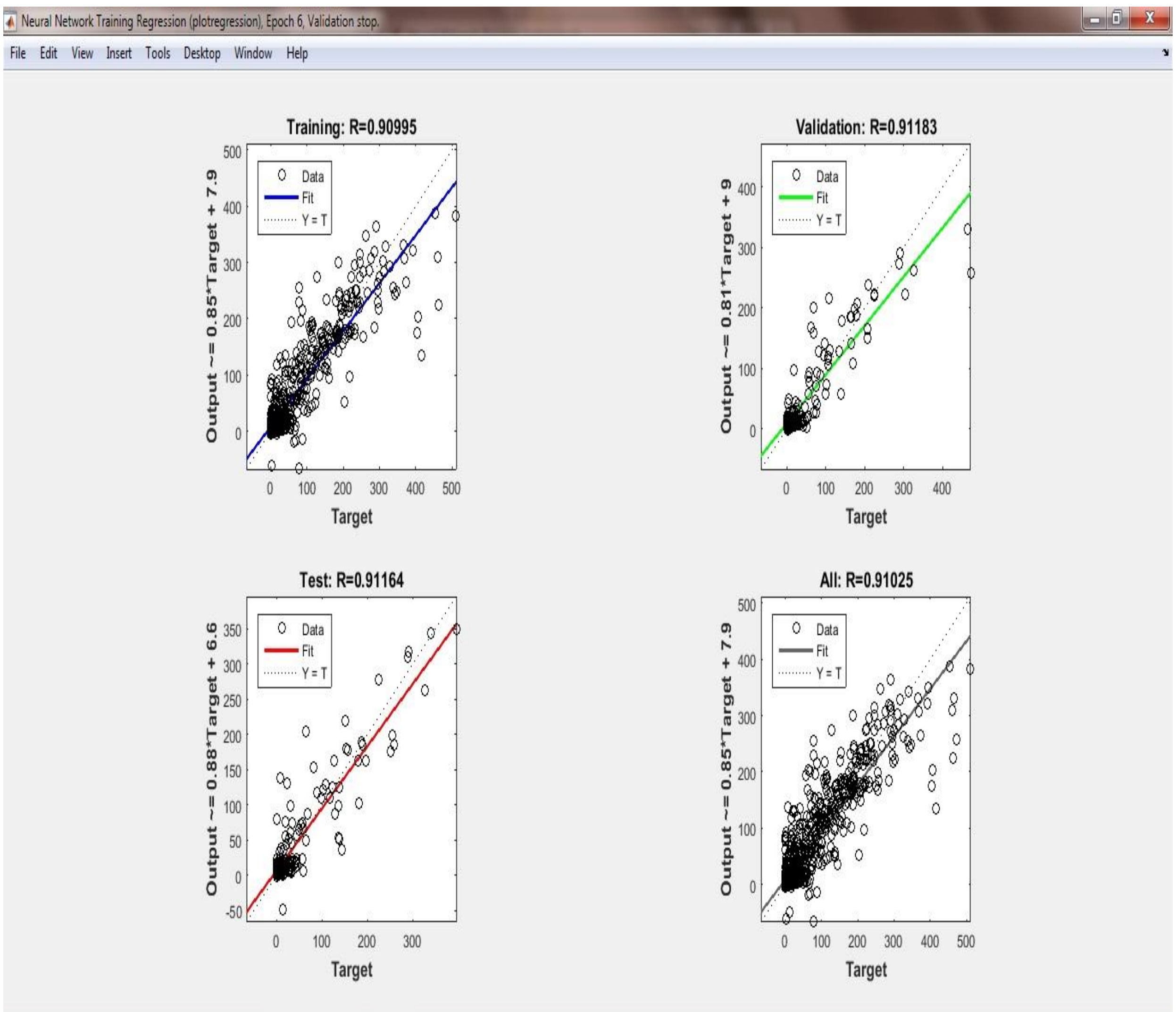

Fig. 7 Regression plot for lm10_3

2. **Error-Autocorrelation –** In this case, the correlations, except for the one at zero lag, fall approximately within the 95% confidence limits around zero, so the model seems to be adequate.

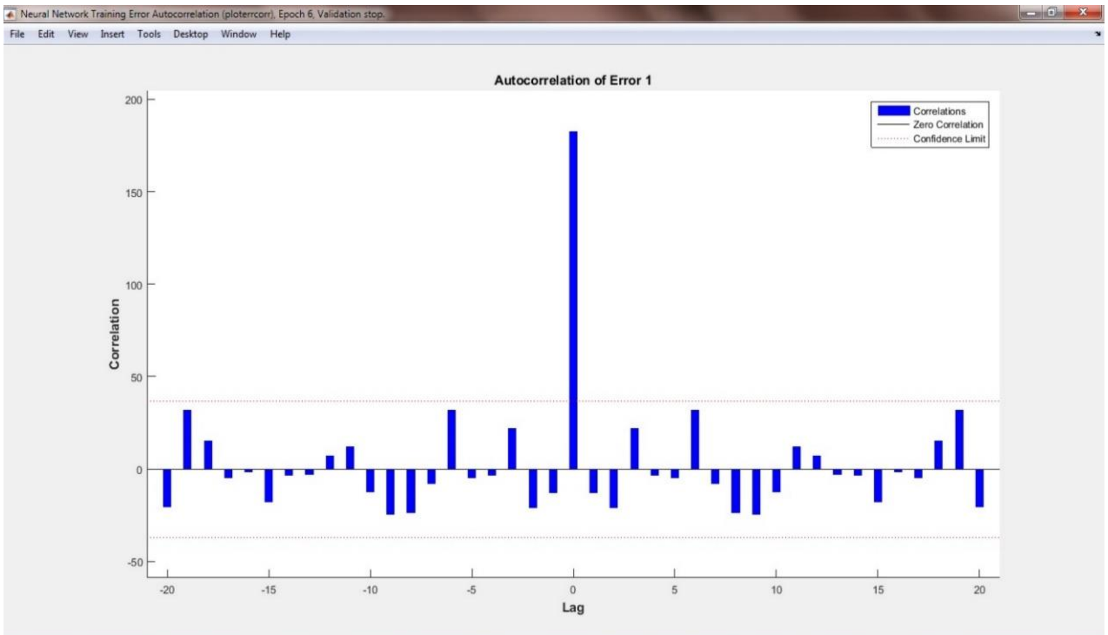

Fig. 8 Error-autocorrelation plot for lm10_3

3. **Input-error cross correlation –** In this case, all of the correlations fall within the confidence bounds around zero.

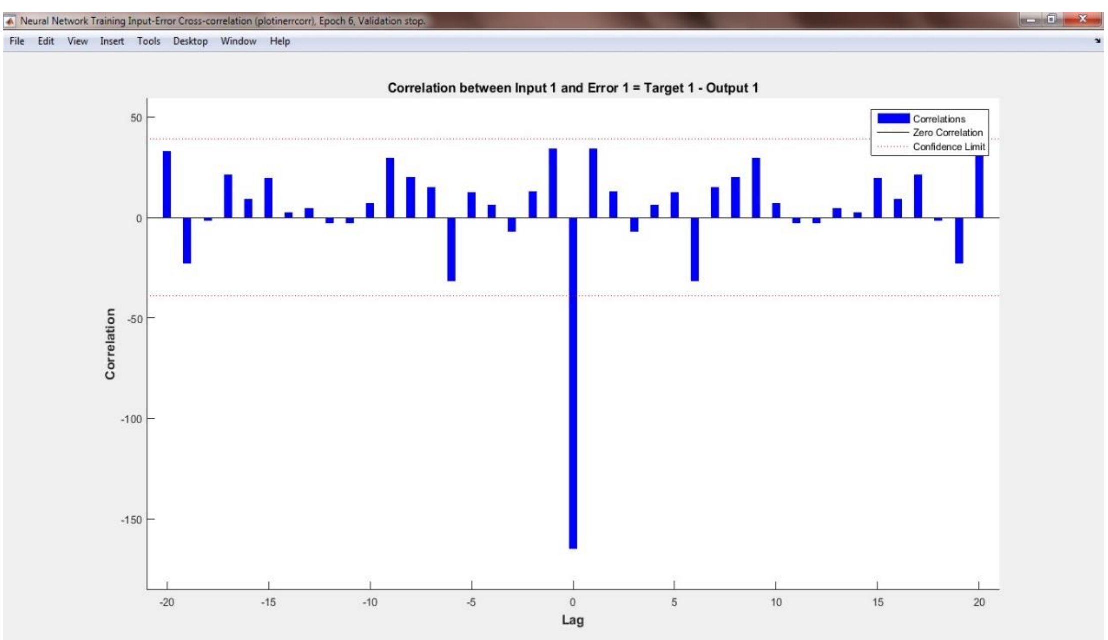

Fig. 9 Input-error cross correlation plot for lm10_3

Br10_3 – In this model, the training algorithm is Bayesian-Regularization backpropagation algorithm with three hidden layers containing 10 number of neurons in each layer. The activation function is hyperbolic-tangent ('tansig'). This model is found to be better model than **lm10_3** in rainfall forecasting but this method of forecasting is time taking which makes it a little slower process. The characteristics regression plot, input-error cross correlation and error auto-correlation are shown below –

1. **Regression plot –** The value of overall correlation coefficient is found to be 0.92856. Therefore, for this problem, the fit is reasonably good for all data sets.

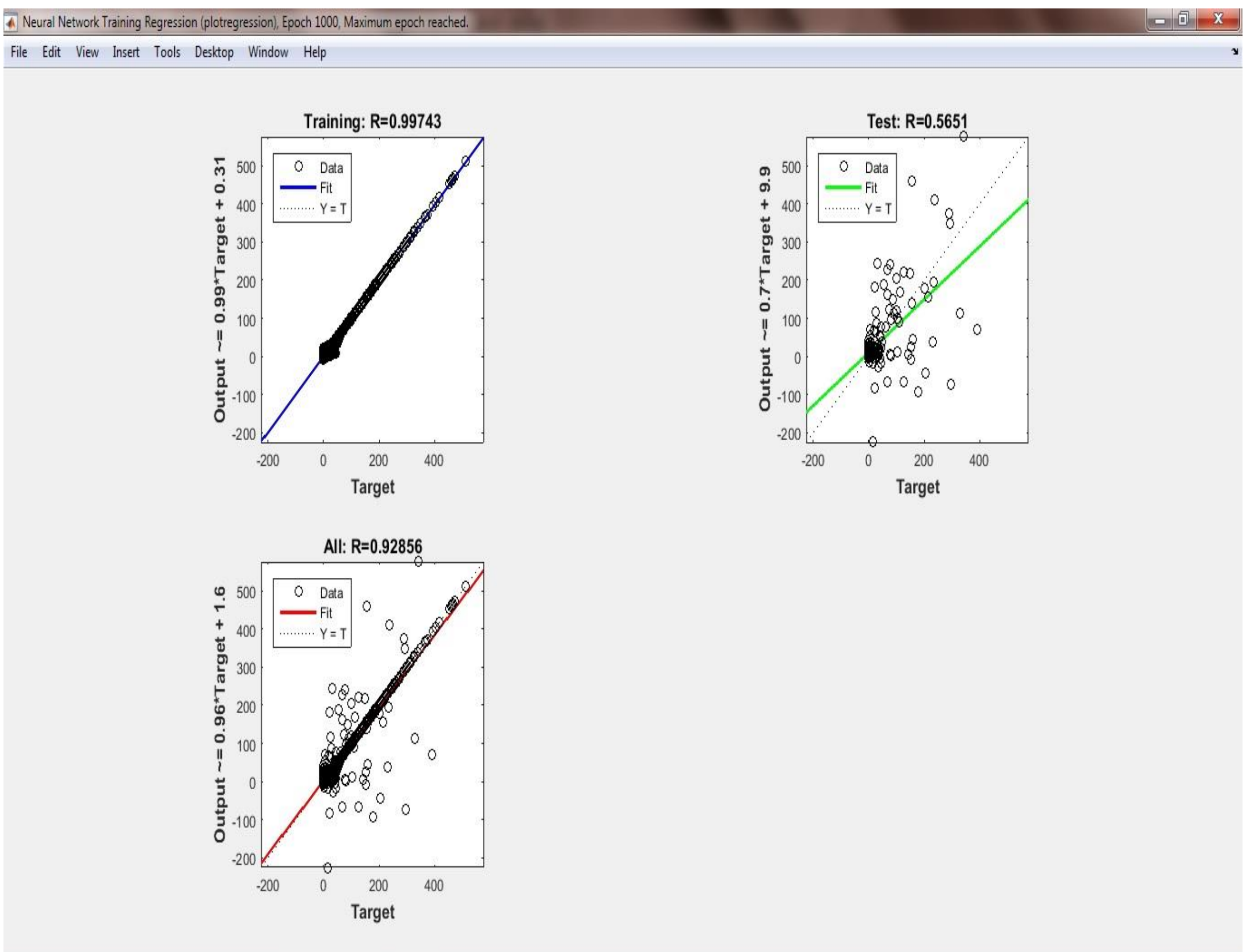

Fig. 10 Regression plot for br10_3

2. **Error-Autocorrelation –** In this case, the correlations, except for the one at zero lag, fall approximately within the 95% confidence limits around zero, so the model seems to be adequate.

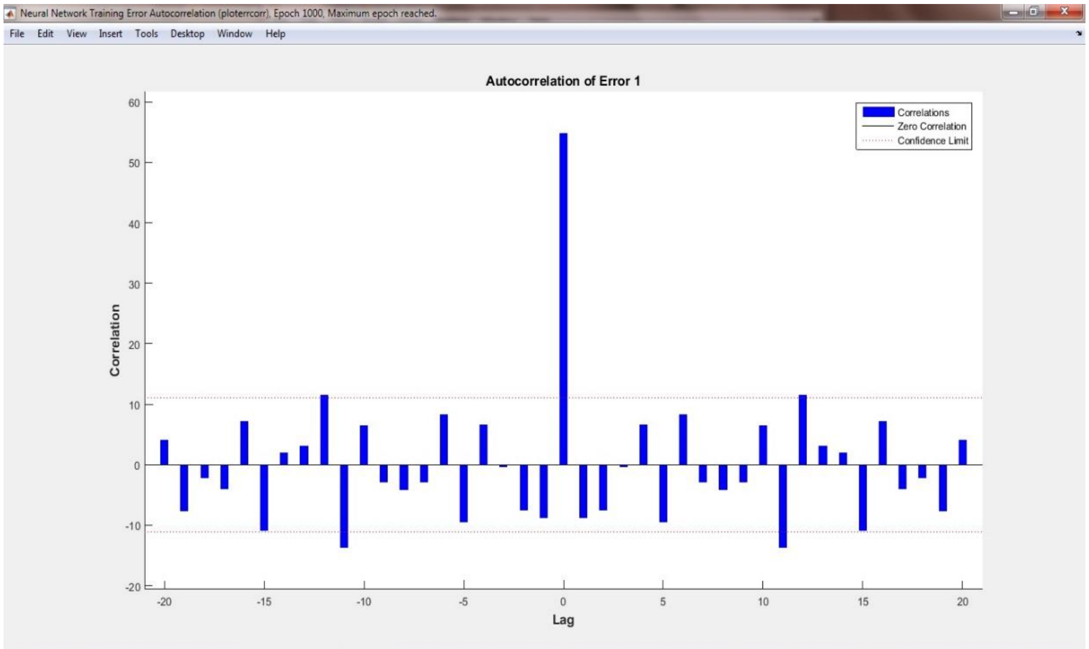

Fig. 11 Error-autocorrelation plot for br10_3

3. **Input-error cross correlation –** In this case, all of the correlations fall within the confidence bounds around zero.

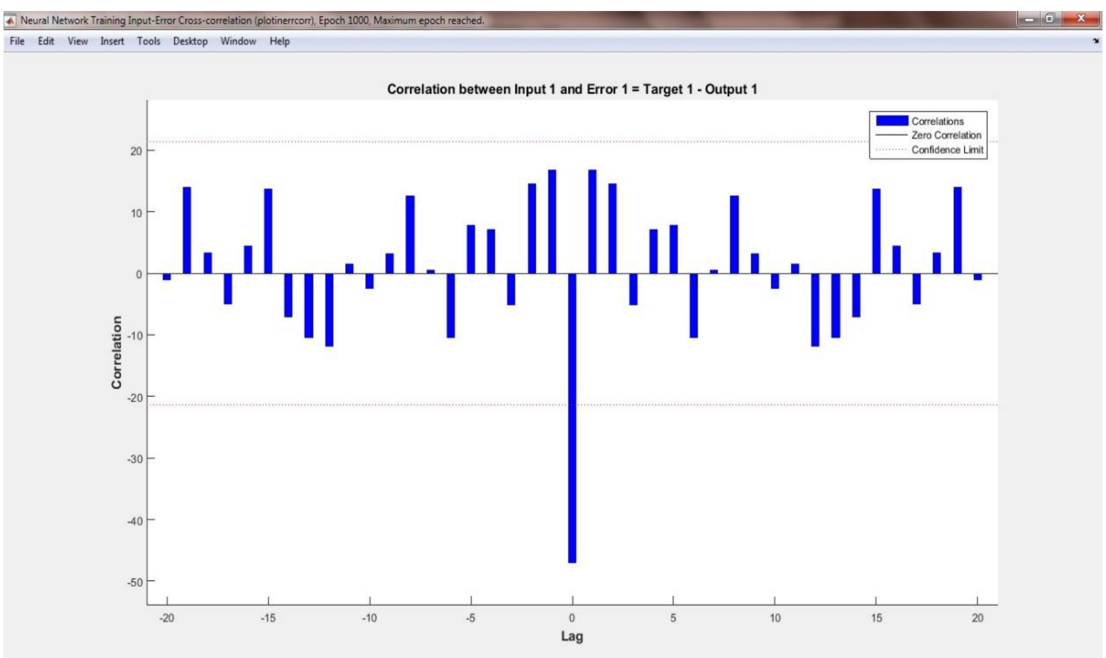

Fig. 12 Input-error cross correlation plot for br10_3

6.1.3 Validation Check of ANN Model

From the two models selected, the output from the network, i.e., the predicted values of rainfall forecasting for year 2001 and 2002 are compared with actual values of rainfall in 2001 and 2002 which is the validation part of the rainfall time series.

Lm10_3 –

	ACTUAL VALUES		PREDICTED VALUES	
Month	**2001**	**2002**	**2001**	**2002**
Jan	9.508	12.935	18.72	13.63
Feb	10.536	12.027	12.27	15.82
Mar	3.645	1.899	15.4	9.53
Apr	25.055	0.909	9.71	10.64
May	57.248	2.636	15.41	13.7
Jun	84.749	33.037	50.67	37.91
Jul	131.645	13.052	205.21	138.03
Aug	221.571	118.931	197.017	115.61
Sept	35.809	142.816	101.02	29.43
Oct	3.438	0.463	11.16	10.32
Nov	0	0.636	14.75	4.95
Dec	0	10.208	0	3.71

Table. 3 Actual v/s Predicted rainfall for lm10_3

Br10_3 –

	ACTUAL VALUES		PREDICTED VALUES	
Month	**2001**	**2002**	**2001**	**2002**
Jan	9.508	12.935	5.61	1.65
Feb	10.536	12.027	14.41	4.86
Mar	3.645	1.899	5.93	4.09
Apr	25.055	0.909	8.47	11.82
May	57.248	2.636	19.7	8.66
Jun	84.749	33.037	91.46	3.96
Jul	131.645	13.052	215.9	127.08
Aug	221.571	118.931	138.07	84.58
Sept	35.809	142.816	63.11	55.71
Oct	3.438	0.463	9.32	14.21
Nov	0	0.636	1.52	0
Dec	0	10.208	8.07	7.09

Table. 4 Actual v/s Predicted rainfall for br10_3

Graphical representation of comparison of actual and predicted values for the purpose of validation of the model is shown below –

1. **Lm10_3 –**

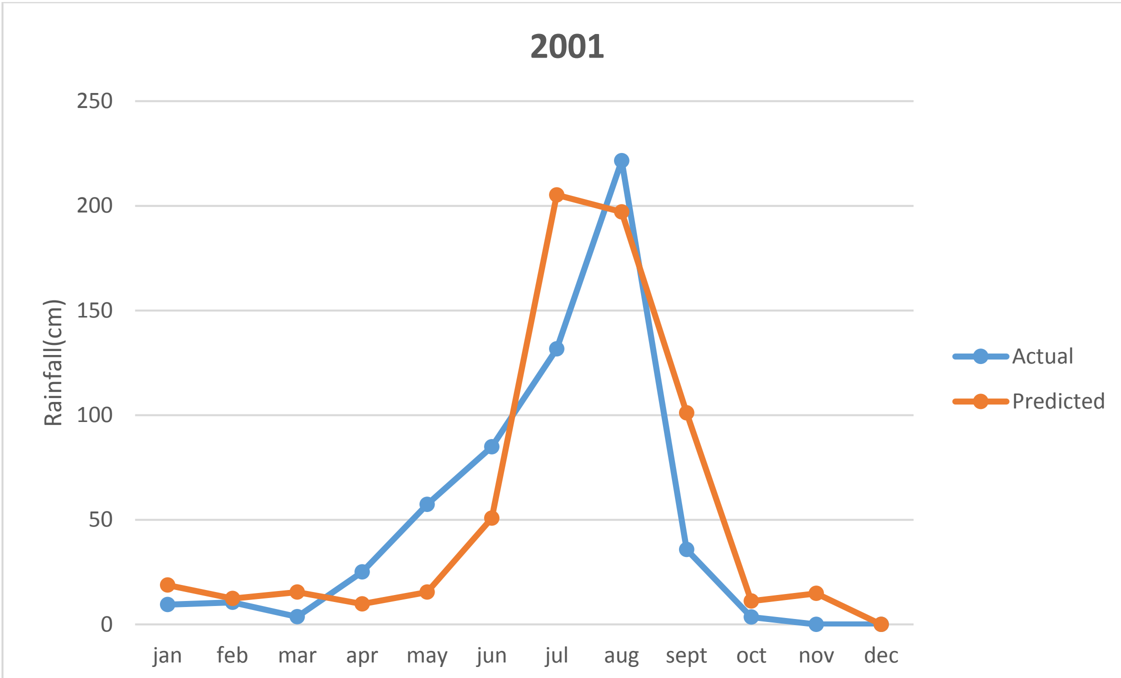

Fig. 13 comparison of Actual and predicted rainfall in 2001 for lm10_3

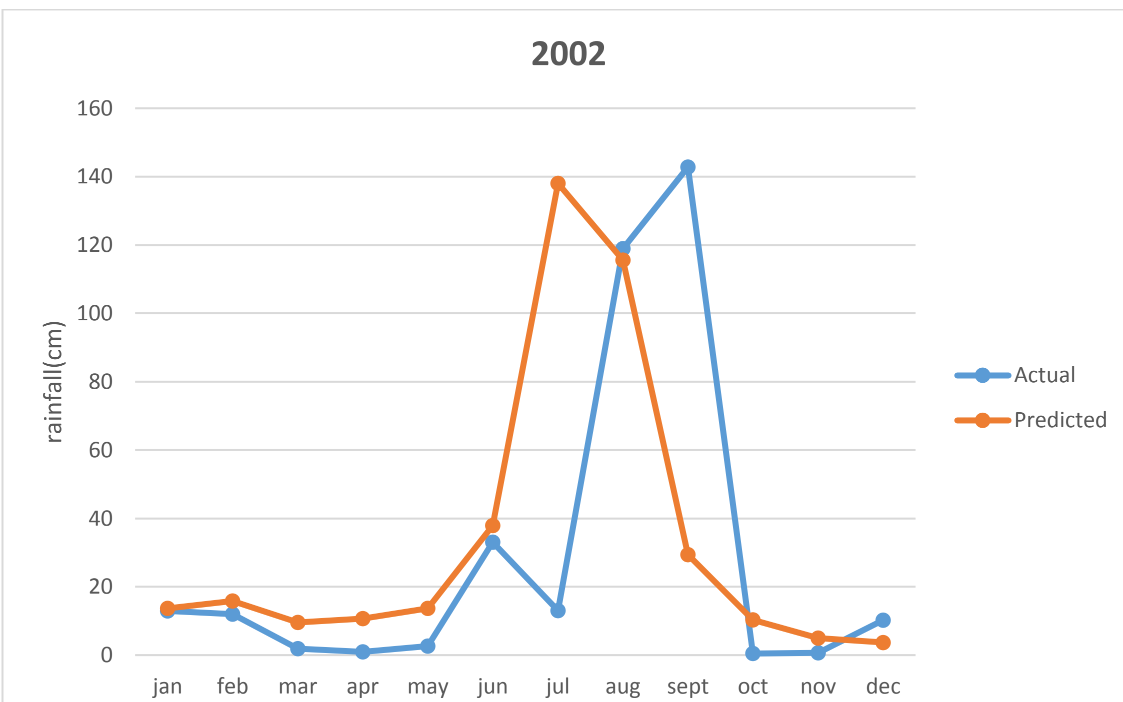

Fig. 14 comparison of Actual and predicted rainfall in 2002 for lm10_3

2. Br 10_3 –

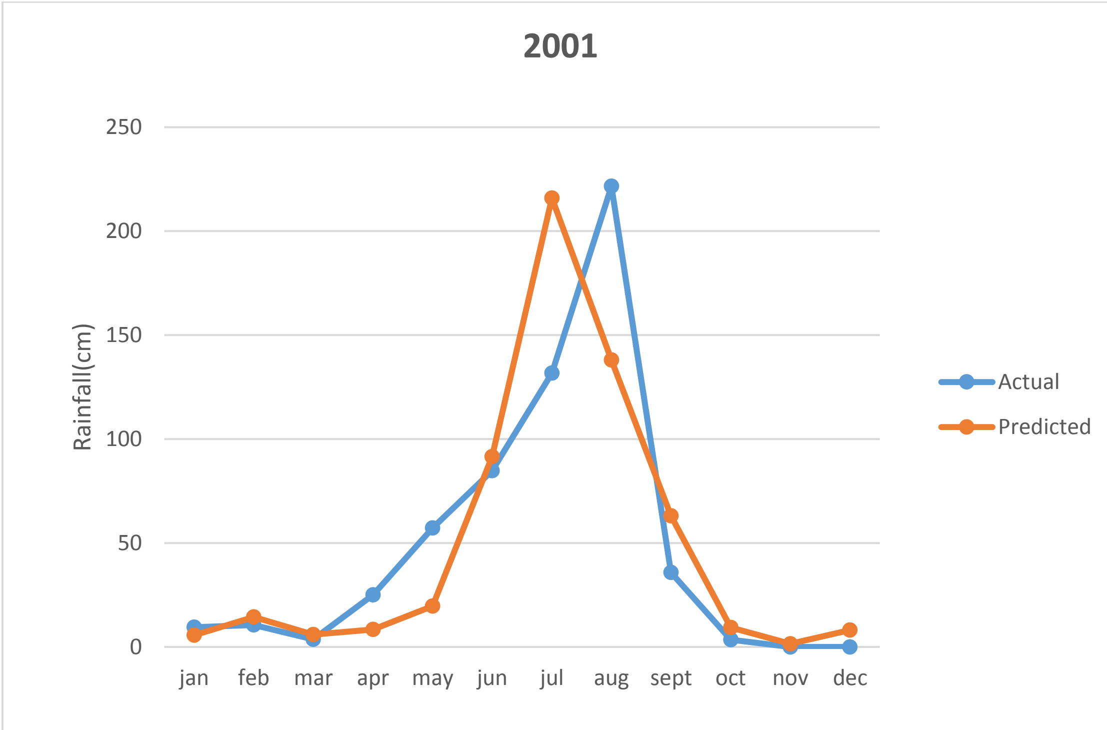

Fig. 15 comparison of Actual and predicted rainfall in 2001 for br10_3

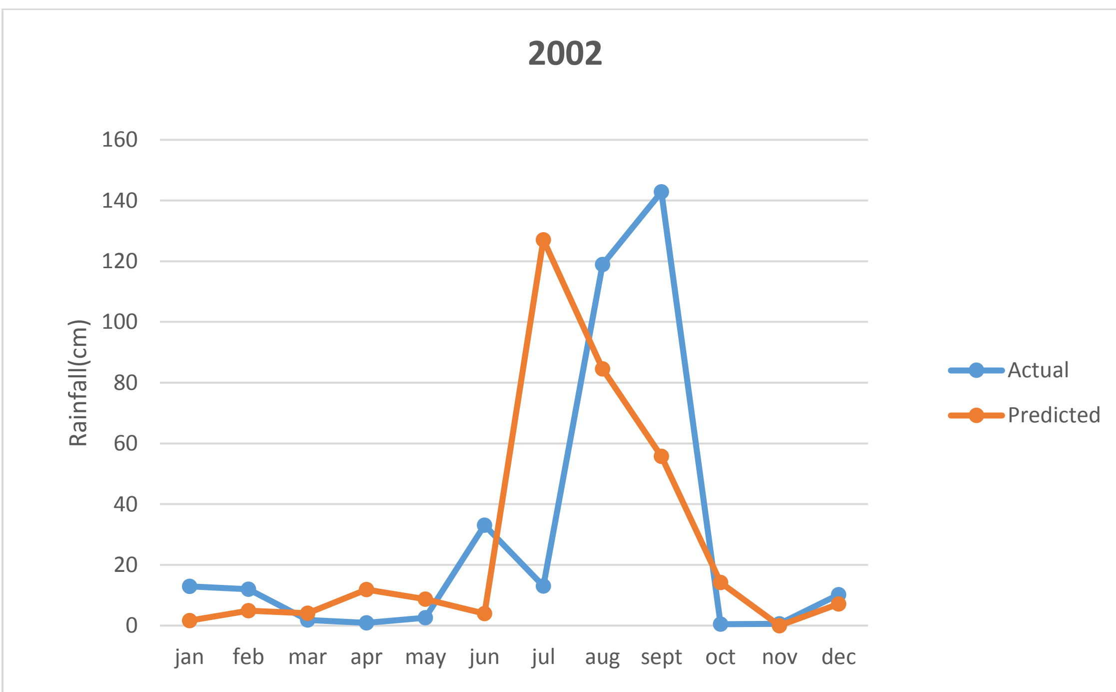

Fig. 16 comparison of Actual and predicted rainfall in 2002 for br10_3

CHAPTER-7
CONCLUSIONS

7.1 Conclusion of the Study

As accurate rainfall forecasting is one of the greatest challenges in operational hydrology, despite of many advances in weather forecasting in recent decades, there are several conclusions that can be drawn from the study. These conclusions are summarized as follows,

1. Various methods exist which may serve the purpose of weather forecasting of which neural network based methods appear to provide better and faster results.

2. Neural network based methods are more robust under noisy environment, more flexible in solving different problems simultaneously and highly adaptive to newer environment.

3. ANN types, training algorithms, activation functions, epochs, number of hidden layers and number of neurons present in each layer, etc. for determination of the best models are different for various problems and different type of raw data. The selection of appropriate structure need to be specified by several trial and errors.

4. Increasing the number of hidden layers decreases the '*mse*', i.e., increases the performance. However, increasing the number of hidden layers above an optimum can adversely increase its performance. Hence, multiple layers may provide greater flexibility necessary to model complex solutions and the exact number of hidden layers need to be found experimentally.

5. Increasing the number of neurons in each layer decreases the '*mse*', i.e., increases the performance but this also leads to higher training time. Therefore, best solutions lie in choosing those many number of hidden neurons which may produce near accurate results without taking long for training.

6. Pure-linear activation function is kept fixed for output layer in all cases. Tan-Sigmoid activation function is our best choice for hidden layers over pure-linear function because of its very fast learning rate and sensitivity towards change in number of samples and neurons/layer.

7. From the three training backpropagation algorithms, Levenberg-Marquardt algorithm gives the fastest and accurate results. Also, Bayesian regularization give accurate results but the process of training is very time consuming.

8. Model, namely lm10_3 (LM algorithm with 3 number of hidden layers and 10 numbers or neuron in each layer) and br10_3 (BR algorithm with 3 number of hidden layers and 10 numbers or neuron in each layer), selected in the study shows satisfactory accuracy in the forecasting problem.

9. This study can be best used to develop supportive statistical plots and concentrate on the trend of weather over a long period of time in a particular area.

10. The ANN methodology has been reported to provide reasonably good solutions for circumstances where there are complex systems that may be poorly defined or understood using mathematical equations, problems that deal with noise or involve pattern recognition, and situations where input data are incomplete and ambiguous by nature.

11. Proper use of ANN requires not only the knowledge of ANN and their operatios but also the physical understanding of the hydrological process involved in the study.

7.2 Future Scope of the Study

1. Analysis of the results indicate that there is a range of parameters involved, these parameters, need to be analysed with suitable non-linear optimization technique which may help in establishing a set of optimal values to the parameters.

2. ANN model is a nonlinear mapping tool, which potentially is more suitable for rainfall forecasts. The inclusion of other hydrological parameters, such as, humidity and temperature data may improve the outcomes of the rainfall forecasting model using ANN methodology.

3. Such hydrological parameters can be individually map out using ANN technique.

4. ANN models in combination with other linear methods (regression based methods) may provide better prediction than the individual application of the methodologies. These combinations are known as hybrid models.

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APPENDIX 1

The input data used in the dissertation is gathered from official website of Indian Meteorological Department (IMD). This data can be tabulated as follows,

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1901	23.353	9.417	8.717	0.181	12.79	25.1	169.846	191.752	1.1	0.046	0	1.219
1902	0	0	2.054	4.209	8.954	100.375	215.463	140.413	64.721	1.091	0	0
1903	1.9	0.018	2.435	0	5.963	2.899	128.411	84.291	53.134	7.855	0	0.582
1904	4.181	0.055	22.972	0.291	21.536	31.512	136.052	162.048	172.034	0.201	25.885	13.809
1905	28.125	11.919	4.2	1.391	1.126	15.837	116.521	2.154	81.673	0.6	0	0.836
1906	0	40.692	14.935	0.145	1.328	92.795	154.29	83.634	217.785	0	0	7.692
1907	13.645	31.684	7.2	31.363	1.473	5.626	31.117	153.38	0.872	0.254	0	0
1908	27.881	9.781	0	3.799	7.882	7.59	310.291	511.537	21.044	0.037	0.046	0.382
1909	7.275	13.135	0	28.355	29.473	143.525	255.477	81.012	137.454	0.646	0	23.671
1910	16.235	8.9	1.319	2.545	0.836	21.255	151.378	139.754	143.826	6.246	0	0.181
1911	41.132	0.145	19.924	0.454	0.908	63.444	32.473	34.234	196.376	14.772	58.462	0.082
1912	31.861	15.489	2.362	20.371	10.481	24.702	142.541	211.465	188.151	0.51	0.957	0.755
1913	1.528	30.636	7.762	2.199	21.871	101.828	91.626	77.266	16.503	0.145	0.345	7.481
1914	1.817	5.373	0.218	15.372	20.672	18.603	257.937	67.899	250.289	10.708	16.53	0.89
1915	22.135	36.112	45.899	23.781	0.609	23.446	61.106	66.914	101.682	3.646	0	0.454
1916	0.054	27.417	0.054	3.217	1.91	35.756	153.817	285.939	107.856	8.572	0	0
1917	7.353	7.974	6.026	11.946	14.676	81.88	214.486	128.197	187.723	24.01	0	3.165
1918	5.855	0	7.699	5.354	2.673	21.608	22.611	181.294	7.628	0	0.272	0.618
1919	45.415	2.217	4.027	2.721	5.518	0.564	113.907	189.96	24.087	0	3.128	8.227
1920	8.1	6.728	14.199	1.135	11.693	73.67	243.13	111.569	2.948	0.364	0	0
1921	22.081	0	0	2.527	0.272	15.153	82.035	289.615	141.394	8.018	0	0.654
1922	14.281	0.682	0.036	0.435	0.308	41.692	100.473	150.926	157.846	2.382	0	16.028
1923	7.016	47.215	0.7	1.49	8.225	1.936	204.751	295.435	23.117	4.845	0	16.003
1924	34.459	17.645	1.637	0.073	13.426	22.219	78.967	235.691	214.897	22.046	3.209	8.646
1925	5.363	0	0.145	0	20.763	74.028	225.6	109.11	1.309	0.891	41.36	0
1926	7.439	0.055	34.262	11.018	11.037	2.019	245.29	246.731	36.9	0	4.455	1.38

1927	0	18.082	15.58	3.209	16.809	12.382	174.937	166.136	4.933	20.147	0.311	16.48
1928	17.39	35.209	8.026	11.636	5.263	36.126	55.508	25.847	33.116	8.776	25.231	10.609
1929	3.145	0	0	16.008	0.745	22.587	94.022	106.781	3.927	0.755	0	18.363
1930	35.188	19.635	0	1.708	8.464	61.213	295.373	39.771	29.511	9.484	1.126	1.027
1931	4.754	16.718	5.473	4.581	6.127	2.064	231.421	118.969	100.563	28.421	0	0
1932	1.363	1.027	11.027	6.527	4.254	6.965	81.853	82.857	214.33	0	0	1.872
1933	1.072	12.492	4.301	1.429	38.328	161.61	115.784	460.266	232.177	14.656	0.982	0.145
1934	21.99	0	35.633	0	2.808	43.851	277.364	219.814	2.102	0	0	6.982
1935	25.217	31.179	4.309	11	0.41	44.673	141.789	108.271	166.082	2.692	8.109	4.864
1936	1.9	16.682	7.992	0.564	0.527	203.094	149.063	155.92	125.933	1.99	3.61	35.644
1937	0	55.808	0.454	14.353	2.846	29.383	187.878	12.985	116.567	0.281	0.064	3.69
1938	43.45	2.836	8.782	1.609	0.955	42.783	97.797	32.511	25.656	2.236	0	0.236
1939	0.464	26.153	6.818	0.018	0.808	73.218	68.219	101.77	68.577	0.254	0	0
1940	33.251	32.954	1.52	0.218	0.455	15.279	179.366	186.936	9.063	0.1	0.073	0.409
1941	42.096	4.744	2.399	0	14.519	54.315	14.096	96.208	41.381	0.046	0	6.509
1942	10.809	12.809	1.091	10.064	6.526	26.752	343.596	154.534	114.533	0.254	0	7.936
1943	8.437	0	0	13.8	3.119	33.127	150.62	63.526	89.01	0	0	0
1944	23.919	40.787	38.198	40.789	0.217	49.409	327.054	58.039	136.325	30.638	0	0.709
1945	19.861	0	0.272	5.971	9.183	25.735	137.356	290.141	122.364	3.936	0	0
1946	0	7.681	0.345	0.181	9.846	93.19	179.372	183.791	41.193	3.799	0	2.027
1947	7.081	6.691	6.763	0.555	3.745	2.365	77.296	57.935	207.225	18.23	0	4.982
1948	38.326	25.672	13.144	0.727	4.137	12.181	179.013	300.91	157.218	5.574	0.881	1.472
1949	2.791	15.563	3.354	0.272	7.873	3.674	416.666	87.421	96.062	0.746	0	0
1950	12.479	2.935	11.598	0	10.045	11.537	403.646	162.605	145.38	0	0	0.018
1951	16.171	0.746	31.125	17.581	3.11	10.068	114.055	78.476	68.037	3.591	30.061	0
1952	6.172	10.901	28.716	3.572	20.253	27.39	59.345	262.19	0.872	0.181	0	0.892
1953	50.424	0	0	3.119	2.591	28.629	208.099	225.851	56.811	0.918	0.436	0.345
1954	20.38	42.337	6.337	0	1.236	18.29	209.109	17.794	75.959	22.773	0.174	0
1955	22.318	0.782	6.581	14.799	6.445	35.248	99.053	202.699	188.488	42.421	0	0.4
1956	23.752	0.755	12.8	2.236	0.199	28.526	255.367	194.891	13.92	45.248	1.827	0.973
1957	38.188	0	25.09	3.553	7.8	32.083	222.34	113.829	145.719	18.264	19.239	9.3
1958	18.152	0.792	10.344	0.818	5.772	8.126	365.544	190.375	221.995	1.855	5.048	5.181
1959	28.497	1.381	2.172	0.054	16.884	17.349	129.865	205.167	88.475	1.181	8.7	0

1960	8.962	0	15.108	5.372	0.373	25.464	187.756	285.123	14.882	41.885	0	0.89
1961	11.153	29.746	0.181	3.055	19.963	49.901	181.5	465.511	68.579	40.228	2.491	4.99
1962	22.916	10.298	5.755	0.018	1.827	17.001	181.875	84.257	139.957	0	4.727	13.272
1963	0.119	8.818	2.036	3.599	12.154	71.492	47.429	239.723	187.073	0.091	2.083	14.826
1964	1.308	0.836	0.855	4.009	13.319	21.526	463.447	369.438	125.893	0.064	0.345	8.728
1965	6.637	7.209	1.6	11.644	5.808	2.346	158.453	152.586	128.273	0.709	1.236	0
1966	2.099	20.743	0.918	1.072	44.89	105.563	87.099	182.583	64.713	15.399	2.638	0
1967	0	2.182	31.809	1.055	0.483	16.504	186.208	454.329	95.541	12.537	17.264	38.562
1968	9.255	7.735	5.664	0.728	5.772	15.428	254.342	209.017	1.119	2.027	0	0.527
1969	1.065	6.736	10.49	1.963	23.6	37.391	205.968	114.764	134.471	0.399	0.037	0
1970	34.434	39.279	34.879	0.236	38.718	77.695	45.789	179.697	110.418	2.299	0	0
1971	9.418	8.846	0.564	10.472	42.552	54.577	166.474	325.457	105.146	4.683	0.027	0
1972	7.553	8.555	0.755	7.827	0.282	23.564	230.99	291.647	34.044	15.637	6.527	0.782
1973	19.772	5.7	0.746	0	12.974	10.985	130.814	295.737	52.935	19.447	0	5.244
1974	0.254	0.436	2.354	0.363	5.62	15.957	329.171	86.048	4.22	9.794	0	5.499
1975	15.562	5.163	7.253	0.254	0.501	69.785	347.431	247.066	221.002	26.284	0	0.163
1976	1.555	17.127	7.781	5.645	52.007	51.765	317.466	337.673	70.19	1.762	0.101	0.845
1977	24.928	0.655	0	30.563	26.971	71.482	374.139	82.54	113.303	17.164	0.363	8.344
1978	0.364	18.527	14.053	9.028	0.199	74.566	245.828	313.182	175.912	0.036	0.829	1.437
1979	13.462	34.61	14.426	3.79	13.637	61.33	110.456	54.258	41.233	2.765	1.182	4.764
1980	3.845	6.309	16.071	1.009	8.582	56.373	339.696	107.877	52.681	4.854	3.754	5.009
1981	25.641	11.953	9.591	0	4.51	123.08	178.463	58.22	53.674	0.963	53.515	9.69
1982	14.837	6.045	35.332	43.254	58.246	57.635	223	225.804	0.936	14.538	8.629	6.819
1983	36.859	16.517	7.672	34.338	54.741	41.984	233.807	197.393	105.75	17.384	0	4.164
1984	0.628	4.862	0.564	21.737	2.2	21.675	163.273	290.532	96.999	0	0	1.145
1985	0.782	0	0.309	14.491	5.575	41.426	391.747	236.064	53.547	34.139	0.181	18.972
1986	17.89	30.835	7.317	4.645	19.202	38.443	74.13	149.085	61.955	1.174	0	17.409
1987	21.545	15.489	12.408	3.109	42.356	15.654	43.709	125.677	18.083	2.717	0	5.201
1988	0.637	14.253	29.806	4.527	3.537	46.084	224.029	395.331	128.186	3.798	0	2.754
1989	55.131	2.972	23.352	0.145	2.7	14.827	56.071	105.128	86.115	1.837	11.737	3.054
1990	0.181	31.062	4.117	3.471	33.544	44.176	138.222	267.174	198.093	0.382	4.081	19.127
1991	0	34.444	2.609	4.281	31.009	40.735	84.193	297.964	74.249	0.454	19.83	18.346
1992	16.472	20.817	0.345	6.045	4.189	7.755	79.804	182.209	84.768	3.646	40.997	0.145

1993	10.271	6.872	5.382	6.026	11.39	99.651	303.667	134.818	170.842	0.418	0.027	0
1994	23.109	4.082	12.182	7.263	17.27	41.701	405.846	213.373	16.396	0.254	0	1.726
1995	47.506	25.996	21.836	1.218	0.199	24.907	62.585	472.549	137.894	1.165	2.354	0.573
1996	6.218	15.735	3.828	0.954	11.43	136.029	157.191	289.638	102.621	9.746	0	0
1997	7.527	2.018	6.436	33.18	41.108	105.745	77.366	195.125	61.354	29.2	25.822	9.546
1998	0	20.019	17.499	5.474	9.518	81.744	137.837	189.91	192.551	27.511	26.894	0.827
1999	40.07	2.011	0.364	0	12.663	49.933	101.662	68.13	57.251	12.157	0	0
2000	22.398	42.016	12.58	0.691	12.074	80.69	272.234	125.493	20.492	0	2.644	21.908
2001	9.508	10.536	3.645	25.055	57.248	84.749	131.645	221.571	35.809	3.438	0	0
2002	12.935	12.027	1.899	0.909	2.636	33.037	13.052	118.931	142.816	0.463	0.636	10.208

Table. 5 Monthly Rainfall Data for Delhi (1901-2002)