

**DAILY AND WEEKLY RAINFALL MODELLING USING
ARTIFICIAL NEURAL NETWORK**

Thesis

Submitted to the



**G. B. Pant University of Agriculture & Technology,
Pantnagar- 263145 (U. S. Nagar), Uttarakhand, India**

By

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B. Tech. (Civil Engineering)**

***IN PARTIAL FULFILMENT OF THE REQUIREMENTS
FOR THE DEGREE OF***

**Master of Technology
in
Agricultural Engineering
(Soil and Water Conservation Engineering)**

August, 2018

Acknowledgements

First and foremost, I would like to thank God Almighty for giving me the strength, knowledge, ability and opportunity to undertake this research study and to persevere and complete it satisfactorily. Without his blessings, this achievement would not have been possible.

*It is my great privilege to express my profound sense of gratitude and veneration to my advisor **Dr Devendra Kumar**, Professor, Department of Soil and Water Conservation Engineering and Chairman of the Advisory Committee for his, sincere exhortation, constructive criticism, meticulous guidance and soothing affection during the course of the investigation and preparation of this manuscript.*

*Words are inadequate to express my sincere and unfathomable sense of gratitude to the members of my advisory committee **Dr Akhilesh Kumar**, Professor, Department of Soil and Water Conservation Engineering Engineering and **Dr Pankaj Kumar** Assistant Professor, Department of Soil and Water Conservation Engineering.*

*I avail this opportunity to express my warm regards and sincere thanks to **Dr. H.C. Sharma**, Dean, College of Technology and **Dr. J.P. Pandey**, Dean, College of Post Graduate Studies, G.B. Pant University of Agriculture and Technology, Pantnagar for providing academic, research facilities to carry out the study.*

*I express my gratitude to **Dr Anil Kumar** Professor & Head, **Dr Pravendra Kumar**, Professor, **Dr. P. S. Kashyap** Associate Professor, **Dr. P.V. Singh**, J.R.O. and **Dr Deepak Kumar** Assistant Professor, Department of Soil and Water Conservation Engineering for their consistent encouragement and support.*

I take this opportunity to extend my thanks and indebtedness to all the staff members of Department of Soil and Water Conservation Engineering.

*My words fell short to acknowledge the love, blessings, support, encouragement and affection of my Father **Mr. Amba Datt Joshi** and Mother **Mrs. Ganga Joshi** that helped me in overcoming all hurdles in my life, they mean everything to me in this world. my elder brother **Sanjay Datt Joshi** and younger brother **Deepak Joshi** for being a constant support system of my life.*

I am grateful to all my seniors, classmates and colleagues for their help and support during my study and research work, I specially thank my friends Ajaykumar, Navneet, Indramani P.S. Gaur, Amit Rawat, Spandana, Namrata Sah, Sanjay Dutt Gahatori, Sanjay Rawat, Rohit, Deepak Pal, Vijay Kumar Singh and Anurag Malik, I also duly acknowledged, the help and support of Bikesh and Yogesh for getting all sorts of help from them during my stay in this university.

I expresses my sincere thanks to the Authorities of G. B. Pant University of Agriculture & Technology who allowed me to pursue studies leading to this degree.

This list is obviously incomplete but let me submit that the omissions are inadvertent and I once again record my deep felt gratitude to all those who have cooperated, either directly or indirectly, with me in this endeavor.

*Pantnagar
August, 2018*



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CERTIFICATE

This is to certify that the thesis entitled “**DAILY AND WEEKLY RAINFALL MODELLING USING ARTIFICIAL NEURAL NETWORK**” submitted in partial fulfilment of the requirements for the degree of **MASTER OF TECHNOLOGY** in **Agricultural Engineering** with major in **Soil and Water Conservation Engineering** of the College of Post Graduate Studies, G. B. Pant University of Agriculture & Technology, Pantnagar, is a record of *bona fide* research carried out by **Mr. Neeraj Joshi**, Id. No. **51224**, under my supervision and no part of the thesis has been submitted for any other degree or diploma.


The assistance and help received during the course of this investigation have been acknowledged.

Pantnagar
August, 2018


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We, the undersigned, members the Advisory Committee of **Mr. Neeraj Joshi, Id. No. 51224**, a candidate for the degree of **Master of Technology in Agricultural Engineering** with major in **Soil and Water Conservation Engineering** agree that the thesis entitled **“DAILY AND WEEKLY RAINFALL MODELLING USING ARTIFICIAL NEURAL NETWORK”** be submitted in partial fulfilment of the requirements for the degree.


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LIST OF SYMBOLS AND ABBREVIATIONS

%	Percentage
ANNs	Artificial neural networks
MLP	Multi-layer perceptron
i	Input layer
j	Hidden layer
k	Output layer
μ	Parameter changed during the training process
M	Number of data points
m	Number of input variables
Γ	Gamma value
V_{ratio}	Variance of the noise to the variance of the output
Q_p	Predicted rainfall, and
Q_0	Observed rainfall,
\bar{Q}_o	Average of the observed rainfall
\bar{Q}_p	Average of predicted rainfall
Db	Dry Bulb Thermometer Temperature
Wb	Wet Bulb Thermometer Temperature
Rh	Relative Humidity
T_{max}	Maximum Temperature
T_{min}	Minimum temperature
Ws	Wind Speed
Dpt	Dew point
Rd	Daily rainfall
Rw	Weekly rainfall
LM	Levenberg-Marquardt
GT	Gamma Test
RMSE	Root Mean Square Error
r	Correlation coefficient

CE	Coefficient of efficiency
PBIAS	Percentage BIAS
ISE	Integral Square Error



Introduction

Water is the most important element for the survival of living beings present on the earth from human being to animals and plants as well. In today's world water plays an important role from generation of electricity to irrigation of agricultural lands and transportation as well. The indispensable source of water on the planet earth is precipitation in the form of rainfall, snowfall, etc. A colossal part of nation collects more than 75% of the annual rainfall during the months, June to September.

The yield of food grains rely on the quantity and dispensation of rainfall over the country. Further the generation of hydroelectric power from the rain water has been traced over the last 20 years. On the downside, Indian economy suffers massive losses due to floods and droughts almost every year. The population of India is rising at a much rapid rate than the total food grain production which may lead to the severe economic crisis. A huge part of rain water which is being unutilized should be made utilized for the various purposes with the help of proper rainfall prediction which may lead to proper irrigation and sufficient hydropower generation as well as help in minimizing the drought and flood losses. The Indian economy is mostly based on agriculture, and its agri produces and crop yield is severely reliant on rainfall. Therefore any fall or rise in annual rainfall will always have severe effect on agricultural sector in India. About 65% of the India's total cultivated land is under the impact of rain fed agriculture system (**Swaminathan, 1998**). There is yearly discrepancy in the dispensation of annual rainfall which leads to the floods, droughts and famines in India. India is the vast country with different regions and different geography as well as different climate so rainfall prediction becomes necessary for the reduction of many natural calamities.

Rainfall is challenging to measure precisely in mountainous areas (**Barros & Lettenmaier, 1994; Fang et al. 2013**), particularly within high and rugged mountains, such as in the Indian Himalaya (**Barros et al. 2000; Bookhagen & Burbank, 2006; Wulf et al. 2010; Burbank et al. 2012**). The necessity for measuring and prediction of rainfall events in the Indian Himalaya has great importance because these events can generate (simultaneous) multiple hazards including large landslides, flash floods,

Landslide lake outburst floods (LLOFs), glacial lake outburst floods (GLOFs), and debris flows (**Sati and Gahalaut, 2013; Ziegler et al. 2014; Kala, 2014**). Landslides and LLOFs occur frequently in regions marked by faults, thrusts, and steep gradient streams in the Indian Himalaya (**Wasson et al. 2013**). High rainfall depths in general generate flash floods that further increase the frequency of other hazards by generating shallow landslides that contribute to debris flows and the formation of landslide lakes. Addressing the risk associated with extreme rainfall events in the Indian Himalaya requires understanding of the occurrence and spatial distribution of rainfall. Thus, the region has a paucity of reliable recording stations, creating a sparse, non-uniform network of measurement points that generates limited data from which the spatio-temporal distribution of rainfall is difficult to determine accurately (**Burbank et al. 2012**).

The prediction of rainfall amount is of crucial importance in the management of water resources, irrigation, soil conservations and water balance. However it is difficult to effectively simulate its variation due to the complex interaction between land and atmosphere system as it depends upon many climatic factors. It is a key factor for irrigation system design and management, crop production, environmental assessment water resources management and planning. Accurate rainfall prediction are essential for the balancing of irrigation water use in arid and semiarid regions. Rainfall prediction is one of the cardinal and exigent task in the present-day world. In general, climate and rainfall are exceedingly non-linear and convoluted phenomena, which require advanced computer modelling and simulation for their precise prediction.

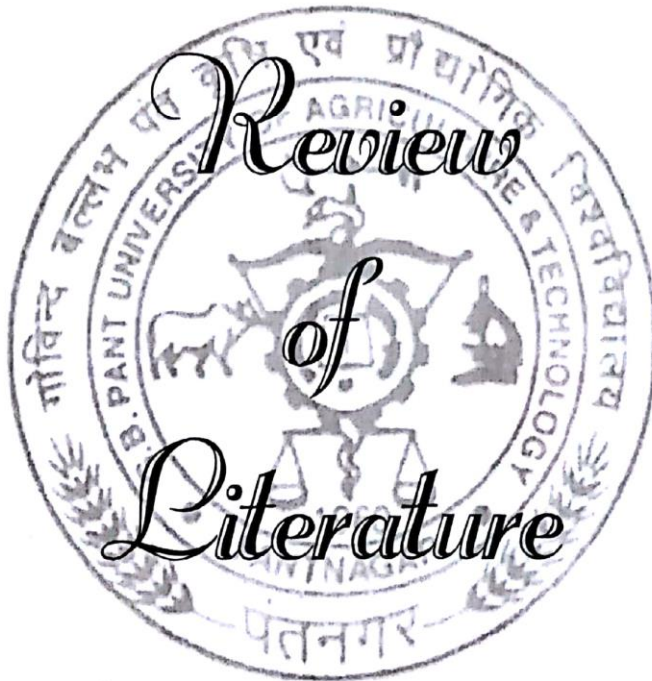
Rainfall prediction models can be classified into two categories: physical models and data driven models. Physical models based on the physical laws to model all of the relevant physical processes that contribute to rainfall process. Data driven models use historical data to make future predictions. Relative studies have shown that data driven models produce better results in prediction of rainfall as compared to physical models (**Abbot and Marohasy, 2012**). Number of data driven prediction models were considered for the rainfall prediction, among which most popular and widely used models are, autoregressive integrated moving average (ARIMA), multiple linear regression (MLR), support vector machines (SVM) and artificial neural networks (ANNs). ANNs performance is best as compare to other models like multiple regression model because neural networks are faster in learning and exhibit excellent system generalization characteristic (**Buch et al., 1993**). ANNs has been proved to be

very powerful tool in dealing with various highly complicated problems due to their capability to model non-linear systems without the need to make any assumptions. A review of ANNs in hydrology was presented by ACSE task committee on application of ANNs in hydrology (ASCE, 2000a and ASCE, 2000b). Hu (1964) commenced the application of ANN, an important soft computing tactic in weather forecasting. Meanwhile in the preceding few decades, Artificial Neural Networks had an enormous growth in the field of application, the application field of ANN has unlocked up novel paths to the forecasting task comprising environment associated phenomenon (Gardener and Dorling, 1998; Hsiesh and Tang, 1998).

Artificial neural networks (ANNs) are half parametric regression forecaster tools, and can estimate nearly any quantifiable function up to an arbitrary degree of precision. An ANN is an info-processing system consists of several nonlinear and closely interlocked processing elements or neurons. Neurons in an ANN are organized in groups called layers or slabs. Each neuron in a layer functions in logical parallelism. Information is conveyed from one layer to others in consecutive operations (Hecht, 1990). The architecture of an ANN is structured by weights between neurons, an activation function that regulates the generation of output in a neuron, and learning laws that describe the comparative importance of weights for input to a neuron (Caudill 1987). The simple structure of a network generally comprises of three layers: the input layer, where the data are introduced to the network; the hidden layer or layers, where data are processed; and the output layer, where the results for known inputs are formed. Therefore ANNs due to their easy self-adaptive mechanisms that learn from examples captures functional relationship between data even if it is difficult to describe the relationship. ANNs are the most extensively applied method for rainfall prediction (Abbot and Marohasy 2012, 2014; Deo and Shahin, 2015; Farajzadeh *et al.* 2014).

As per above points, in the present study ANN models has been developed for predicting daily and weekly rainfall of Nainital station, which is located in Uttarakhand state (India), using weather parameters as inputs and rainfall as output with the following objectives:

- (i) To develop ANN models to predict daily and weekly rainfall of Nainital
- (ii) To evaluate the performance and adequacy of the developed models



*Review
of
Literature*

It is very foremost and valuable to have a state-of-art review of literature before undertaking any project work. Accordingly, in view of the objectives of the present study, the literature available on prediction of rainfall using Artificial Neural Networks were thoroughly reviewed. Some of them found valuable and relevant to the study are being concisely reproduced in the following section. The potential of networks modelling and forecasting of rainfall have been examined by many analysts. The literature associated to the use of ANNs in the field of hydrology is present in the following section.

ASCE (2000a) described an introduction of ANNs and the role and impact of ANNs in the field of hydrology. Apart from description of various aspect of ANN, a few rules on their uses were displayed in the paper offered brief comparison of ANNs and other modeling philosophies in hydrology. A discussion on the potential and the limitations of ANN brought up the similarities they have with modeling approaches.

ASCE (2000b) examined the importance of ANN in the field of hydrology and found that ANNs are essential tool for modelling of various nonlinear hydrologic processes for example rainfall overflow, stream flow, ground water management, water quality simulation and precipitation. There are still some queries regarding the application of this developing technique in engineering which needs further study on some vital aspects such as physical interpretation of ANN models, optimal training data set, adaptive learning, and extrapolation. The constraints and benefits of ANN application were discussed, and potential research have been explored in detail.

Luk et al. (2000) developed ANN model to forecast the short term rainfall in an urban catchment. The well trained ANNs were used to recognize historical rainfall patterns as recorded by the number of gauges installed in that study catchment. in order to compare the prediction accuracy a comparison test is carried out among the different (ANNs) configured with various order of lag and different number of inputs. In developing the ANNs were trained to an ideal level to have good results of data. It was evidently found that the ANNs with less input network and with lower lag produce better accuracy as well as better performance.

Sahai et al. (2000) described the artificial neural network (ANN) procedure for prediction of Indian Summer Monsoon (ISM) Rainfall on monthly and seasonal time scales with error back-propagation algorithm. The ANN procedure was applied to the months of June, July, August and September monthly means and seasonal mean (June + July + August + September) rainfall from 1871 to 1994 based on Parthasarathy dataset. The previous five years lag values from all the five time series were used to train the ANN to forecast for the next year. Various statistical parameters were calculated to examine the performance of the model and it was found that the model could be used as a forecasting tool on seasonal and monthly time scales. It is found by the various researchers that with the elapse of time the relationships between various predictors and Indian monsoon were changing day by day, leading to changes in monsoon predictability. This issue is discussed and it was found that the monsoon system inherently has a decadal scale variation in predictability.

Silverman et al. (2000) explored the possibility of long range prediction of rainfall for California climate zones making use of Artificial Neural Networks models and weather parameters. The results of Neural Networks models with one year lag were closer to the observed rainfall.

Tokar and markaus. (2000) predicted runoff using data of rainfall, snow and temperature. Monthly stream was predicted using ANNs and conceptual water balance model. Daily rainfall runoff was modelled with ANNs and Sacramento Soil Moisture Accounting method.

Toth et al. (2000) studied and compared the accuracy of the small duration rainfall forecast obtained with time series analysis techniques utilized past rainfall depths as the single input information. The technique proposed were direct stochastic auto-regressive moving average (ARMA) models, artificial neural networks (ANN) and the non-parametric nearest neighbors' method. The rainfall forecast obtained through the considered methods were then steered through a lumped, conceptual rainfall-runoff model, thus implementing a coupled rainfall-runoff forecasting method for a case study on the Apennines Mountains, Italy. The study analyzed and compared the relative benefits and constraints of each time series analysis technique, used for issuing rainfall forecasts for lead-times varying from 1 to 6 hours. The results also indicated how the considered time series analysis techniques, and especially those based on 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 are often applied in hydrological practice.

Zhang and Govindaraju (2000) modelled complex rainfall runoff of three watersheds data having high, low and medium stream flows with Artificial Neural Networks with modular architecture. Different models of the networks were trained and getting network has used for mediation of response of all the experts. Identification of the expert was accomplished through training of getting network and then expert were trained. Three modular method architecture with mean monthly rainfall of current and previous months and mean monthly temperatures were selected as input to the models. The results of the study demonstrated that prediction of runoff by modular network is good.

Dawson and Wilby (2001) presented exhaustive review application of ANNs to rainfall runoff modelling and flood forecasting. Basic principles of ANN modelling architecture of network commonly used and algorithms used for training were reported. They developed a template to help in development of ANN models for application to rainfall runoff modelling.

Jain (2001) developed a relationship between sediment discharges for two gauging stations of Mississippi river using Artificial Neural Networks models. The results obtained from this technique were compared with existing method. ANNs technique results were found to be nearer to measured values.

Luk *et al.* (2001) presented the results of a study investigating the application of ANNs to forecast the spatial distribution of rainfall for an urban catchment. Three alternative types of ANNs, namely multilayer feed-forward neural networks, partial recurrent neural networks and time delay neural networks were identified, created and found to provide reasonable predictions of the rainfall depth one time-step in advance.

Sugimoto *et al.* (2001) developed an enhanced method for short-term rainfall prediction. The technique for most part comprise of a physically based conceptual rainfall model that incorporate water balance and thermodynamics. The crucial component in this study is the translation of radar data to the model parameter of the conceptual model which is incorporated into the numerical scheme of the mono scale

model. The extended Kalman filter is utilized as a state estimator to update the model parameter to the conceptual model with new Radar data and with forecasts from a numerical weather prediction model. The performance of the stochastic method is examined for a radar observation area that includes a mountainous region with a rainfall event that occurred along a front. The stochastic method performed superior to the deterministic method.

Brath *et al.* (2002) applied linear stochastic models, ANNs and nearest neighborhood method for forecasting the short term future rainfall and updating the discharge forecast. The rainfall forecast made by ANNs technique was better and much superior to the forecast made by the other two models. The same has found to be use in case of updating discharge.

Perera *et al.* (2002) predicted occurrence of daily rainfall data from nine meteorological stations in sri lanka using two models based on first order and second order Markov process. The models were able to forecast the satus of a given day at an average of 73% but better results were obtained in dry zones in comparison to wetzones. The models were insensitive to the range of data 9used in study.

Rajurkar *et al.* (2002) studied the application of artificial neural network methodology for modeling daily flows during monsoon flood events for a large size catchment of the Narmada River in Madhya Pradesh, India. The spatial variation of rainfall was accounted for by subdividing the catchment and treating the average rainfall of each sub catchment as a parallel and separate lumped input to the model. A linear multiple-input single-output (MISO) model coupled with the ANN was shown to provide a better representation of the rainfall-runoff relationship in such large size catchments compared with linear and nonlinear MISO models. The model provides a systematic approach for runoff estimation and represents improvement in prediction accuracy over the other models.

Tayfur *et al.* (2003) implemented ANNs in bare soils for estimation of sediment load from these surfaces. For this purpose, a fuzzy logic algorithm was developed in which rainfall intensity and slope was taken as input variables. Fuzzy subsets were made from slope and rainfall intensity variables and then triangular membership function was assigned to them. Results obtained through this fuzzy

algorithm were much similar to the observed data or to the sediment measured. Comparison between fuzzy models under, ANNs models and physical based models indicate good performance of fuzzy models under this study when high values of rainfall intensities over different slope values with different values of rainfall intensities were feed as data input parameter.

Wilby *et al.* (2003) considered precipitation, evaporation and discharge data for developing conceptual and neural network rainfall-runoff model. Three different experiments were conducted with progressively decreasing amount of information, to determine the extent to which neural networks can safely imbibe the hydrological processes. The study showed that, a neural network with seven inputs and three hidden nodes were able to grasp the behavior of the conceptual model. The correlation analysis was used and it was observed that the two hidden nodes corresponded to the base flow and quick flow components whereas; the third hidden unit represented the seasonal variations in the soil moisture deficit.

Kisi (2004) studied the ANN and AR model for prediction of mean monthly stream flow in Turkey State. It was observed that performance of the ANN was similar with that of the statistical method for the same data.

Olsson *et al.* (2004) used neural networks for rainfall forecasting by atmospheric down scaling. Attempts were made to improve the performance of ANN by using two approaches: (1) two ANNs were coupled in series, the first to determine the rainfall occurrence, and the second to determine rainfall intensity during rainy periods, and (2) rainfall was categorized on the basis of intensity. The neural network was trained to reproduce categorized intensities rather than the actual intensities. The two ANNs in series greatly improved the performance while categorization was useful for probabilities.

Raid *et al.* (2004) applied MLPNNs for modelling of relationship of rainfall and runoff for a semiarid watershed in Morocco. The results showed the powerfulness of this model in comparison to regression model for river flow prediction and suitability of its application in the field of hydrology.

Ramireza *et al.* (2005) applied feed forward neural network resilient propagation learning algorithm for daily rainfall forecasting at 6 locations at Brazil.

Input data in terms of ANNs models meteorological variables of ETA model. The performance of ANNs models were compared with a multiple linear regression model through statistical analysis and performance of ANN was observed to be better than multiple linear regression models. Strong bias in prediction of rainfall on dry day in case of multiple linear regression model was observed. The MLR model was successful in forecasting of rain of wet day. The results of ANNs showed better than the results of the ETA model.

Chen and Adams (2006) developed semi distributed form of conceptual rainfall runoff models with integrating of ANNs models to study the impact of variation in rainfall in space and characteristics of homogeneous watershed on runoff. Surface runoff and ground water runoff were simulated with model parameters distributed in space and input of rainfall. ANNs networks were used for routing of runoff from all sub catchments for generating runoff at outlet of watershed. Application of three conceptual models showed encouraging results for rainfall runoff modelling.

Guhathakurta *et al.* (2006) developed artificial neural network model for long-range monsoon rainfall prediction for the Districts and Sub-Division of Kerala based on the area weighted value of all districts forecast. Finally, he has found that the performance of the model was better than the statistical technique.

Kumarasiri *et al.* (2006) forecasted both short term and long term date of a meteorological station in Colombo using artificial neural networks based on feed forward back propagation architecture. Three neural network nodes for a one day ahead monthly and yearly rainfall depth. The prediction accuracy of neural network models for one day ahead monthly and yearly rainfall depth was 74.25%, 58.33% and 76.67% respectively i.e. within a 5% uncertainty level. The accuracy was decreased with the interim in the number of time. The rainfall trend within the monsoon seasons studied were also reported.

Somvanshi *et al.* (2006) studied two fundamentally different approaches for designing a model the statistical method based on autoregressive integrated moving average (ARIMA) and the emerging computationally powerful based on ANN in order to evaluate the prediction efficiency, 104 years of mean annual rainfall data from year 1901 to 2003 of Hyderabad region (India) was used. The models were trained with 93

Years of mean annual rainfall data. The ANN and ARIMA approaches were applied to the data to drive the weights and regression coefficients respectively. The study revealed that ANN model can be used as an approximate forecasting tool to predict the rainfall, which outperforms the ARIMA model.

Guo *et al.* (2007) developed a nonlinear perturbation model (NLPM) based on artificial neural network (ANN), defined as NLPM-ANN, for the purpose of improving the rainfall–runoff forecasting efficiency and accuracy. The NLPM-ANN model structure was similar to that of the linear perturbation model (LPM). The difference was that ANN, instead of the linear response function, was used to simulate the unknown relationship between the input perturbations and the output perturbations. The proposed model was also compared with the LPM, a nonlinear perturbation model considering catchment wetness (NLPM-API) and two different ANN models. It was observed that the model efficiency of NLPM-ANN model was significantly higher than that of the LPM. The results demonstrated that the relationship between the perturbations was highly nonlinear though subtracting the seasonal means and ANN was capable to simulate this relationship. Comparing with the NLPM-API, the NLPM-ANN also showed advantages in simulating the nonlinear relationship between the rainfall and runoff. The study also indicated that consideration of the seasonal information can improve the model efficiency of not only the linear models but also the ANN models.

Kumar *et al.* (2007) forecasted monsoon months and seasonal rainfall with the help of ANNs after identifying lag relationship between climate indices and monthly rainfall. After training the models separately for monthly and seasonal rainfall, the models were tested to evaluate the performance of the models. Accurate results were found in the forecasting of monthly and seasonal rainfall by the models.

Nasseri *et al.* (2008) developed feed-forward type networks to simulate the rainfall field and so called back-propagation (BP) algorithm coupled with genetic algorithm (GA) used to train and optimize the networks. The technique was implemented to forecast rainfall for a number of times using rainfall hyetograph of recording rain gauges in the upper Parramatta catchment in the western suburbs of Sydney, Australia. 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.

Tripathi *et al.* (2008) applied ANN technique for prediction of Indian summer monsoon using various combinations of four indices. Best prediction was achieved when combination of sea surface temperature indices of southern Indian ocean region, southern Indian ocean indices +Antarctic circumpolar current indices and central southern Indian ocean + southern Indian ocean indices + Antarctic circumpolar current indices, were used collectively. For prediction of Indian summer monsoon region (IMSR) performance of ANN model was found better than regression model.

Ghalhary *et al.* (2009) developed ANN models and found the technique useful for prediction of rainfall. The model was able to prediction of rainfall. The root mean square error of the model was 41mm which is very less on the yearly basis. Efficiency of the model would increase with the increase in numbers of years of data.

Hung *et al.* (2009) developed the ANN model and applied for real time rainfall forecasting and flood management in Bangkok, found that ANN forecasts have significant than the one obtained by the persistent model. Rainfall forecast for Bangkok from 1 to 3 h ahead were found highly satisfactory.

Lin and Wu (2009) proposed a hybrid neural network model to forecast the typhoon rainfall. Two different types of artificial neural networks, the self-organizing maps (SOM) and Multilayer perceptron network (MLPN), combined to develop the proposed model. In the proposed model, a data analysis technique were developed based on the SOM, which can perform cluster analysis and discrimination analysis in one step. The MLPN was used as the nonlinear regression technique to construct the relationship between the input and output data. First, the input data were analyzed using SOM based data analysis technique. Through the SOM based data analysis technique, input data with different properties were first divided into distinct clusters which can help the multivariate nonlinear regression of each cluster. Additionally, the topological relationships among data were discovered from which more insight into the typhoon rainfall process can be revealed. Then, for each cluster, the individual relationship between the input and output data was constructed by a specific MLPN. For evaluating the forecasting performance of the proposed model, an application is conducted. The

proposed model was applied to the Tanshui river basin to forecast the typhoon rainfall. The results showed that the proposed model can forecast more precisely than model developed by conventional neural network approach.

Tan *et al.* (2009) stated that for rainfall prediction the best way is that to construct a fully connected neural network with a sufficiently large number of neurons in the hidden layer, and then iterate the architecture-building process with a smaller number of neurons.

Vamsidhar *et al.* (2010) developed back-propagation neural network model for predicting the rainfall based on humidity, dew point and pressure in India. The numbers of training and testing patterns are 250 and 120 respectively. During training and testing .79 % and 94.28 % accuracy were obtained.

El-Shafie *et al.* (2011) developed two rainfall prediction models and implemented 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 results of both models, statistical parameters 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. The FFNN model has shown better performance than the MLR model. The MLR model revealed a humble prediction performance. The linear nature of MLR model estimators made it inadequate to provide good prognostics for a variable characterized by a highly nonlinear physics. On the other hand the ANN model was a nonlinear mapping tool which potentially was more suitable for rain (nonlinear physics) forecast.

Gadgay *et al.* (2011) developed artificial neural network (ANN) models to predict the rainfall in the one of the large cities of the India i.e. Bangalore using Single neural network (SNN) and Ensemble neural network (ENN) models. The ANN models were trained and tested with the corresponding rainfall data which was collected in the last three years on hourly basis. The data collected was in form of rain gauge data. Different network models were developed to match the predicted results with the actual data and the ANN model with hyperbolic tangent function found be the better model among all. Finally, the results predicted by the SNN and ENN models are compared with the actual data and error as well as percentage errors were computed.

Ghumman *et al.* (2011) developed artificial neural networks for short length and poor quality of data for a watershed in Karachi, Pakistan. The generalization of ANNs models was done through cross validation approach. The comparison of results with mathematical conceptual model showed that ANN model is better than conceptual model when data length is short and is of low standard.

Abbot and Marohasy (2012) used artificial intelligence techniques for monthly and seasonal rainfall forecasting in Queensland, Australia. It was assessed by inputting recognized climate indices, monthly historical rainfall data and atmospheric temperatures into a prototype stand-alone, dynamic, recurrent, time delay, artificial neural network. Outputs, as monthly rainfall forecasts 3 months in advance for the period 1993 to 2009, were compared with rainfall data using time series plots, root mean square error (RMSE), and Pearson correlation coefficients. A comparison of RMSE values with forecasts generated by the Australian Bureau of Meteorology's predictive Ocean Atmosphere Model for Australia (POAMA) 1.5 general circulation models (GCM) indicated that the prototype achieved a lower RMSE for 16 of the 17 sites compared. The application of artificial neural networks to rainfall forecasting was reviewed. The prototype design is considered preliminary, with potential for significant improvement such as inclusion of output from GCMs and experimentation with other attributes.

El-Shafie *et al.* (2012) focused on investigating the potential of introducing a neural network that could address the temporal relationships of the rainfall series. Two different static neural networks and one dynamic neural network namely; Multilayer perception Neural Network (MLP-NN), Radial basis Function neural network (RBFNN) and Input delay neural network (IDNN), respectively have been examined. Those models had been developed for two time horizon in monthly and weekly rainfall basis forecasting at Klang River, Malaysia. Comprehensive comparison analyses were carried out to evaluate the performance of the proposed static and dynamic neural network results showed that MLP-NN neural network model was able to follow the similar trend of the actual rainfall, yet it still relatively poor. RBFNN model achieved better accuracy over the MLP-NN model. Moreover, the forecasting accuracy of the IDNN model outperformed during training and testing stages which proved a consistent level of accuracy with seen and unseen data. Furthermore, the IDNN significantly

enhanced the forecasting accuracy if compared with the other static neural network as they could memorize the sequential or time varying pattern.

Kumar *et al.* (2012) established the artificial neural network (ANN) models to bring out the structural relationship between the various entities. The paper explained the applicability of ANN approach by developing effective and reliable nonlinear predictive models for weather analysis, also compared and evaluated the performance of the developed models using different transfer functions, hidden layers and neurons to forecast maximum temperature for 365 days of the year.

Pucheta *et al.* (2012) forecasted cumulative monthly rainfall time series with feed forward neural network based nonlinear autoregressive filter approach. Five time series of Mackey-Glass delay differential equations and two time series of Cordoba, Argentina were used to test this approach. 18 future values for each time series were simulated for performance of the approach was shown by the results of forecasting.

Kumar *et al.* (2013) applied feed forward neural network both levenberg marquadt back proportion to forecast rainfall of Mirzapur with monthly temperature, evaporation, relative humidity, cloud cover and frequency as inputs to the model. Statistical parameters such as standard deviation, standard deviation ratio, error mean, mean, and error standard deviation for predicted and observed rainfall. The high value of correction coefficient of 0.9858 indicated best fit of the developed model.

Nastos *et al.* (2013) developed predictive models in order to forecast rain intensity (mm/day) in Athens, Greece, using artificial neural network (ANN) models. The ANN's outcomes concern the projected mean, maximum and minimum monthly rain intensity for the next four consecutive months in Athens. The metrological data used to estimate the rain intensity were the monthly rain totals (mm) and respective rain days which were acquired from the National observatory of Athens, for a 111 year period (1899-2009). The results of the developed and applied ANN models showed fairly reliable forecast of rain intensity for the next four months.

Nayak *et al.* (2013) reported that rainfall prediction using ANN technique is more suitable than traditional and numerical methods. A detailed survey on rainfall prediction using different neural networks architectures over twenty-five years was provided. From the survey, it has been found that most of the researchers used back

propagation network for rainfall prediction and got significant results. The survey also gave a conclusion that the forecasting techniques that use MLP, BPN, RBFN, SOM and SVM are suitable to predict rainfall than other forecasting techniques such as statistical and numerical methods. However, some limitations of those methods have been found. The extensive references in support of the different developments of ANN research provided with the paper should be of great help to ANN researchers to accurately predict rainfall in the future.

Gupta et al. (2014) applied multi-layer perceptron artificial neural network with back propagation for rainfall time series forecasting using rainfall and discharge data. Different topologies of neural networks were created with change in number of hidden layer, neurons and also activation functions. The collecting data was divided in three parts the first part is training part, second part for validation and third part for testing. The model performance was evaluated by calculating mean absolute error, mean squared error and correlation coefficient. The results of multilayer perceptron network were better than other traditional methods.

He et al. (2014) studied the potential of three different data driven methods, artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region, north-western China. The performance of the ANN, ANFIS and SVM models in training and validation sets are compared with the observed data. The model which consists of three antecedent values of flow has been selected as the best fit model for river flow forecasting. Four quantitative standard statistical performance evaluation measures, the coefficient of correlation (R), root mean squared error (RMSE), Nash Sutcliffe efficiency coefficient (NS) and mean absolute relative error (MARE), were employed to evaluate the performances of various models developed. The results indicated that the performance obtained by ANN, ANFIS and SVM in terms of different evaluation criteria during the training and validation period does not vary substantially; the performance of the ANN, ANFIS and SVM models in river flow forecasting was satisfactory. A detailed comparison of the overall performance indicated that the SVM model performed better than ANN and ANFIS in river flow forecasting for the validation data sets. The results also suggest that ANN, ANFIS and SVM method can be successfully applied to establish river flow with complicated topography forecasting models in the semiarid mountain regions.

Muttaleb (2014) developed and implemented three rainfall prediction models based on past observations such as time series models such as autoregressive integrated moving average (ARIMA), artificial neural network (ANN) and multi linear regression (MLR) models. A feed-forward neural network (FNN) model was applied to predict the rainfall on monthly basis. In order to evaluate the performance of three models, statistical parameters were used to make the comparison between these models. These parameters include the correlation coefficient (r) and root mean square error (RMSE). The study revealed that ANN model can be used as an appropriate forecasting tool to predict the monthly rainfall which is preferable over the ARIMA model and MLR model.

Pai et al. (2014) forecasted southwest Indian monsoon rainfall making use of artificial neural network with sea level pressure, sea surface temperature, humidity and zonal and meridional winds. Input parameters data of 36years and 9 years were used for training and testing of the models respectively. The results of validation period of June, July, August and September showed very closeness with observed values which clearly shows that the method can be used for rainfall prediction.

Shrivastav et al. (2014) studied the applications of the feed forward network for the runoff prediction with various algorithms namely Back-Propagation (BP), conjugate gradient (CG) and Levenberg-Marquardt (L-M). In order to evaluate the output of models, statistical parameters were used to make the comparison between models. These parameters include mean squared error 'MSE' and coefficient of determination ' R^2 '. The results shown that the best model is composed of the feed-forward networks trained by the Levenberg-Marquardt algorithm and considering only one hidden layer.

Dubey et al. (2015) used feed forward back pack propagation algorithm, layer recurrent and feed forward time delay algorithm for artificial neural networks models for the rainfall prediction of Pondicherry. The number of neurons for all the models was 20. The mean squared error value of 0.0083 in case feed forward distributed time delay algorithm shows that the model is best for rainfall prediction.

Mesgari et al. (2015) forecasted monthly rainfall data of the Zab watershed, iran. With the help of multi layer perceptron ANN model. Results clearly indicated that

the effectiveness of multi-layer perceptron , sigmoid and linear functions and Marquardt-Levenberg network in prediction of annual and monthly rainfall for the zab watershed and its surrounding regions.

Mislan *et al.* (2015) developed an artificial neural network with the backpropagation neural network algorithm tested using two hidden layers of BPNN architectures with three different epochs. The mean square error is used to measure the performance of the models. The results of the study showed that the architecture [2-50-20-1, epoch 1000] produced a good result with the lowest value of MSE were 0.00096. BPNN algorithm also proved to be a good model in rainfall prediction in Tenggara, Indonesia.

Tanty (2015) review conducted on artificial neural network (ANN) which was employed in the field of hydrological related problems, whereas the conventional approaches were cumbersome and complex in view of computational analysis. Artificial intelligence operation can be well exemplified through application in rainfall-runoff modelling, modelling stream flow, water quality modelling, and application in ground water. A good physical understanding of the hydrologic process being modelled can help in selecting the input vector and designing a more efficient network. This review provides examples for ANN model that provides reasonable accuracy for hydrological problems, and a more effective tool for engineering applications.

Devi Nirmala (2016) integrated Artificial Neural Network and Fuzzy Logic approved for rainfall forecasting. The forecasted results were compared with existing models and it was observed that the proposed approach performed better. The results showed that the integrated approach provides accuracy when comparing to the accuracy of either model i.e. ANN and Fuzzy Logic separately.

Patel and Joshi (2016) developed artificial neural network (ANN) model using feed forward back propagation algorithm for simulating monthly and annual rainfall-runoff correlation. ANN model developed is applied to Dharoi reservoir watershed of Sabarmati River basin of Gujarat, India. The whole computation was done by using nntoolbox in MATLAB software. Single and two hidden layer neural network with the tansig transfer function, TRAINLM training function and MSE performance function was developed. The rainfall and runoff data for twenty-nine years (1986-2014) were

used to develop ANN model. The performance of developed models was evaluated by statistical evaluation measurements, such as root mean square error (RMSE) and Pearson correlation (R). The results show that artificial neural network model had capability to capture the non-linear relation between rainfall and runoff.

Khalili *et al.* (2016) utilized ANN modelling for the prediction of monthly rainfall in Mashhad synoptic station which is located in Iran. Used monthly rainfall data from 1953 to 2003 for this synoptic station. First, the Hurst rescaled range statistical (R/S) analysis is used to evaluate the predictability of the collected data. Then, to extract the rainfall dynamic of this station using ANN modelling, a three-layer feed- forward perceptron network with back propagation algorithm was utilized. Using this ANN structure as a black-box model, realized the complex dynamics of rainfall through the past information of the system. The approach employs the gradient decent algorithm to train the network. The different parameters, two structures, M531 and M741, have been selected which give the best estimation performance. The performance statistical analysis of the obtained models shows with the best tuning of the developed monthly prediction model the correlation coefficient (r), root mean square error (RMSE), and mean absolute error (MAE) are 0.93, 0.99, and 6.02 mm, respectively, which confirms the effectiveness of the developed models.

Kashiwao *et al.* (2017) developed and tested a local rainfall (precipitation) prediction system based on artificial neural networks (ANNs). There system can automatically obtain meteorological data used for rainfall pre-diction from the Internet. Meteorological data from equipment installed at a local point is also shared among users in our system. The final goal of their study was the practical use of “big data” on the Internet as well as the sharing of data among users for accurate rainfall prediction. They predicted local rainfall in regions of Japan using data from the Japan Meteorological Agency (JMA). As neural network (NN)models for the system, they used a multi-layer perceptron (MLP) with a hybrid algorithm composed of back-propagation (BP) and random optimization (RO) methods, and radial basis function network (RBFN)with a least squares method (LSM), and compared the prediction performance of the two models. Precipitation (total amount of rainfall above 0.5 mm between 12:00 and 24:00 JST (Japan standard time)) at Matsuyama, Sapporo, and Naha in 2012 was predicted by NNs using meteorological data for each city from 2011. The

volume of precipitation was also predicted (total amount above 1.0 mm between 17:00 and 24:00 JST) at 16 points in Japan and compared with predictions by the JMA in order to verify the universality of the proposed system. The experimental results showed that precipitation in Japan can be predicted by the proposed method, and that the prediction performance of the MLP model was superior to that of the RBFN model for the rainfall prediction problem. However, the results were not better than those generated by the JMA. Finally, heavy rainfall (above 10 mm/h) in summer (Jun.–Sep.) afternoons (12:00–24:00 JST) in Tokyo in 2011 and 2012 was predicted using data for Tokyo between 2000 and 2010. The results showed that the volume of precipitation could be accurately predicted and the catching rate of heavy rainfall was high. This suggests that the proposed system can predict unexpected local heavy rainfalls as “guerrilla rainstorms.”

Purnomo *et al.* (2017) studied two neural network models were proposed for monthly rainfall rate forecasting. The performance of the proposed model was assessed based on monthly rainfall rate in Ampel, Boyolali, from 2001-2013. The results show that the accuracy of the first model is much better than the accuracy of the second model. Its average accuracy was just above 98%, while the accuracy of the second model was approximately 75%. In addition, both models tend to perform better when the fluctuation of rainfall is low.

Sukanya and Prabha (2017) discussed about data mining technique which was suitable to predict the rainfall. This was carried out using several Classification algorithms such as Decision tree and artificial neural network. ANN was a non-linear data modelling tool which was used to enhance the capability of Data Mining. It provides high accuracy, flexibility, good robustness, distributed storage and parallel processing. In this paper back propagation Neural Network, Support Vector Machine was used for rainfall prediction. ANN improves the efficiency of Rainfall prediction by analyzing the historical and current facts to make accurate predictions about future. For rainfall prediction, several Data mining techniques are used with ANN and comparison has been done by many researches are discussed

Bagirov *et al.* (2018) studied the performance of data driven models such as the support vector machines for regression, the multiple linear regression, the k-nearest neighbors and the artificial neural networks for monthly rainfall prediction in Australia

depending on climatic conditions. Rainfall data with five meteorological variables over the period of 1970–2014 from 24 geographically diverse weather stations are used for this purpose. The prediction performance of each model was evaluated by comparing observed and predicted rainfall using various measures for prediction accuracy

Mehdizadeh *et al.* (2018) studied two novel types of hybrid models, namely gene expression programming-autoregressive conditional heteroscedasticity (GEP-ARCH) and artificial neural networks-autoregressive conditional heteroscedasticity (ANN-ARCH) to estimate monthly rainfall time series. To fulfill this purpose, five stations with various climatic conditions were selected in Iran. The lagged monthly rainfall data was utilized to develop the different GEP and ANN scenarios. The performance of proposed hybrid models was compared to the GEP and ANN models using root mean square error (RMSE) and coefficient of determination (R^2). The results show that the proposed GEP-ARCH and ANN-ARCH models give a much better performance than the GEP and ANN in all of the studied stations with various climates. Furthermore, the ANN-ARCH model generally presents better performance in comparison with the GEP-ARCH model.

Mishra *et al.* (2018) analysed that with the help of time series data method, accurate rainfall can be predicted and it will help in effective evaluation of drought and floods. They used ANN technique for rainfall prediction using time series data for one-month and two-month ahead rainfall forecasting model using monthly time series rainfall data of North India for the period 1871 to 2012 (i.e. 141 years). They also suggested some future directions for rainfall prediction and time series data analysis research in their study.



Materials
and
Methods

This chapter deals with the description of location and climate of study area, collection of meteorological data and methodology adopted for daily and weekly rainfall modelling using artificial neural networks. Procedure used for calibration and validation of the ANNs models and different criteria for evaluating performance of the models is also discussed here.

3.1 General Description of Study Area

3.1.1 Location

Nainital is a hill station located in the Kumaon region of Uttarakhand, India. Geographically it is located at 29° 22' 28.05" N latitude and 79° 27' 52.44" E longitude, at 1907 meters above mean sea level. The location of Nainital in the map of India is shown in Fig 3.1.

3.1.2 Rainfall and climate

Nainital due to its high altitude experiences a cool climate all over the year, the town is little dry during winter and very wet in summer. The lowest monthly rainfall occurs in November with total 7.9 mm, while the highest monthly rainfall occurs in July with total 725 mm. The warmest month is July with temperature ranging from 16.4 °C to 23.5 °C, while the coolest month is January with temperature ranging from 1.7 °C to 10.7 °C, the town gets snow between the months of December and February.

3.2 Data Collection

The daily data (from May 2003 to March 2018) of rainfall (mm), maximum temperature (°C), minimum temperature (°C), dry bulb thermometer temperature (°C), wet bulb thermometer temperature (°C), relative humidity (%), dew point (°C) and wind speed (km/h) were collected from Saheed Major Rajesh Adhikari Government Inter College Nainital (Uttarakhand).



Fig. 3.1 location of the study area

3.3 Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) are statistical learning models inspired by biological neural networks of brain and that depends on a large number of inputs. Artificial neural networks are commonly presented as structures of interconnected "neurons" which send messages to each other. The networks have numeric weights that can be modified based on experience, creating neural networks adaptive to inputs and proficient of learning. Artificial neural networks are used in several studies of various disciplines such as mathematics, statistics, computer science, and engineering to realize many tasks modelling, time series analysis, signal processing, pattern recognition, and classification (**Haykin, 1999**).

ANNs are distributed, adaptive, usually nonlinear learning tools that are made from several different nonlinear processing elements called "neurons" each of which connects from other neurons or itself according to the training algorithm. The signals moving on the networks are scaled by changeable parameters known as weights (**Principe et al. 2000**). Artificial neural networks (ANNs) are easy to use and best method for computation of the complex networks which are not easy to compute by any other techniques, and are used in various fields of technology and sciences for example, artificial neural networks are used as prediction tools for rainfall, etc.

A neural network is a parallel, disseminated information processing structure comprising of processing elements (which consists of a local memory and can convey localized information processing operations) interconnected via unidirectional signal networks called branches, into as many validatory connections as wanted; each conveys the same signal – the processing element output signal. The processing element output signal can be of any mathematical type desired. The information processing that goes in within each processing element can be defined randomly with the limitation that it must be completely local; that is, it must rely only on the present values of the input signals reaching at the processing element via impinging connections and on values stored in the processing element's local memory.

An ANN is an information-processing system comprised of various nonlinear and closely inter-connected processing elements or neurons. The key function of the ANN models is to map a set of inputs to a set of outputs. A single processing unit or

neuron is shown in Fig.3.2. The entering signals are multiplied by respective weights through which they are circulated toward the neurons or node, where they are collected (summed up) and the net input is passed through the activation function to give the output. The signal flows in the neurons from the dendrites through the soma converging at the axon hillock and then down the axon and end bulbs. A neuron usually has several dendrites but simply a single axon.

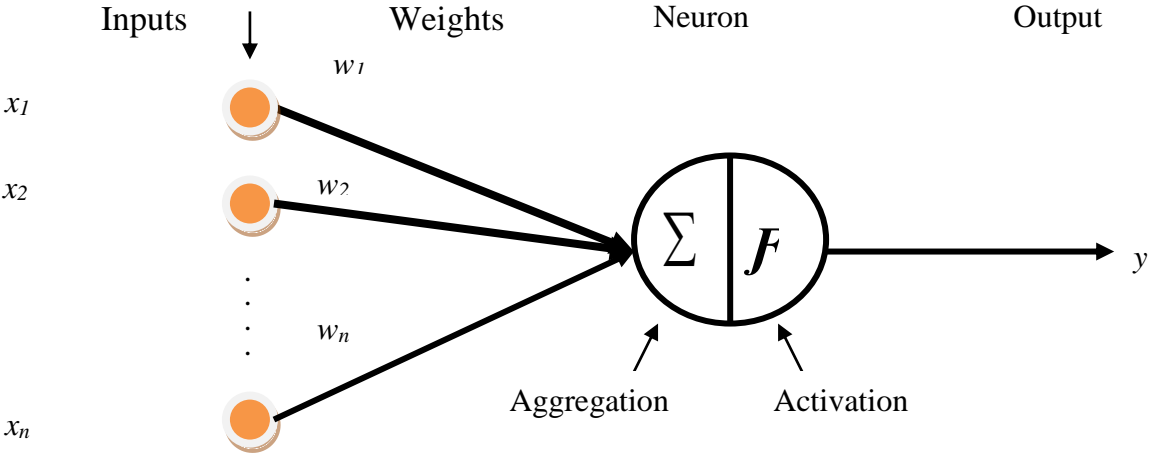


Fig. 3.2 A single artificial neuron (perceptron)

Let $x_i (i = 1, 2, \dots n)$ are inputs and $w_i (i = 1, 2, \dots n)$ are respective weights. The net input to the node can be expressed as

$$net = \sum_{i=1}^n x_i w_i \quad \dots (3.1)$$

The net input is then passed through an activation function f and the output y of the node is computed as-

$$y = f (net)$$

... (3.2)

Single neuron cannot solve a complex problems therefore several neurons are used for guiding complex problems. One of the utmost frequently used architecture is the multi-layer perceptron (MLP). In such a networks, all neurons and outputs of the previous layer are linked with neurons inputs of the following layer. A signal is conveyed in the single direction from the input to the output and therefore this architecture is called feed-forward. The basic structure of a feed-forward multilayer

network generally comprises of three or more layers: the input layer, where the input data is introduced to the network; the hidden layer or layers, where data is processed; and the output layer, where the result of the given input is produced. In these networks, the signal passes in forward direction from input layer to output layer through hidden layer.

3.3.1 Multilayer feed-forward network

The most significant characteristic of a multilayer feed-forward network is that it can learn a mapping of any complexity. This network consists of multiple layers of neurons. In this architecture, besides the input layer and the output layer, the network also has one or more than one intermediate layer called hidden layer. Each layer is completely connected to the previous layer by interconnection strengths or weights. Fig.3.3 illustrates this type of network consisting of a single hidden layer. As can be seen, the generic feed-forward network is characterized by the lack of feedback. Even though this network has no explicit feedback connection when the input is mapped into the output, the output values are often compared with the desired output values, and also an error signal can be employed for adapting the network's weights during the learning process.

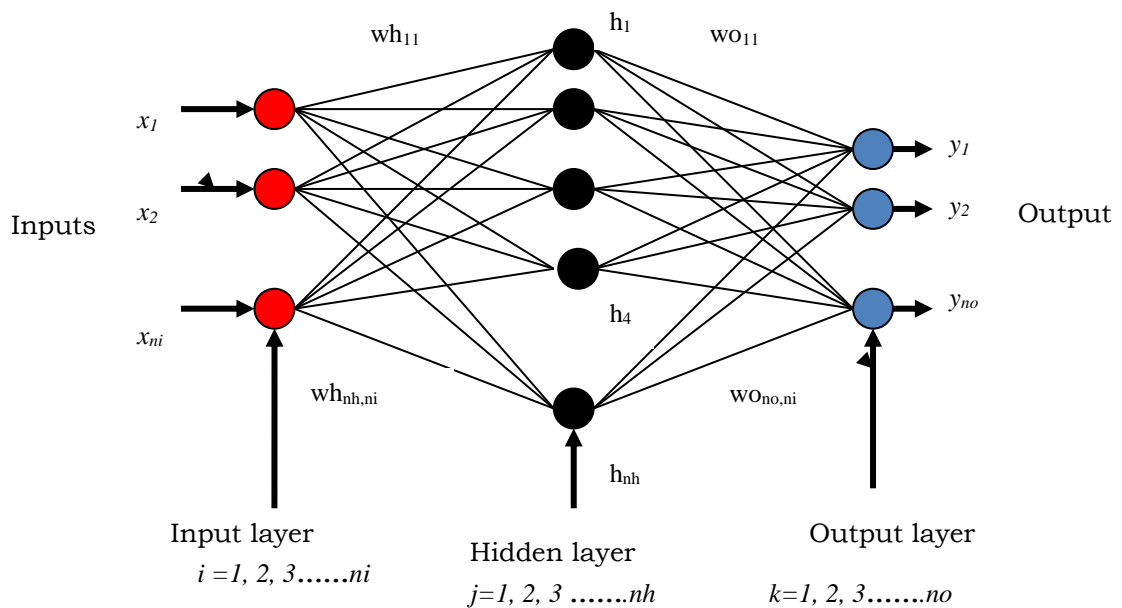


Fig. 3.3 Multilayer artificial neural network

3.3.3 Learning in multilayer feed-forward networks

Learning is a process of making a network to give a specific reaction to a particular input. In this process, free parameters, i.e. weights of the ANN are adapted by recurring presentations of the training samples. There are two types of learning, supervised and unsupervised. In supervised learning, a set of input pattern and its known output pattern is used to train the network. An external teacher finds the error between computed output and desired output during the training and this error is used to make adjustments in the weights to minimize the error. On the other hand, there is no teacher present to train the patterns in unsupervised learning. Here the system learns of its own detecting regularities in the input space through correlation, without direct feedback from the teacher. Supervised learning is used in present study. There are several algorithms for supervised learning.

The back propagation algorithm (Rumelhart and McClelland, 1986) is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals “forward”, and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The back propagation algorithm uses supervised learning, which means that examples of the inputs and outputs are provided to the network and then the error (difference between actual and expected results) is calculated. The idea of the back-propagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

In the back-propagation algorithm, the network weights are modified by minimizing the error between desired (targets) and calculated (predicted) outputs. This algorithm is based on the error-correction learning rule.

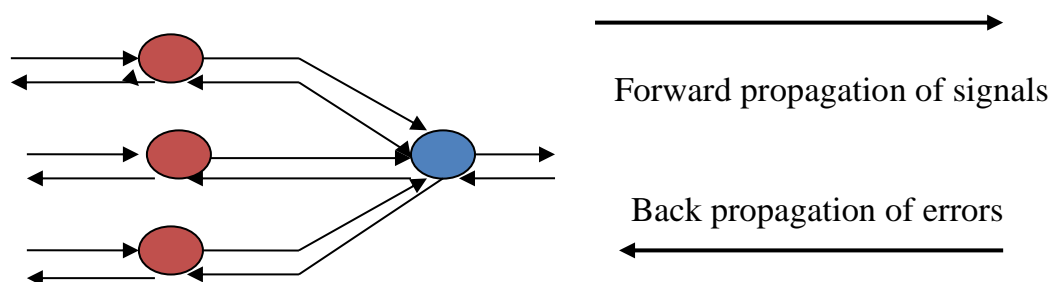


Fig. 3.4 Directions of signal flow in a multilayer ANN

Fig.3.4 shows the directions of signal flow and error propagation in a multilayer artificial neural network. Back-propagation is an iterative learning process in which all weight parameters are randomly initialized and then updated (in each iteration) through feed-forward calculations and back-propagation of errors.

3.4 Activation Functions

The activation function is the formulation used to define the output of a processing neuron. The contacts between the input layer and the middle or hidden layer comprise weights which are commonly determined through training the system. The hidden layer sums the weighted inputs and utilizes the transfer function to build an output value. The activation functions of a node express the output of that node given an input or set of inputs. The transfer function is a bond between the internal activation level of the neuron (called activation function) and the outputs. In this present study, the Sigmoid Axon and Tanh Axon activation functions were used.

3.4.1 Sigmoid axon

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

$$S(x) = \frac{1}{1+e^{-x}} \quad \dots(3.3)$$

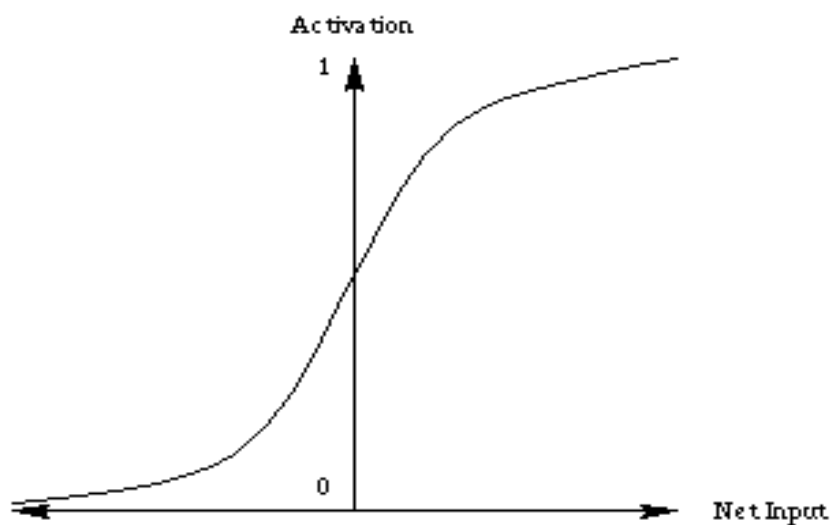


Fig. 3.5 Sigmoid activation function

3.4.2 Hyperbolic tangent (Tahn axon)

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

$$\text{Tanh}(x) = \frac{\sinh(x)}{\cosh(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad \dots (3.4)$$

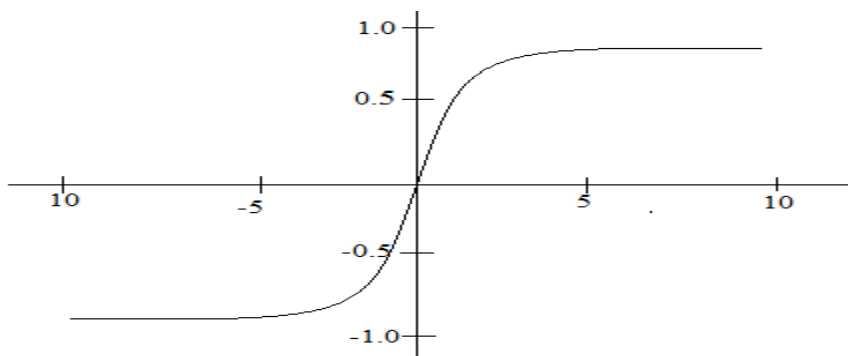


Fig 3.6 Hyperbolic tangent function

This function is well-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 3.6. The hyperbolic tangent function is similar to sigmoid function with its outputs between -1 to 1.

3.5 Learning Algorithms

A learning rule defines how exactly the network weights are being adjusted (updated) between successive training cycles (epochs). In addition, each layer has an associated learning rule and learning parameters. The number of processing element and learning parameters are entered in the corresponding fields. The learning rule is the means by which the correction term is specified. Once the particular rule is selected, the user must still specify how much correction should be applied to the weights, referred to as the learning rate. If the learning rate is too small, learning takes a long time. If it is set too high, the adaptation diverges and the weights are unusable. In this study, Levenberg-Marquardt learning algorithm was used.

3.5.1 Levenberg–Marquardt

The Levenberg–Marquardt algorithm (LM) was adopted for neural network training by **Hagan and Menhaj (1994)**. It is one of the most suitable higher-order adaptive algorithms known for minimizing the mean square error (MSE) of a neural network. It is a member of a class of learning algorithms called “pseudo second- order methods”. Standard gradient descent algorithms use only the local approximation of the slope of the performance surface (error vs. weights) to determine the best direction to move the weights for lowering the error. A key advantage of the LM approach is that it defaults to the gradient search when the local curvature of the performance surface deviates from a parabola, which may happen often in neural computing. To apply LM, the problem of training the MLP has to be formulated as a nonlinear optimization (Ham and Kostanic 2001). The main drawback of this algorithm is the computational complexity of calculating the matrix inversion with several thousand variables (Mukherjee and Routroy 2012).

$$W_{k+1} = W_k - (J_k^T J_k + \mu I)^{-1} J_k^T e \quad \dots (3.5)$$

where,

μ = Parameter changed during the training process.

If μ is 0 Algorithm works as LM method and for large values of μ algorithm works as steepest decent method.

3.6 ANN Architecture

A neural network is characterized by its architecture that present the pattern of connection between nodes. The architecture of an ANN is designed by weights between neurons, a transfer function the controls the generation of output in a neuron, and learning laws that define the relative importance of weights for input to a neuron. The architecture of ANN is classified into two types: single hidden layer and multi hidden layer ANN model.

Neurons in an Artificial Neural Networks are organized in sets called layers. The nodes in single layer are linked to those in the next, but not to those in the same layer. ANN can also be characterized based on the directions of information flow and processing. In a feed-forward network, the weighted connections feed activations only

in the forward directions from the input layer to output layer. A single hidden layer ANN consists of one input layer, one hidden layer and one output layer. Multi hidden layer ANN is one of the most extensively used classes of ANN. Individually such ANN comprises of an input layer, an output layer and one or more mediums and hidden layers.

3.7 Selection of Network Architecture

The utmost significant features of a layered neural network design is selecting the architecture (**Zurada, 1992**). The number of input nodes is basically determined by the dimension of the input vector to be generalized or related with a certain output feature. The dimension of the input vector resembles to the number of distinctive feature of the input pattern. The size of Hidden layer is the most imperative consideration when solving the genuine complications using multilayer feed-forward neural networks. The most prevalent and effective technique for choosing the suitable number and size of the hidden layer is trial and error method. A sum of networks with one or two hidden layers are trained with diverse combinations of hidden neurons and a network is chosen based on minimum Root Mean Square Error (RMSE) and Correlation Coefficient (r).

3.8 Gamma Test

Gamma Test (GT) is one of the best non-linear exhibiting tool whereby an appropriate input combination from input variables can be studied for modelling the output data and in addition building up a model in smooth manner. Gamma Test (GT) analyses the minimum square errors which are obtainable in continuous non-linear models and hidden data. Gamma Test has been used by hydrologists as a novel model to define the number of requisite models for training to build a smooth out model (**Moghaddammia et al., 2009**). In the present study different input models for daily rainfall and weekly rainfall with minimum gamma values were chosen using WinGamma software, for daily rainfall model the input combination with minimum gamma value were (dry bulb thermometer temperature, wet bulb thermometer temperature, maximum temperature, minimum temperature and wind speed). Whereas, for weekly rainfall model the input combination with minimum gamma value were (dry bulb thermometer temperature, wet bulb thermometer temperature, maximum temperature, minimum temperature and dew point).

For a set of n independent variables, there are 2^{n-1} evocative combinations as inputs to the model. Various techniques has been adopted in literature for best inputs selection to reduce trial and error drudgery for hydrological modelling, for instance, principal component analysis, forward selection and Gamma test are foremost (**Moghaddammia et al., 2008, 2009; Niu, 2013; Chang et al., 2014 and Dehghani, et al., 2014**). Present study utilizes the potential of Gamma test (GT) approach for selection of input combinations for rainfall prediction models.

Gamma test firstly described by **Agalbjörn et al. (1997), Koncar (1997)** and later on updated and modified by **Durrant (2001)**. For a given input/output data:

$$\{x_1(i), \dots, x_m(i), y_i\} = \{(x_i, y_i) \mid 1 \leq i \leq M\} \quad \dots (3.6)$$

where, the vectors $x = (x_1, \dots, x_m) \in \mathcal{R}^m$ contains the inputs and the corresponding scalar, y_i is the output, M is the number of data points, and m denotes the number of input variables.

The Gamma test algorithm constructs the $k^{\text{th}} (1 \leq k \leq p)$ nearest neighbor lists $x_{N[i,k]} (1 \leq i \leq M)$ of the input vectors $x_i (1 \leq i \leq M)$. Afterwards, Gamma test algorithm computes following parameters:

$$\delta_M(k) = \frac{1}{M} \sum_{i=1}^M |x_{N[i,k]} - x_i|^2 \quad (1 \leq k \leq p) \quad \dots (3.7)$$

where, $|\dots|$ is the Euclidean distance, and

$$\gamma_M(k) = \frac{1}{2M} \sum_{i=1}^M |y_{N[i,k]} - y_i|^2 \quad (1 \leq k \leq p) \quad \dots (3.8)$$

where, $y_{N[i,k]}$ is the associated with $x_{N[i,k]}$. The relationship between $\delta_M(k)$ and $\gamma_M(k) (1 \leq k \leq p)$ is approximately linear (**Evans and Jones, 2002**) for sufficiently small p . Therefore, regressing $\gamma_M(k)$ on $\delta_M(k) (1 \leq k \leq p)$ gives an estimate for the variance of the noise (σ^2) at intercept $\delta = 0$. This estimate is denoted by Γ .

A small Γ value, close to zero is desirable for a smooth model (**Jones, 2004**). Another parameter of Gamma test, V_{ratio} (variance of the noise to the variance of the output) is computed as:

$$V_{ratio} = \frac{\Gamma}{\text{Var}(y)} \quad \dots (3.9)$$

A V_{ratio} close to 1 (i.e. $V_{ratio} \approx 1$) state that the described model is not smooth. Thus a desirable value of V_{ratio} is close to 0 ($V_{ratio} \approx 0$) for a smooth model. The GT statistics can be performed on WinGamma software.

3.9 Development of ANN Models

In the present study two different combinations were used with one learning algorithm and two different activation functions in multilayer perceptron (MLP) of artificial neural networks. These combinations of learning algorithm and transfer functions were used to choose the best ANN model on the basis of performance indices of the models. There are total 5437 data points for daily rainfall model out of which 3086 data points are used for training of the daily rainfall model and remaining 1631 data points are used for testing of the daily rainfall model. Similarly, there are total 778 data points for weekly rainfall model out of which 545 data points are used for training of the weekly rainfall model and remaining 233 data points are used for testing of the weekly rainfall model. The list of different combinations of learning algorithm and activation functions for daily and weekly rainfall model are shows in Table 3.1.

Table 3.1 Different combinations of learning algorithm and activation functions for daily and weekly rainfall model

S. No.	Learning algorithm	Activation function
1	Levenberg-Marquardt	Tanh Axon
2	Levenberg-Marquardt	Sigmoid Axon

3.10 Model Performance Evaluation

Performance evaluation of developed models were done on the basis of qualitative and quantitative assessments. Qualitative assessment were be done by comparing the predicted daily and weekly rainfall with observed ones in graphical forms. Quantitative prediction performance of the models were evaluated in regards to several statistical measures such as Root Mean Square Error (RMSE), Correlation Coefficient (r), Coefficient of Efficiency (CE), Percentage BIAS and Integral Square Error (ISE).

3.10.1 Root mean square error (RMSE)

The root mean square error is used to define the estimate precision of the model. It equates difference between estimated and observed values and acquires the information on short term performance. It creates positive values ranging from 0 to ∞ by squaring the errors. The root mean square error is zero for best fit and bigger values shows greater deviation between estimated and observed values. The root mean square error (RMSE) between estimated and observed values is calculated using the following relationship:

$$RMSE = \sqrt{\frac{\sum(Q_o - Q_p)^2}{n}} \quad \dots (3.10)$$

Where, Q_p =predicted rainfall,

Q_o =observed rainfall

3.10.2 Correlation coefficient (r)

The correlation coefficient (r) is an indicator of degree of closeness between observed and estimated values and offers the level of variance described between observed and estimated. If observed and estimated values are totally free, then the value of correlation coefficient (r) will be zero. The correlation coefficient is calculated using the following equation:

$$r = \left[\frac{\sum\{(Q_o - \bar{Q}_o)(Q_p - \bar{Q}_p)\}}{\sqrt{\sum(Q_o - \bar{Q}_o)^2} \sqrt{\sum(Q_p - \bar{Q}_p)^2}} \right] \quad \dots (3.11)$$

Where,

Q_p = predicted rainfall,

Q_o = observed rainfall,

\bar{Q}_o = average of the observed rainfall

\bar{Q}_p = average of predicted

3.10.3 Coefficient of efficiency (CE)

The coefficient of efficiency was developed by Nash and Sutcliffe in 1970. It provides the amounts of variance of the observation for model and used very frequently in hydrology. Nash-Sutcliffe coefficient of efficiency has range between $-\infty$ to 1. The

coefficient of efficiency is 1 for impeccable match between observed and forecast values. Similarly, coefficient of efficiency equal to zero indicate that the model estimates are equal to mean of observed data series. The coefficient of efficiency is determined by using the following equation:

$$CE = 1 - \frac{\sum(Q_o - Q_p)^2}{\sum(Q_o - \bar{Q}_o)^2} \quad \dots (3.12)$$

Where,

Q_P =predicted rainfall,

Q_0 =observed rainfall

\bar{Q}_o = average of the observed rainfall

3.10.4 Percentage BIAS

It measures the average tendency of simulated values to be larger smaller the observed ones. The optimal value of PBIAS is zero, with low-magnitude values indicating accurate model simulation.

$$PBIAS (\%) = \frac{\sum(Q_p - Q_o)}{\sum Q_o} \times 100 \quad \dots (3.13)$$

Where,

Q_P = predicted rainfall

Q_o = observed rainfall

3.10.5 Integral Square error (ISE)

Integral squared error (ISE) is a measure of system performance and is calculated by following equation:

$$ISE = \frac{\sqrt{\sum(Q_p - Q_o)^2}}{\sum Q_o} \times 100 \quad \dots (3.14)$$

Where,

Q_P =predicted rainfall

Q_o =observed rainfall



*Results
and
Discussion*

This chapter deals with the development and applications of artificial neural network (ANNs) models for daily and weekly rainfall prediction of Nainital station, Uttarakhand. Out of various meteorological variables best input combinations were selected based on Gamma test for both daily and weekly rainfall prediction models. The daily meteorological data i.e. wet bulb thermometer temperature (Wb), dry bulb thermometer temperature (Db), maximum temperature (Tmax), minimum temperature (Tmin) in °C and wind speed (Ws) in Km/hr, were taken as inputs and rainfall (Rd) in mm was considered as output for daily rainfall prediction models. Whereas, wet bulb thermometer temperature (Wb), dry bulb thermometer temperature (Db), maximum temperature (Tmax), minimum temperature (Tmin) and dew point (Dpt) were taken as inputs and Rainfall (Rw) was considered as output for weekly rainfall prediction models. For both daily and weekly rainfall prediction models 70% data were used for calibration (training) period and remaining 30% data were used for validation (testing) period. The total 14 year 8 months (2003-2018) daily meteorological data were taken for daily rainfall prediction models, out of which 3086 data points (2003-2013) were used for training period and remaining 1631 data points (2014-2018) were used for testing period respectively. Similarly, for weekly rainfall prediction models the total number of weeks for 14 year 8 months were found to be 778 weeks, out of which 545 data points (2003-2013) were used for training period and remaining 233 data from (2014-2018) were used for testing periods respectively.

The Performance of the developed models were evaluated qualitatively and quantitatively by visual observations and quantitatively employing various statistical indices viz. correlation coefficient (r), coefficient of efficiency (CE), root mean square error (RMSE), percent bias (PBIAS) and Integral Square Error (ISE) for modelling of daily and weekly rainfall models.

4.1 Selection of Inputs for Rainfall Prediction Model by Gamma Test

In the present study Gamma test was used for the identification of input parameters for daily and weekly rainfall prediction models. With the help of Gamma approach it is easy to remove those input parameters which has irrelevant role to output and which

increase the complications of model and leads to overfitting of models. Number of inputs were designated on the basis of gamma value (γ), standard error and V-ratio.

Various combinations of input data were explored to assess their effect on the daily and weekly rainfall prediction models. Based on the comparison of Gamma values, standard error and V-ratio for different combinations, the combination achieving the least values of gamma, standard error and V-ratio were selected as the input parameters and rest were omitted. After the selection of best input combination, the daily and weekly rainfall prediction models were developed by artificial neural network approach.

4.1.1 Selection of input combinations for daily rainfall prediction models

Gamma test was conducted for the selection of input parameters for daily rainfall prediction models of Nainital station. Seven different meteorological parameters i.e. dry bulb thermometer temperature (Db), wet bulb thermometer speed (Ws) and dew point (Dpt) were taken into consideration with different combinations from which the combinations giving the least gamma values, standard error and V-ratio were selected as the input parameter. The various combinations for selecting the daily input parameters using gamma test are shown in Table 4.1. Here the mask value 1 represent selection of parameter whereas, 0 value represent omission of parameter in sequential order. From table 4.1 it is clear that the combination of five meteorological parameters i.e. (Db, Wb, Tmax, Tmin and Ws) have least values of Gamma, standard error and V- ratio as 0.155, 0.0124 and 0.621 respectively. Therefore, meteorological parameters Db, Wb, Tmax, Tmin and Ws were selected as inputs for ANN based daily rainfall prediction models.

4.1.2 Selection of input combinations for weekly rainfall prediction models

Similarly for weekly data Gamma test was conducted for the selection of input parameters for weekly rainfall prediction models of Nainital station. Seven different meteorological parameters i.e. dry bulb thermometer temperature (Db), wet bulb thermometer temperature (Wb), maximum temperature (Tmax), minimum temperature (Tmin), relative humidity (Rh), wind speed (Ws) and dew point (Dpt) were taken under consideration with different combinations from which the combination having the least gamma values, standard error and V-ratio was selected as the input parameter.

Table 4.1 Selection of best input parameters using Gamma Test for daily rainfall prediction models for Nainital station

Sr.no	Output	Input	Mask	Gamma	SE	V-ratio
1	Rd	Db,Wb,Tmax,Tmin,Rh,Ws,dpt	1111111	0.1754	0.0098	0.7016
2	Rd	Db,Wb,Tmax,Tmin,Rh,dpt	1111101	0.1802	0.0075	0.7208
3	Rd	Db,Wb,Tmax,Tmin,Ws,dpt	1111011	0.1628	0.0086	0.6513
4	Rd	Db,Wb,Tmax,Rh,Ws,dpt	1110111	0.1711	0.0080	0.6846
5	Rd	Db,Wb,Tmin,Rh,Ws,dpt	1101111	0.1790	0.0123	0.7162
6	Rd	Db,Tmax,Tmin,Rh,Ws,dpt	1011111	0.1825	0.0098	0.7298
7	Rd	Wb,Tmax,Tmin,Rh,Ws,dpt	0111111	0.1687	0.0078	0.6749
8	Rd	Db,Wb,Tmax,Tmin,Rh,Ws	1111110	0.1804	0.0099	0.7215
9	Rd	Tmax,Tmin,rh,ws,dpt	0011111	0.1691	0.0107	0.6765
10	Rd	Db,Wb,Rh,Ws,dpt	1100111	0.1590	0.0156	0.6361
11	Rd	Db,Wb,Tmax,Tmin,dpt	1111001	0.1788	0.0124	0.7151
12	Rd	Db,Wb,Tmax,Tmin,rh	1111100	0.1804	0.0065	0.7215
13	Rd	Wb,Tmax,Tmin,Rh,Ws	0111110	0.1771	0.0100	0.7085
14	Rd	Db,Tmin,Rh,Ws,dpt	1001111	0.1729	0.0115	0.6914
15	Rd	Wb,Tmin,Rh,Ws,dpt	0101111	0.1814	0.0098	0.7256
16	Rd	Wb,Tmax,Rh,Ws,dpt	0110111	0.1750	0.0100	0.7009
17	Rd	Wb,Tmax,Tmin,Ws,dpt	0111011	0.1829	0.0057	0.7315
18	Rd	Wb,Tmax,Tmin,Rh,dpt	0111101	0.1702	0.0091	0.6809
19	Rd	Db,Tmax,Rh,Ws,dpt	1010111	0.1638	0.0096	0.6553
20	Rd	Db,Tmax,Tmin,Ws,dpt	1011011	0.1673	0.0086	0.6691
21	Rd	Db,Wb,Tmax,Tmin,Ws	1111010	0.1553	0.0124	0.6212

Table 4.2 Selection of best input parameters using Gamma Test for weekly rainfall prediction models for Nainital station

Sr.no	Output	Input	Mask	Gamma	SE	V-ratio
1	Rw	Db,Wb,Tmax,Tmin,Rh,Ws,dpt	1111111	0.1145	0.0110	0.4579
2	Rw	Wb,Tmax,Tmin,Rh,Ws,dpt	0111111	0.1161	0.0057	0.4643
3	Rw	Db,Tmax,Tmin,Rh,Ws,dpt	1011111	0.1088	0.0138	0.4351
4	Rw	Db,Wb,Tmin,Rh,Ws,dpt	1101111	0.1162	0.0097	0.4649
5	Rw	Db,Wb,Tmax,Rh,Ws,dpt	1110111	0.1212	0.0101	0.4847
6	Rw	Db,Wb,Tmax,Tmin,Ws,dpt	1111011	0.1202	0.0127	0.4808
7	Rw	Db,Wb,Tmax,Tmin,Rh,dpt	1111101	0.1189	0.0127	0.4757
8	Rw	Db,Wb,Tmax,Tmin,Rh,Ws	1111110	0.1181	0.0171	0.4725
9	Rw	Tmax,Tmin,Rh,Ws,dpt	0011111	0.1104	0.0114	0.4417
10	Rw	Db,Wb,Rh,Ws,dpt	1100111	0.1212	0.0100	0.4847
11	Rw	Db,Wb,Tmax,Tmin,dpt	1111001	0.1058	0.0088	0.4232
12	Rw	Db,Wb,Tmax,Tmin,Ws	1111010	0.1238	0.0116	0.4954
13	Rw	Db,Wb,Tmax,Tmin,Rh	1111100	0.1183	0.0124	0.4733
14	Rw	Wb,Tmin,Rh,Ws,dpt	0101111	0.1208	0.0104	0.4832
15	Rw	Db,Tmax,Rh,Ws,dpt	1010111	0.1083	0.0136	0.4331
16	Rw	Db,Wb,Tmin,Ws,dpt	1101011	0.1323	0.0118	0.5290
17	Rw	Db,Wb,Tmax,Rh,dpt	1110101	0.1246	0.0144	0.4986
18	Rw	Db,Wb,Tmin,Rh,Ws	1101110	0.1141	0.0106	0.4562
19	Rw	Db,Wb,Tmax,Rh,Ws	1110110	0.1167	0.0143	0.4670
20	Rw	Wb,Tmax,Tmin,Rh,Ws	0111110	0.1148	0.0078	0.4593
21	Rw	Db,Tmax,Tmin,Rh,Ws	1011110	0.1132	0.0077	0.4527

The various combinations of weekly input parameters with gamma test are shown in Table 4.2. From Table 4.2 it is clear that the combination of five meteorological parameters i.e. (Db, Wb, Tmax, Tmin and Dpt) have least values of Gamma, standard error and V- ratio as 0.1058, 0.00881 and 0.4232 respectively. So meteorological parameters Db, Wb, Tmax, Tmin and Ws were selected as inputs for ANN based daily rainfall prediction models.

It is clear from Table 4.1 and table 4.2 that the meteorological parameters (Db, Wb, Tmax, Tmin and Ws) are significant inputs for daily rainfall prediction whereas, meteorological parameters i.e. (Db,Wb,Tmax,Tmin and Dpt) are significant inputs for weekly rainfall prediction. In case of weekly rainfall prediction wind speed (Ws) is replaced by dew point temperature (Dpt) and all other parameters are same. It may be due to that wind speed is highly variable in hilly terrain and for weekly data the averaging eliminate the dependency of it to dependent variable.

4.2 Development of Artificial Neural Network Based Rainfall Prediction Models

In the present study, Multilayer Perceptron (MLP) neural network was used to train daily and weekly rainfall prediction models of Nainital station by Levenberg-Marquardt learning rule with Sigmoid axon and Tanh axon transfer functions. Table 4.3 and 4.4 shows the various models with different combinations of inputs, activation functions for daily and weekly rainfall prediction respectively. The suitable architecture assortment has been one of utmost necessary task for multilayer perceptron neural network and the number of hidden layer in architecture has been the topmost concern while solving the genuine complications based on the Multilayer Perceptron neural network models. The precise and easy way of selecting the correct number of hidden layers was trial and error method. Also, the processing elements (neurons) in the architecture of ANN models were generally selected by means of the trial and error method. In the present study, Models were trained using the processing elements (neurons) with different neurons for different hidden layers and the threshold value for error stopping criteria of mean square was chosen as 0.001 for both daily and weekly rainfall prediction models.

Table 4.3 Daily rainfall prediction ANN Models for Nainital station

Models	Input parameters	Transfer Function	Learning Rules	Hidden Layers
MD-1	Db,Wb,Tmax,Tmin,Ws	Tahn Axon	Levenberg-Marquardt	Single and double
MD-2	Db,Wb,Tmax,Tmin,Ws	Sigmoid Axon	Levenberg-Marquardt	Single and double

Table 4.4 weekly rainfall prediction ANN models for Nainital station

Models	Input parameters	Transfer Function	Learning Rules	Hidden Layers
MW-1	Db,Wb,Tmax,Tmin,Dpt	Tahn Axon	Levenberg-Marquardt	Single and double
MW-2	Db,Wb,Tmax,Tmin,Dpt	Sigmoid Axon	Levenberg-Marquardt	Single and double

4.3 Performance Assessment of the Developed ANN Models

The visual observations and quantitative assessment of the developed daily and weekly rainfall prediction models were executed to evaluate the goodness of fit between observed and predicted values of daily and weekly rainfall. The quantitative assessment of the daily and weekly rainfall prediction models were executed based on different statistical indices viz., root mean square error (RMSE), correlation coefficient (r), coefficient of Efficiency (CE), Percent bias (PBIAS) and Integral square error (ISE). These indices were calculated using Equation 3.10 to Equation 3.14 respectively as described in Chapter 3. Quantitative performances in term of statistical indices of the

4.3.1 Performance assessment of Artificial Neural Networks (ANN) based daily rainfall prediction Models

The ANN models are developed by using daily meteorological data of dry bulb thermometer temperature (Db), wet bulb thermometer temperature (Wb), maximum temperature (Tmax), minimum temperature (Tmin) and d speed (Ws), as a set of inputs and daily rainfall (Rd) as the output for the network. In the present study, for daily

rainfall prediction modelling one learning algorithms (i.e. Levenberg–Marquardt) along with the two activation functions (i.e. Sigmoid axon and Tanh axon) are used for identifying the best ANN model. Various neurons with different hidden layers are used for different combinations and the best-suited networks are selected based on the minimum values of root mean square error (RMSE) and maximum values coefficient of efficiency (CE). The different combinations of learning algorithm and activation functions for daily rainfall prediction models of Nainital station are discussed as follows:

4.3.1.1 Performance assessment of Levenberg-Marquardt and Tahn Axon based daily rainfall prediction model

Levenberg-Marquardt (LM) algorithm was used to train the neural network for the rainfall prediction with Tanh axon activation function. Various networks of single and two hidden layers were trained for a maximum iteration of 2000, with different combination of hidden neurons and the best suited network was selected.

The performance assessment of the Levenberg-Marquardt and Tahn axon daily rainfall prediction model was assessed by comparing the ordinates of daily observed and predicted values of rainfall. The observed and predicted values of daily rainfall for training and testing period are shown in Fig 4.1 and Fig 4.2 and scatter plots are shown in Fig 4.3 and Fig 4.4 respectively. It is observed from Figures that there is a close agreement between observed and predicted daily rainfall and overall shape of the plot of predicted daily rainfall is similar to that of the observed daily rainfall. period found to be 9.97 and 9.39 respectively for model MD-10. The value of r for testing and training period for model MD-10 found to be 0.87 to 0.86 respectively. Based on RMSE and r the model MD-10 outperformed. For model MD-10 the value of CE were found to be 0.75 and 0.74 during training and testing period whereas values of PBIAS were 7.37 to 15.20 respectively for training and testing period. The value of ISE was 2.03 for training period and 4.17 during testing period for the model MD-10. The lower values of RMSE, PBIAS, ISE and higher values of correlation coefficient in both training and testing periods shows that model MD-10 is best suited for ANN model with Levenberg-Marquardt learning rule and Tahn axon activation function.

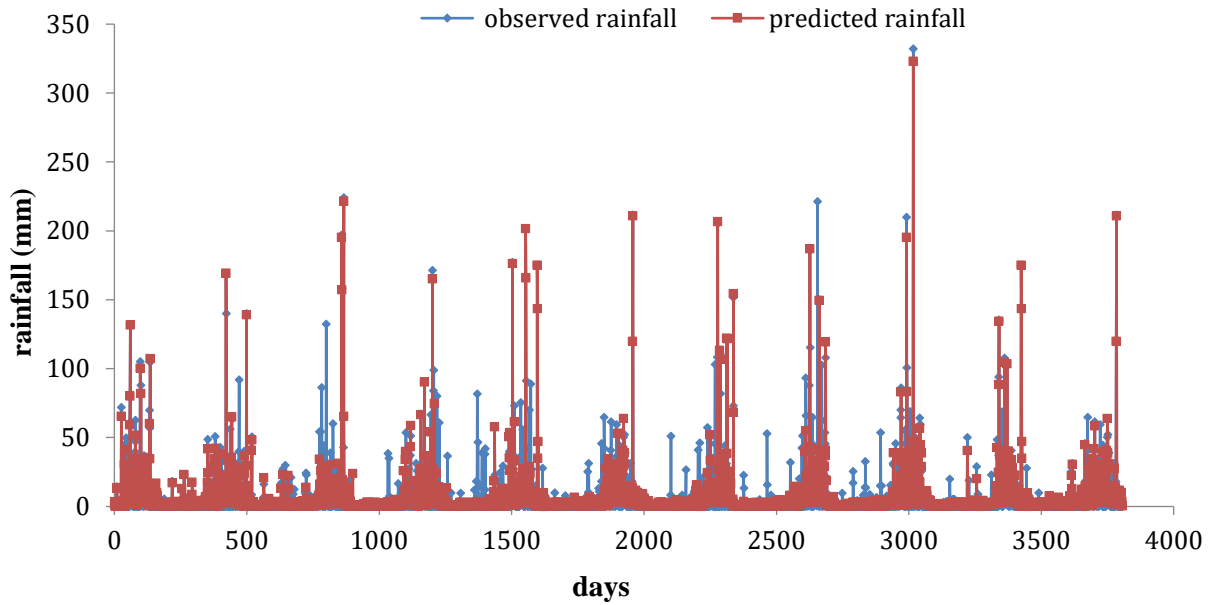


Fig. 4.1 observed and predicted daily rainfall for Levenberg-Marquardt and Tahn Axon ANN model MD-10 for the training period

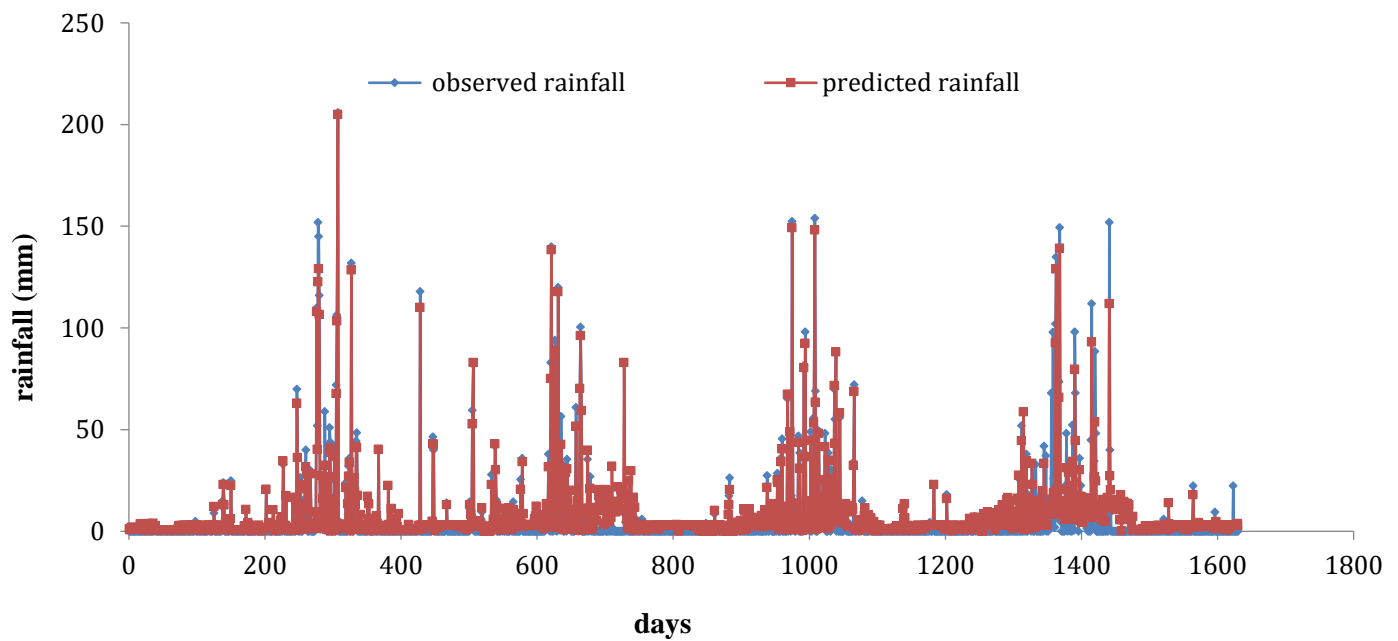


Fig.4.2 observed and predicted daily rainfall for Levenberg-Marquardt and Tahn Axon ANN model MD-10 for the testing period

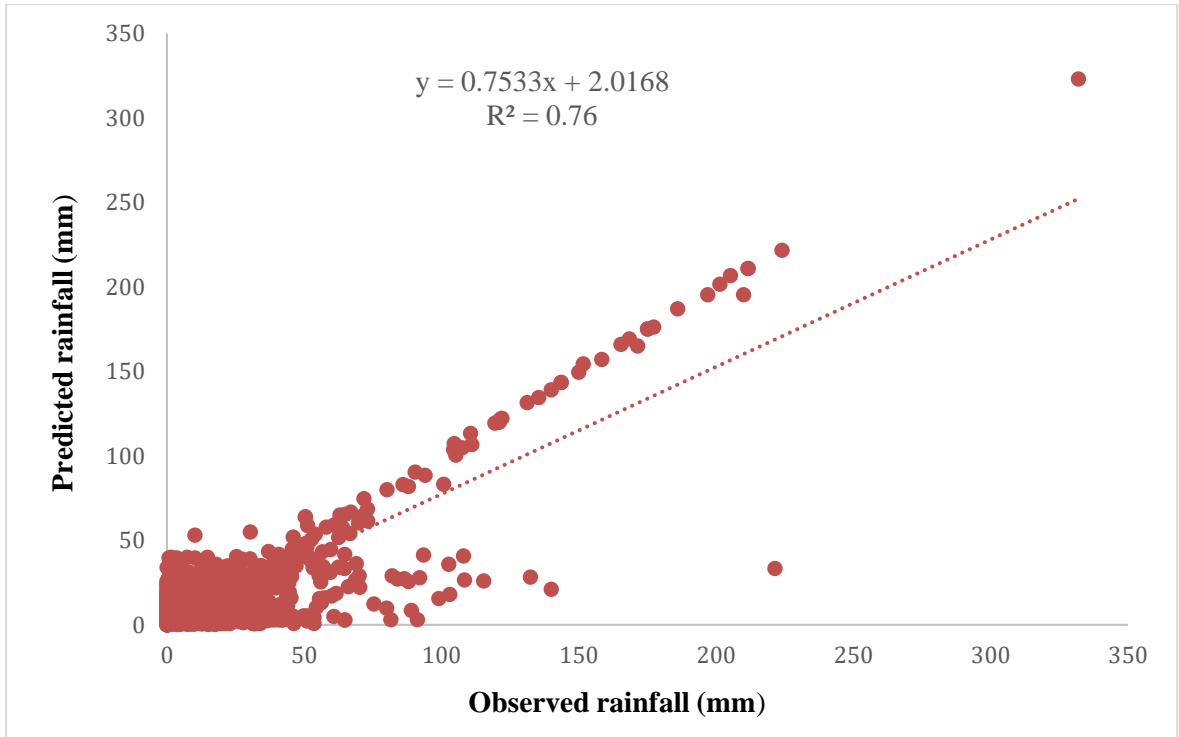


Fig.4.3 Scatter diagram of daily rainfall prediction by Levenberg-Marquardt and Tahn Axon ANN model MD-10 for the training period

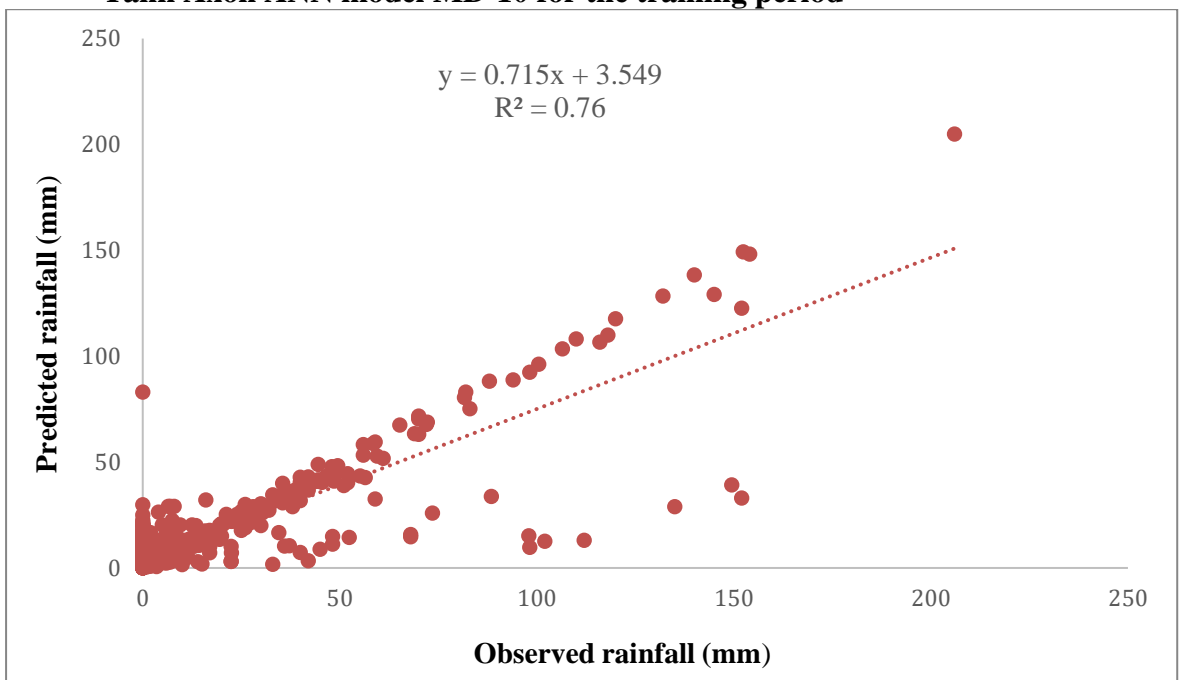


Fig.4.4 Scatter diagram of daily rainfall prediction by Levenberg-Marquardt and Tahn Axon ANN model MD-10 for the testing period

The quantitative performance assessment of this model is assessed by statistical and hydrologic indices as given in Table 4.5. The value of RMSE for training and testing

Table 4.5 Comparison of various ANN models for the Levenberg-Marquardt and Tanh Axon combination during training and testing periods for daily rainfall prediction models

Model	Architecture	Training					Testing				
		R	RMSE	CE	PBIAS	ISE	r	RMSE	CE	PBIAS	ISE
MD-1	5-5-1	0.63	15.76	0.39	10.37	4.24	0.61	15.06	0.33	37.85	6.69
MD-2	5-10-1	0.71	14.19	0.51	4.49	1.26	0.71	13.32	0.48	32.71	5.92
MD-3	5-12-1	0.75	13.36	0.56	4.27	1.18	0.75	12.37	0.55	25.52	5.5
MD-4	5-15-1	0.76	13.05	0.58	10.66	4.74	0.75	12.47	0.54	26.13	5.54
MD-5	5-18-1	0.78	12.63	0.61	8.37	2.35	0.76	12.42	0.54	24.56	5.52
MD-6	5-20-1	0.79	12.39	0.62	12.69	5.05	0.77	18.87	0.58	24.15	5.27
MD-7	5-3-3-1	0.73	13.79	0.54	7.96	2.10	0.69	13.46	0.47	25.70	5.98
MD-8	5-4-4-1	0.78	12.71	0.6	5.45	1.85	0.74	12.44	0.54	20.34	5.53
MD-9	5-7-7-1	0.81	11.91	0.65	4.47	1.64	0.81	10.83	0.65	16.84	4.81
MD-10	5-8-8-1	0.87	9.97	0.75	7.37	2.03	0.86	9.39	0.74	15.20	4.17
MD-11	5-10-10-1	0.86	10.13	0.75	3.04	1.13	0.82	10.91	0.73	15.67	4.85

4.3.1.2 Performance assessment of Levenberg-Marquardt and Sigmoid Axon based daily rainfall prediction model

Levenberg-Marquardt (LM) algorithm is used to train the neural network for the rainfall prediction with Sigmoid activation function. Various networks of single and two hidden layers were trained for a maximum iteration of 2000, with different combination of hidden neurons and the best suited network was selected. The performance assessment of the Levenberg-Marquardt and Sigmoid axon daily rainfall prediction model is assessed by comparing the ordinates of daily observed and predicted values. The observed and predicted values of daily rainfall for training and testing period are shown in Fig. 4.5 and Fig. 4.6 and scatter plots are shown in Fig 4.7 and Fig 4.8 respectively. It is observed from Figures that there is a close agreement between observed and predicted daily rainfall and overall shape of the plot of predicted daily rainfall is similar to that of the observed daily rainfall.

The quantitative performance assessment of this model is assessed by the use of various statistical and hydrologic indices viz. root mean square error, coefficient of efficiency, correlation coefficient, Percentage BIAS and integral square error, as shown in Table 4.6. The value of RMSE for training and testing period found to be 9.18 and 10.57 respectively for model MD-11. The value of r for testing and training period for model MD-10 found to be 0.89 to 0.86 respectively. Based on RMSE and r the model MD-11 outperformed. For model MD-11 the value of CE were found to be 0.79 and 0.73 during training and testing period whereas values of PBIAS were 1.83 to 16.83 respectively for training and testing period. The value of ISE was 1.12 for training period and 4.70 during testing period for the model MD-11. The lower values of RMSE, PBIAS, ISE and higher values of correlation coefficient in both training and testing periods shows that model MD-11 is best suited for ANN model with Levenberg-Marquardt learning rule and Sigmoid activation function.

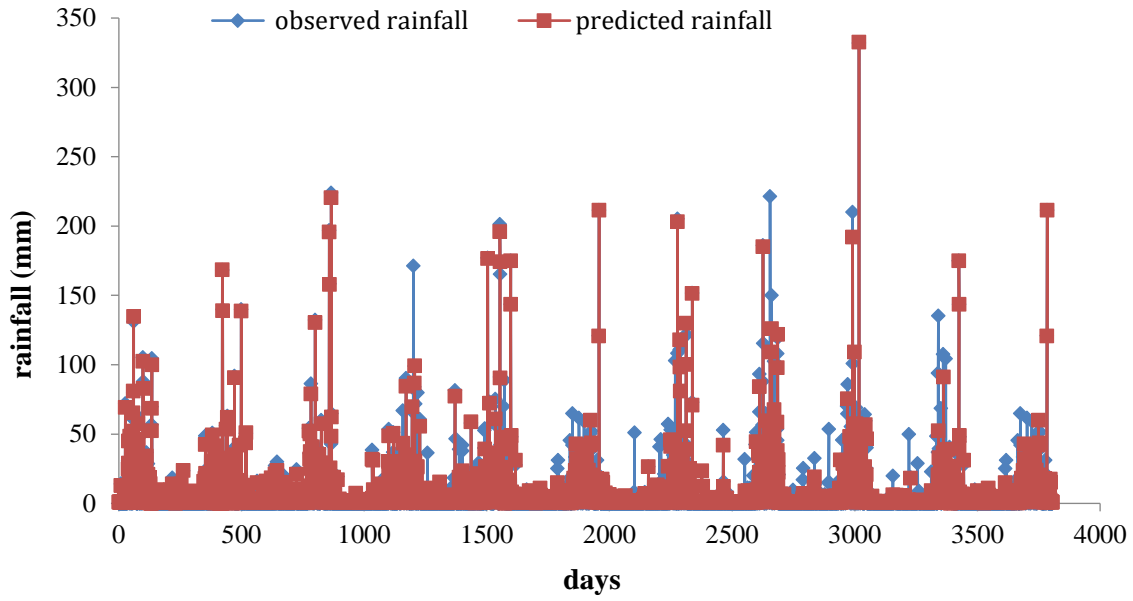


Fig.4.5 observed and predicted daily rainfall for Levenberg-Marquardt and Sigmoid Axon ANN model MD-11 for the training period

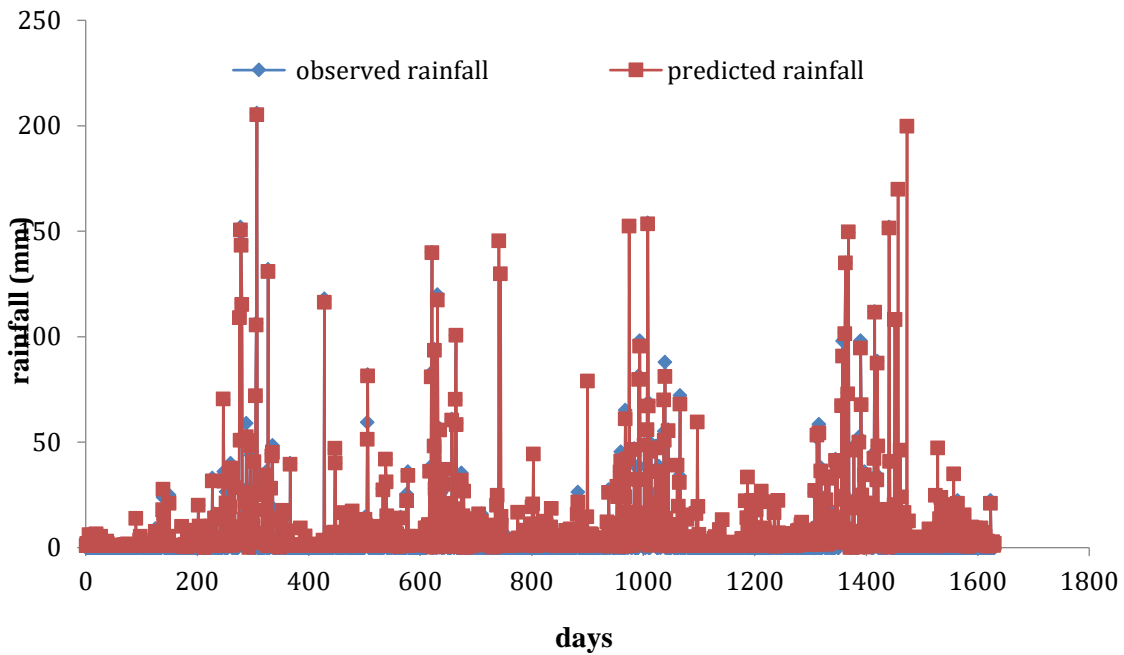


Fig.4.6 observed and predicted daily rainfall for Levenberg-Marquardt and Sigmoid Axon ANN model MD-11 for the testing period

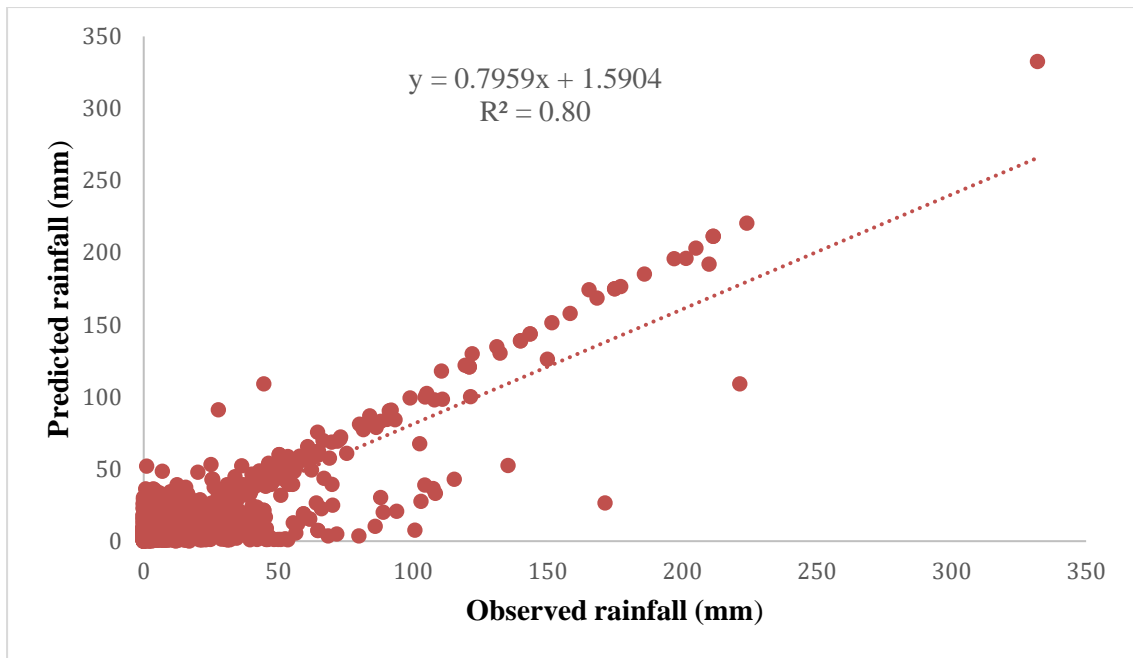


Fig.4.7 Scatter diagram of daily rainfall for Levenberg-Marquardt and Sigmoid Axon ANN model MD-11 for the training period

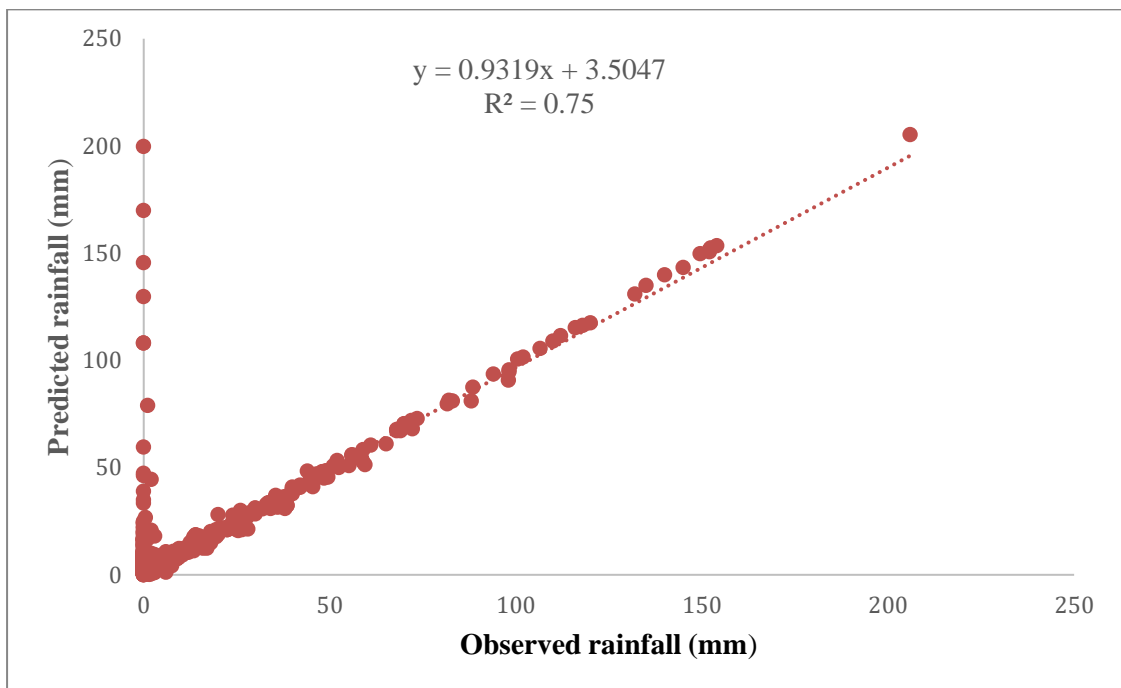


Fig.4.8 Scatter diagram of daily rainfall for Levenberg-Marquardt and Sigmoid Axon ANN model MD-11 for the testing period

Table 4.6 Comparison of various ANN models for the Levenberg-Marquardt and Sigmoid Axon combination during training and testing periods for daily rainfall prediction models

Model	Architecture	Training					Testing				
		R	RMSE	CE	PBIAS	ISE	r	RMSE	CE	PBIAS	ISE
MD-1	5-5-1	0.64	15.47	0.42	20.87	5.17	0.61	14.95	0.34	34.06	6.6
MD-2	5-10-1	0.72	13.96	0.52	1.27	1.06	0.68	13.64	0.46	30.94	6.1
MD-3	5-14-1	0.75	13.36	0.56	4.94	1.35	0.75	12.77	0.54	26.08	5.7
MD-4	5-15-1	0.77	13.44	0.56	23.04	5.25	0.73	15.80	0.52	39.52	7.0
MD-5	5-18-1	0.79	12.46	0.62	7.35	2.35	0.79	12.59	0.59	28.34	5.6
MD-6	5-20-1	0.78	12.59	0.61	7.54	2.39	0.76	12.42	0.56	23.65	5.5
MD-7	5-4-4-1	0.74	13.45	0.56	3.96	1.16	0.68	13.58	0.46	30.36	6.0
MD-8	5-7-7-1	0.84	10.84	0.71	7.29	2.23	0.80	12.55	0.64	25.3	5.6
MD-9	5-8-8-1	0.87	10.01	0.75	5.38	1.92	0.82	11.00	0.67	16.86	4.9
MD-10	5-9-9-1	0.82	11.68	0.66	7.56	2.59	0.79	11.32	0.62	17.40	5.03
MD-11	5-10-10-1	0.89	9.18	0.79	1.83	1.12	0.86	10.57	0.73	16.83	4.7

4.3.2 Performance assessment of Artificial Neural Networks (ANN) based weekly rainfall prediction models

The prediction of weekly rainfall has been carried out using weekly data of dry bulb thermometer temperature (Wb), wet bulb thermometer temperature (Db), maximum temperature (Tmax), minimum temperature (Tmin) and dew point (Dpt), as a set of inputs and weekly rainfall (Rw) as the output of the ANN model.

In the present study, for weekly rainfall prediction modelling one learning algorithms (i.e. Levenberg–Marquardt) along with the two activation functions (i.e. Sigmoid axon and Tanh axon) are used for identifying the best ANN model. Various neurons with different hidden layers are used for different combinations and the best-suited networks are selected based on the minimum values of root mean square error (RMSE) and maximum values coefficient of efficiency (CE). The different combinations of learning algorithm and activation functions for weekly rainfall prediction models of Nainital station are discussed as follows:

4.3.2.1 Performance assessment of Levenberg-Marquardt and Tahn Axon based weekly rainfall prediction model

In this approach, Levenberg-Marquardt learning rule and activation function Tanh axon are used for prediction of weekly rainfall ANN models. Different networks of hidden layers with different neurons sizes are trained by trial and error method. The performance assessment of the Levenberg-Marquardt and Tahn axon weekly rainfall prediction model is assessed by comparing the ordinates of observed and predicted weekly values. The observed and predicted values of weekly rainfall for training and testing period are shown in Fig 4.9 and Fig.4.10 and scatter plots are shown in Fig 4.11 and Fig 4.12 respectively. It is observed from Figures that there is a close agreement between observed and predicted weekly rainfall and overall shape of the plot of predicted weekly rainfall is similar to that of the observed weekly rainfall. The quantitative performance assessment of this model is assessed by the use of various statistical and hydrologic indices viz. root mean square error, coefficient of efficiency, correlation coefficient, Percentage BIAS and integral square error as shown in Table 4.7.

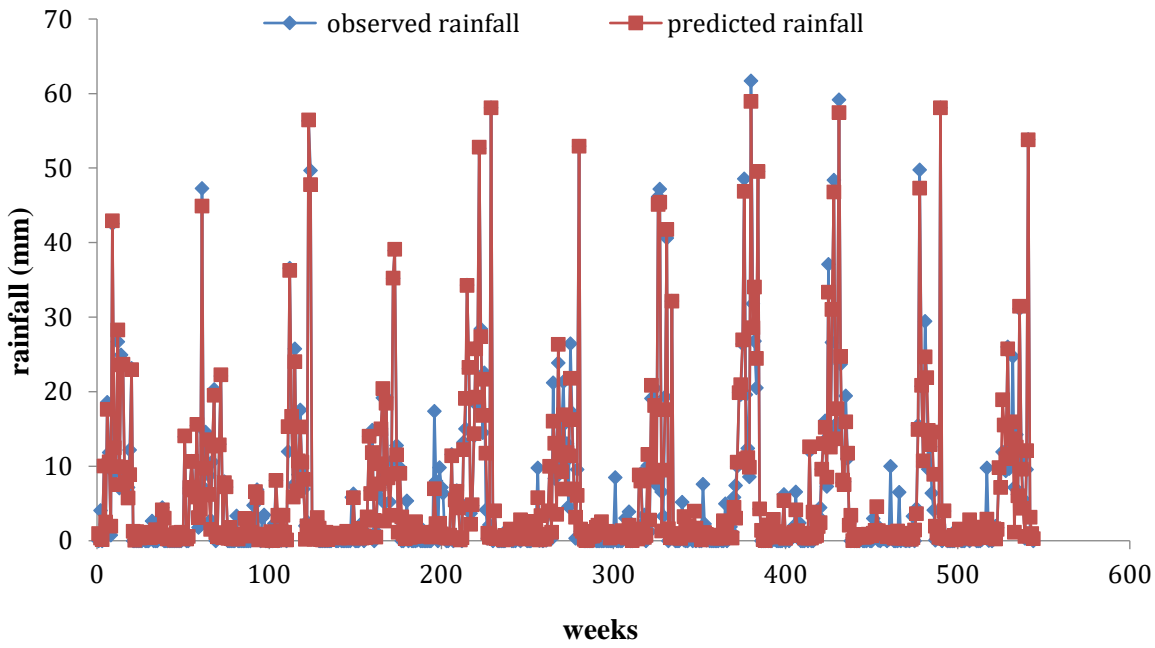


Fig.4.9 observed and predicted weekly rainfall for Levenberg-Marquardt and Tahn Axon ANN model MW-13 of Nainital station for the training period

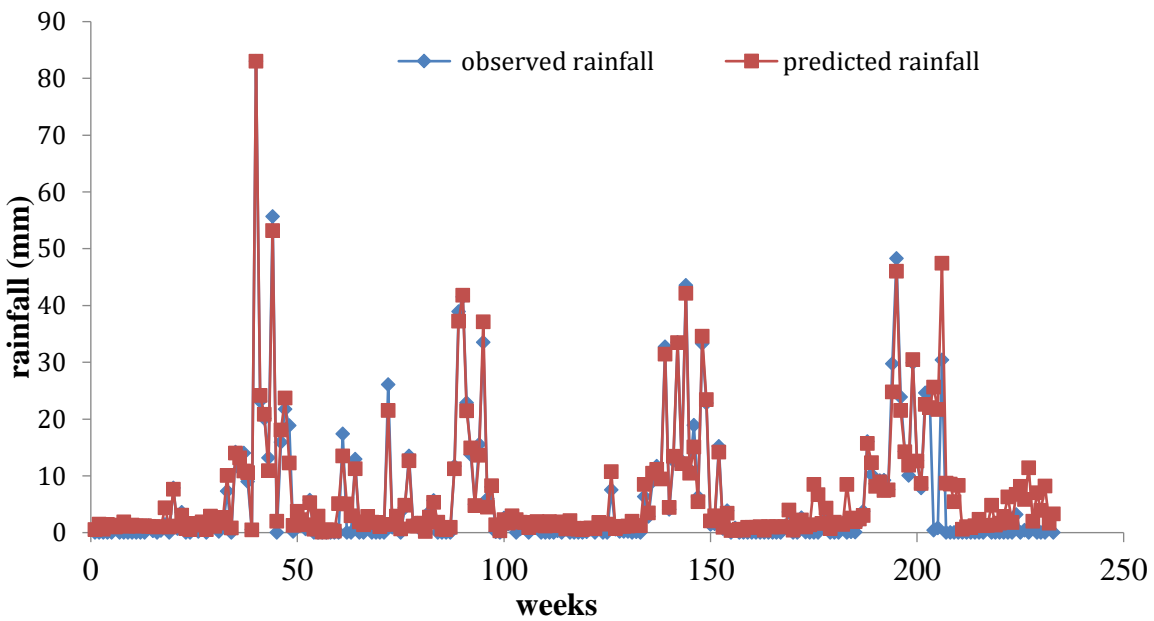


Fig.4.10 observed and predicted weekly rainfall for Levenberg-Marquardt and Tahn Axon ANN model MW-13 of Nainital station for the testing period

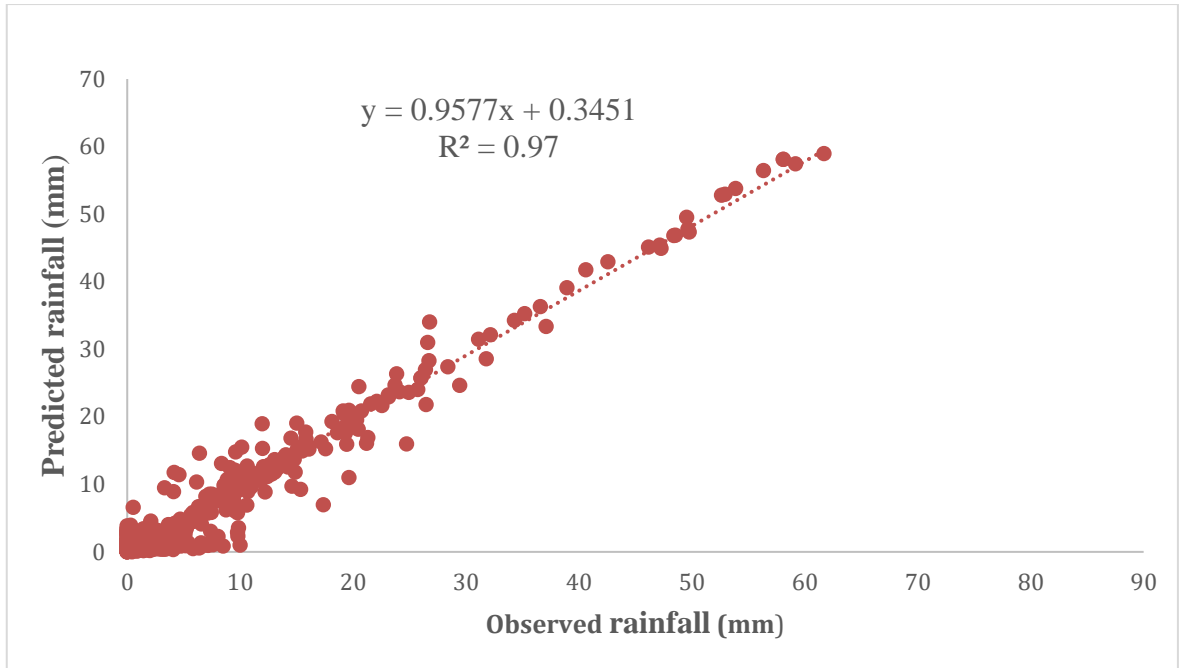


Fig.4.11 Scatter diagram of weekly rainfall for Levenberg-Marquardt and Tahn Axon ANN model MW-13 of Nainital Station for the training period

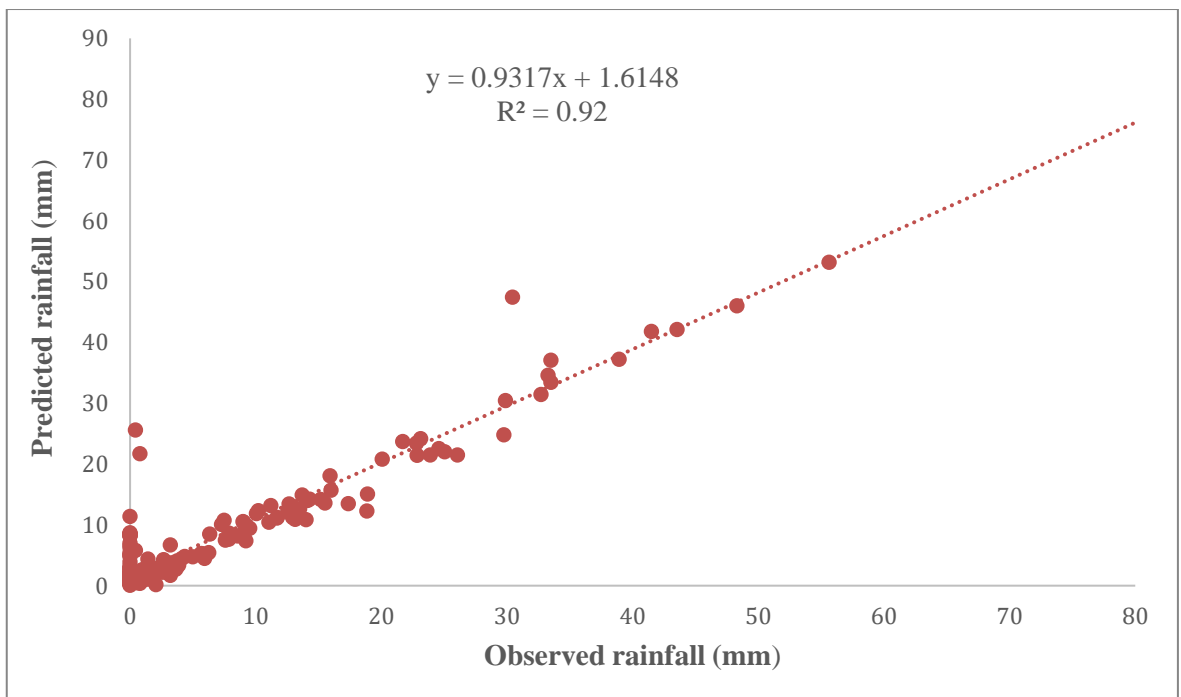


Fig.4.12 Scatter diagram of weekly rainfall for Levenberg-Marquardt and Tahn Axon ANN model MW-13 of Nainital Station for the testing period

Table 4.7 Comparison of various ANN models for the Levenberg-Marquardt and Tanh Axon combination during training and testing periods for weekly rainfall prediction models

Model	Architecture	Training					Testing				
		r	RMSE	CE	PBIAS	ISE	r	RMSE	CE	PBIAS	ISE
MW-1	5-2-1	0.74	7.54	0.54	5.17	5.14	0.67	9.22	0.29	42.40	10.85
MW-2	5-5-1	0.83	6.19	0.69	1.50	4.21	0.75	8.93	0.33	49.57	10.50
MW-3	5-8-1	0.87	5.38	0.76	5.11	3.66	0.76	7.3	0.55	30.48	8.58
MW-4	5-10-1	0.89	4.99	0.80	3.28	3.4	0.77	7.79	0.49	18.60	9.17
MW-5	5-15-1	0.94	4.04	0.87	21.38	2.75	0.83	6.34	0.66	28.37	7.46
MW-6	5-18-1	0.93	4.17	0.86	10.25	2.84	0.84	6.74	0.62	28.96	7.93
MW-7	5-19-1	0.95	3.26	0.91	5.03	2.22	0.81	7.11	0.57	28.96	8.37
MW-8	5-20-1	0.95	3.25	0.91	8.82	2.21	0.85	6.41	0.65	31.40	7.54
MW-9	5-5-5-1	0.84	5.94	0.71	1.70	4.05	0.80	7.51	0.53	24.04	8.83
MW-10	5-7-7-1	0.91	4.57	0.83	11.08	3.11	0.88	5.55	0.74	21.20	6.53
MW-11	5-8-8-1	0.94	3.59	0.89	3.33	2.44	0.91	4.69	0.81	16.28	5.25
MW-12	5-9-9-1	0.95	3.50	0.90	1.78	2.38	0.92	4.45	0.83	17.12	5.24
MW-13	5-10-10-1	0.98	2.13	0.96	2.17	1.45	0.95	3.43	0.90	12.17	4.03

The value of RMSE for training and testing period is found to be 2.13 and 3.43 respectively for model MW-13. The value of r for testing and training period for model MW-13 found to be 0.98 to 0.95 respectively. Based on RMSE and r the model MW-13 outperformed. For model MW-13 the value of CE were found to be 0.96 and 0.90 during MW-13. The lower values of RMSE, PBIAS, ISE and higher values of correlation coefficient in both training and testing periods shows that model MW-13 is best suited for ANN model with Levenberg-Marquardt learning rule and Sigmoid activation function.

4.3.2.2 Performance assessment of Levenberg-Marquardt and Sigmoid Axon based weekly rainfall prediction model

In this approach, Levenberg-Marquardt learning rule with Sigmoid activation function are used for prediction of weekly rainfall.

The performance assessment of the Levenberg-Marquardt and Sigmoid activation function based weekly rainfall prediction model was assessed by comparing the ordinates of observed and predicted weekly values. The observed and predicted values of weekly rainfall for training and testing period are shown in Fig 4.13 and Fig 4.14 and scatter plots are shown in Fig 4.15 and Fig 4.16. It is observed from Figures that there is a quiet similarity between observed and predicted weekly rainfall and overall plot of predicted weekly rainfall is similar to that of the observed weekly rainfall. The quantitative performance assessment of this model is assessed by the use of various statistical and hydrologic indices viz. root mean square error, coefficient of efficiency, correlation coefficient, Percentage BIAS and integral square error as shown in Table 4.8. The value of RMSE for training and testing period found to be 2.25 and 3.15 respectively for model MW-12. The value of r for testing and training period for model MW-12 found to be 0.97 to 0.96 respectively. Based on RMSE and r the model MW-12 outperformed. For model MW-12 the value of CE are found to be 0.95 and 0.91 during training and testing period whereas values of PBIAS are 3.03 to 12.44 respectively for training and testing period. The value of ISE is 1.53 for training period and 3.71 during testing period for the model MW-12. The lower values of RMSE, PBIAS, ISE and higher values of correlation coefficient in both training and testing periods shows that model MW-12 is best suited for ANN model with Levenberg-Marquardt learning rule and Sigmoid activation function.

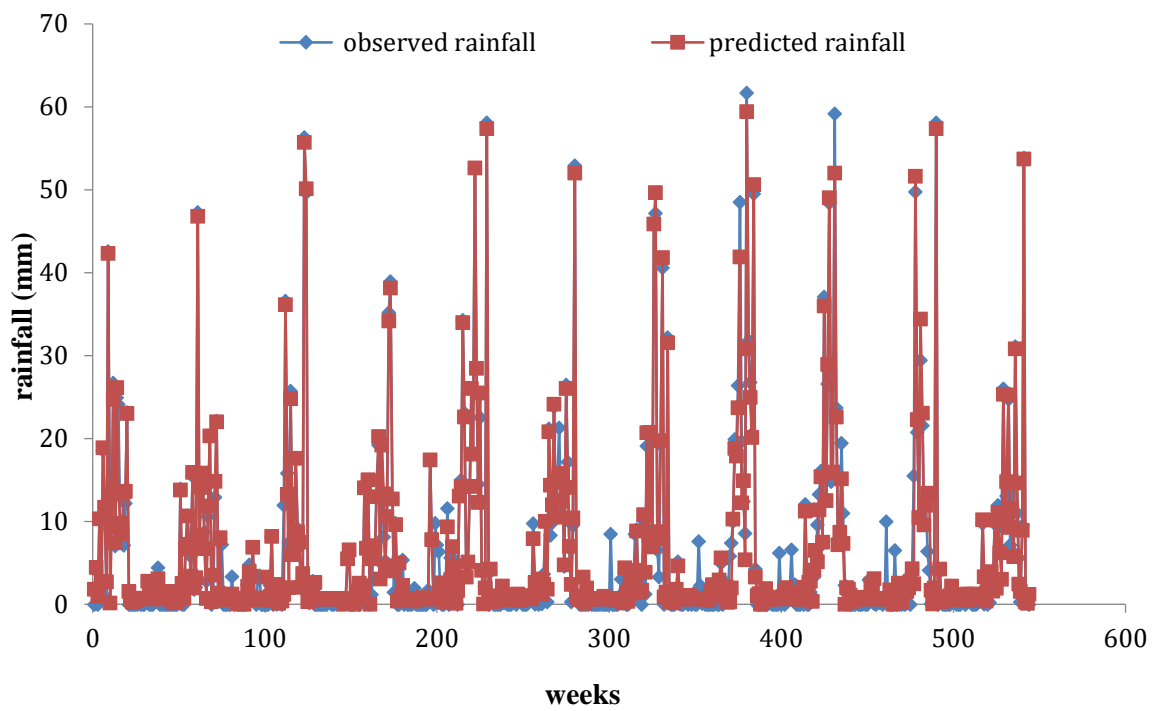


Fig.4.13 observed and predicted weekly rainfall for Levenberg-Marquardt and Sigmoid Axon ANN model MW-12 for the training period

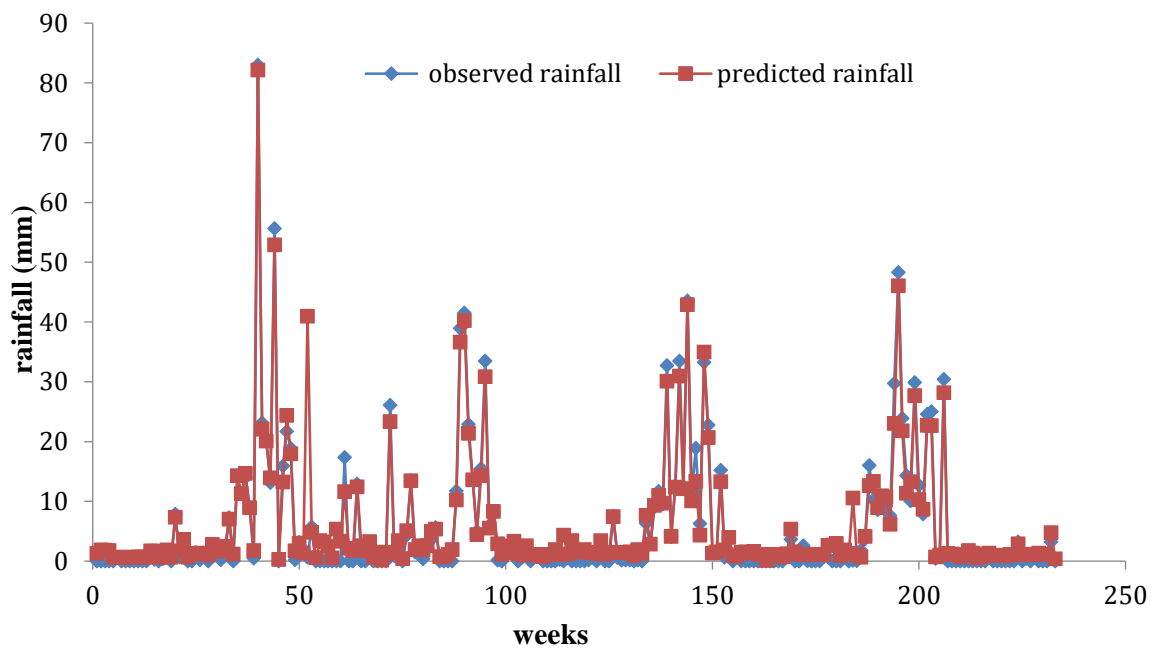


Fig.4.14 observed and predicted weekly rainfall for Levenberg-Marquardt and Sigmoid Axon ANN model MW-12 for the testing period

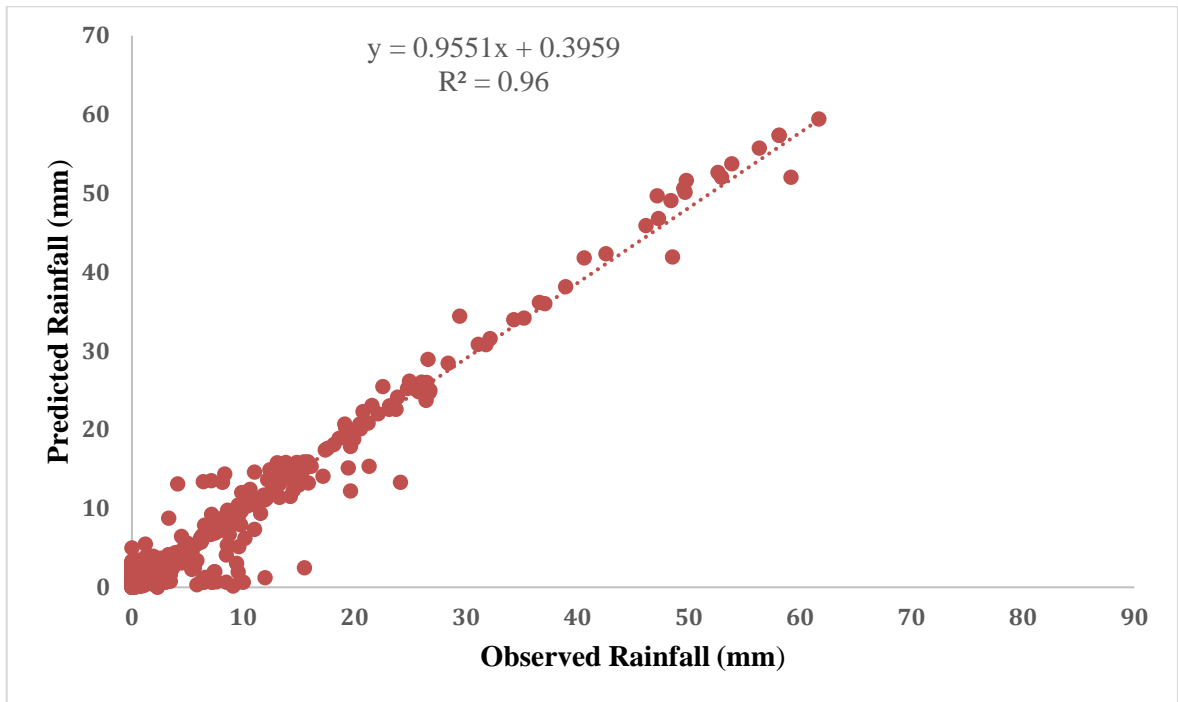


Fig.4.15 Scatter diagram of weekly rainfall for Levenberg-Marquardt and Sigmoid Axon ANN model MW-12 for the training period

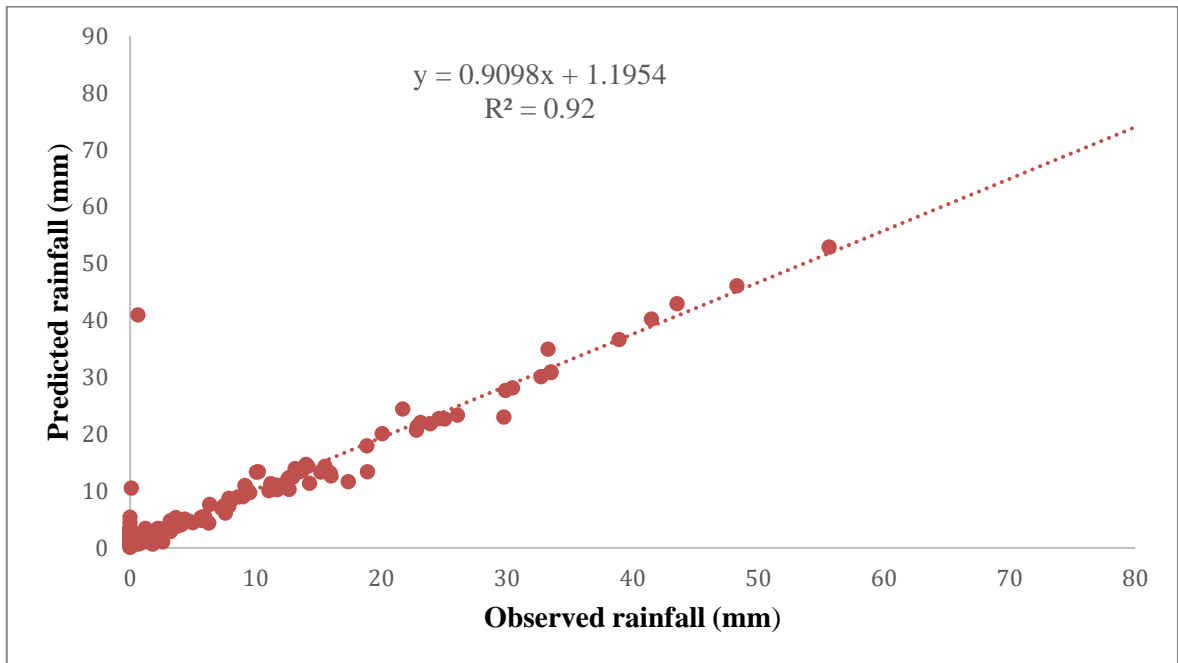


Fig.4.16 Scatter diagram of weekly rainfall for Levenberg-Marquardt and Sigmoid Axon ANN model MW-12 for the testing period

Table 4.8 Comparison of various ANN models for the Levenberg-Marquardt and Sigmoid Axon combination during training and testing periods for weekly rainfall prediction

Model	Architecture	Training					Testing				
		r	RMSE	CE	PBIAS	ISE	r	RMSE	CE	PBIAS	ISE
MW-1	5-2-1	0.74	7.54	0.54	5.11	5.14	0.67	10.08	0.15	51.33	11.86
MW-2	5-5-1	0.83	6.12	0.7	3.28	4.17	0.73	8.93	0.33	42	10.5
MW-3	5-8-1	0.89	5.06	0.79	0.002	3.45	0.76	8.19	0.44	34.8	9.63
MW-4	5-10-1	0.89	5.07	0.79	5.48	3.46	0.74	8.92	0.33	44.41	10.5
MW-5	5-15-1	0.92	4.2	0.85	7.49	2.86	0.81	7.52	0.53	38.81	8.85
MW-6	5-18-1	0.95	3.25	0.91	4.97	2.21	0.85	6.69	0.62	37.78	7.88
MW-7	5-20-1	0.96	3.03	0.92	5.33	2.07	0.91	4.66	0.81	23.42	5.48
MW-8	5-5-5-1	0.89	4.93	0.80	0.65	3.36	0.85	6.38	0.66	30.27	7.51
MW-9	5-7-7-1	0.94	3.79	0.88	2.87	2.58	0.92	4.24	0.85	15.06	4.99
MW-10	5-8-8-1	0.96	2.85	0.93	1.83	1.94	0.94	3.85	0.87	15.9	4.53
MW-11	5-9-9-1	0.95	3.20	0.91	2.31	2.18	0.94	3.77	0.88	14.66	4.44
MW-12	5-10-10-1	0.97	2.25	0.95	3.03	1.53	0.96	3.15	0.91	12.44	3.71
MW-13	5-6-6-1	0.90	4.23	0.81	5.42	3.32	0.86	6.11	0.67	19.96	5.34

4.4 Selection of Best Daily and Weekly Rainfall predicting Model

For daily rainfall prediction model Levenberg-Marquardt learning rule was chosen with Tahn axon and Sigmoid axon activation functions. The best performing models for daily rainfall prediction by both activation functions is presented in Table 4.9. It is clear from table that both activation functions have capability to map input output relation competently. In the case of training period Sigmoid activation function (model MD-11) surmounted the Tahn axon (model MD-10) for all indices with slight margin, but for testing period Tahn axon surpassed sigmoid activation function except CE. The model MD-11 (5-10-10-1) is more complex than model MD-10 (5-8-8-1) and need more computational efforts.

Model MD-10 performed well in testing period and less complex than MD-11 so keeping this in view, Tahn axon activation function (model MD-10) with Levenberg-Marquardt learning rule may be used for daily rainfall prediction of Nainital.

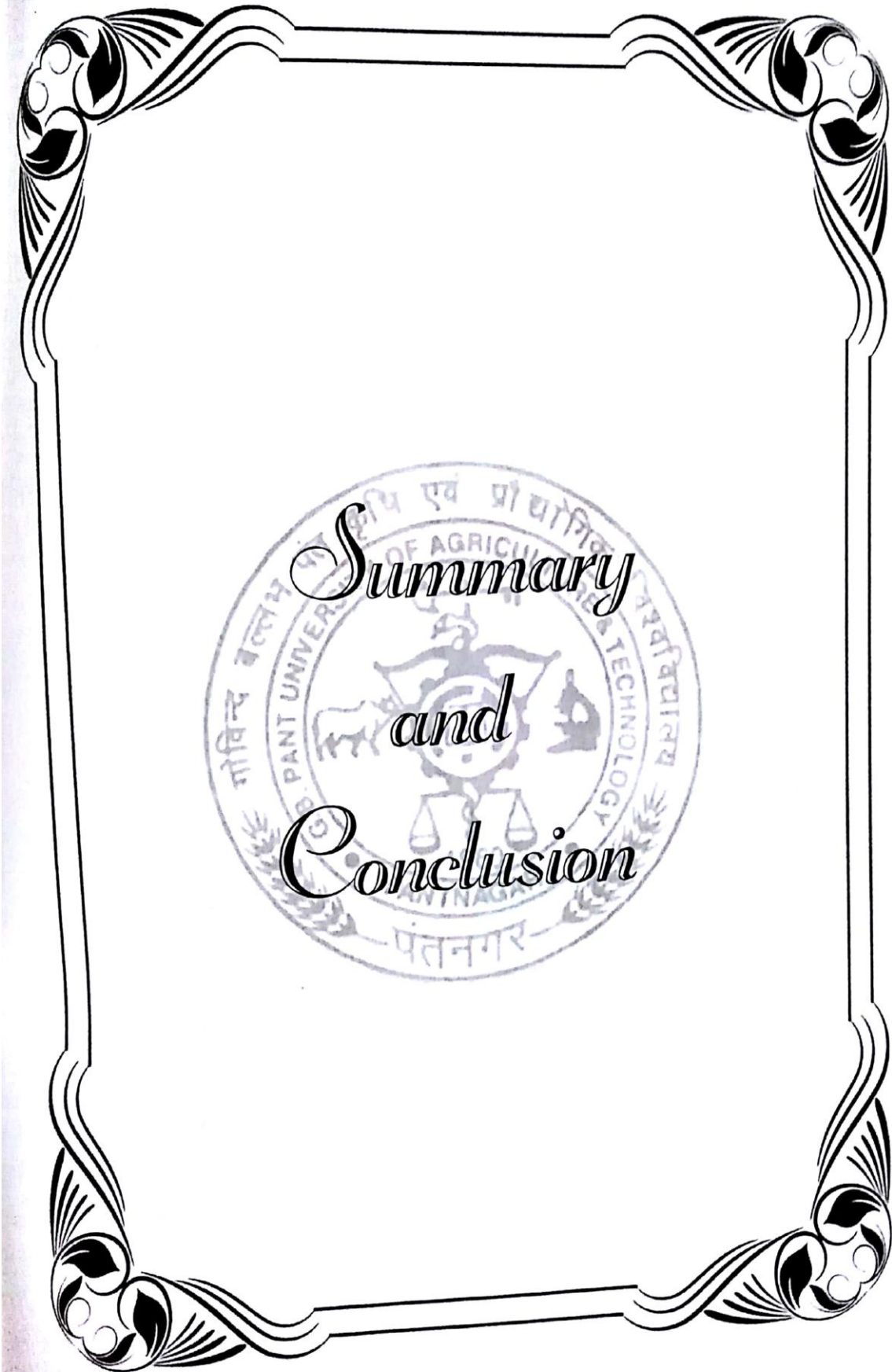
Weekly rainfall predicting models in this study utilized efficacies of Levenberg-Marquardt learning rule with Tahn axon and Sigmoid axon activation functions. The comparison between best performing Tahn axon and Sigmoid axon activation for weekly rainfall prediction models are presented in Table 4.10. It is clear from table that both activation functions are able to map input output relationship agreeably. It is clear from table that in case of training period Tahn axon (MW-13) activation function outperformed for all indices. For testing period except PBIAS all other indices lean towards Sigmoid (MW-12) activation function. MW-12 (5-10-10-1) and MW-13 (5-10-10-1) both models have same number of neurons in two hidden layers and have same complexities. Since the function Tahn axon (MW-13) performed well for unseen data (testing period), hence keeping view of good generalization aptness it may be chosen for weekly rainfall prediction of Nainital.

Table 4.9 Performance indices of daily rainfall prediction models to choose the best model

ANN MODEL	MODEL NAME	Training					Testing				
		r	RMSE	CE	PBIAS	ISE	r	RMSE	CE	PBIAS	ISE
Levenberg-Marquardt and Sigmoid axon	MD-10	0.89	9.18	0.79	1.83	1.12	0.86	10.57	0.73	16.83	4.7
Levenberg-Marquardt and Tahn axon	MD-11	0.87	9.97	0.75	7.37	2.03	0.86	9.39	0.74	15.20	4.17

Table 4.10 Performance indices of weekly rainfall prediction models to choose the best model

ANN MODEL	MODEL NAME	Training					Testing				
		r	RMSE	CE	PBIAS	ISE	r	RMSE	CE	PBIAS	ISE
Levenberg-Marquardt and Sigmoid axon	MW-12	0.97	2.25	0.95	3.03	1.53	0.96	3.15	0.91	12.44	3.71
Levenberg-Marquardt and Tahn axon	MW-13	0.98	2.13	0.96	2.17	1.45	0.95	3.43	0.90	12.17	4.03



*Summary
and
Conclusion*

Present study in focuses the development and applications of artificial neural network (ANNs) models for daily and weekly rainfall prediction of Nainital station, Uttarakhand. Out of various meteorological variables best input combinations were selected based on Gamma test for both daily and weekly rainfall prediction models. The daily meteorological data i.e. wet bulb thermometer temperature (Wb), dry bulb thermometer temperature (Db), maximum temperature (Tmax), minimum temperature (Tmin) and wind speed (Ws) were taken as inputs and rainfall (Rd) was considered as output for daily rainfall prediction models. Whereas, wet bulb thermometer temperature (Wb), dry bulb thermometer temperature (Db), maximum temperature (Tmax), minimum temperature (Tmin) and dew point (Dpt) were taken as inputs and rainfall (Rw) was considered as output for weekly rainfall prediction models. For both daily and weekly rainfall prediction models 70% data were used for calibration (training) period and remaining 30% data were used for validation (testing) period .The total 14 year 8 months (2003-2018) daily meteorological data were taken for daily rainfall prediction models, out of which 3086 data points (2003-2013) were used for training period and remaining 1631 data points (2014-2018) were used for testing period respectively. Similarly, for weekly rainfall prediction models the total number of weeks for 14 year 8 months were found to be 778 weeks, out of which 545 data points (2003-2013) were used for training period and remaining 233 data from (2014-2018) were used for testing periods respectively. The model with highest value of correlation coefficient (r) and lowest value of root mean square error (RMSE) is considered as the best fit model.

Multi-layer perceptron neural network was used to train daily and weekly rainfall prediction models of Nainital station by Levenberg-Marquardt learning rule with Sigmoid axon and Tanh axon transfer functions. Various models with different combinations of inputs, activation functions were developed for daily and weekly rainfall prediction. The Performance of the developed models were evaluated qualitatively and quantitatively by visual observations and quantitatively employing various statistical indices viz. correlation coefficient (r), coefficient of efficiency (CE),

root mean square error (RMSE), Percent bias (PBIAS) and Integral Square Error (ISE) for modelling of daily and weekly rainfall models. The following are the findings of this study.

1. Rainfall is dependent on meteorological data i.e. wet bulb thermometer temperature (Wb), dry bulb thermometer temperature (Db), maximum temperature (Tmax), minimum temperature (Tmin), wind speed (Ws) and dew point temperature.
2. Gamma test revealed that daily rainfall is dependent on wet bulb thermometer temperature (Wb), dry bulb thermometer temperature (Db), maximum temperature (Tmax), minimum temperature (Tmin), wind Speed (Ws), whereas for weekly rainfall wet bulb thermometer temperature (Wb), dry bulb thermometer temperature (Db), maximum temperature (Tmax), minimum temperature (Tmin), dew point temperature are significant inputs.
3. In case of weekly rainfall prediction wind speed (Ws) is replaced by dew point temperature (Dpt) and all other parameters are same. It may be due to that wind speed is highly variable in hilly terrain and for weekly data the averaging of wind speed eliminated the dependency of it to weekly rainfall.
4. In daily rainfall prediction scenario, ANN model (5-8-8-1) having Levenberg-Marquardt learning rule outperformed for Tahn axon activation function, whereas for Levenberg-Marquardt and Sigmoid axon combination model (5-10-10-1) performed well.
5. For weekly rainfall prediction ANN model (5-10-10-1) having Levenberg-Marquardt learning rule outperformed for Tahn Axon activation function, whereas for Levenberg-Marquardt and Sigmoid Axon combination model (5-10-10-1) performed well.
6. It is concluded that both activation functions have capability to map input output relation competently. However the difference in performance measures between them is very slight.
7. For weekly rainfall predicting models, in case of training period Tahn Axon (5-10-10-1) activation function outperformed for all indices. For testing period

8. except PBIAS all other indices lean towards Sigmoid (5-10-10-1) activation function. Sigmoid (5-10-10-1) and Tahn Axon (5-10-10-1) both models have same number of neurons in two hidden layers and have same complexities. Since the function Tahn axon (5-10-10-1) performed well for unseen data (testing period), hence keeping view of good generalization aptness it may be chosen for weekly rainfall prediction of Nainital.

Conclusion: - following are the conclusion drawn from the study.

1. As per the objectives of this study the models based on Levenberg-Marquardt & Tahn Axon and Levenberg-Marquardt & Sigmoid Axon were developed in terms of meteorological parameters to predict daily and weekly rainfall for Nainital station.
2. It was observed that both Tahn Axon and Sigmoid Axon activation functions are capable of predicting daily and weekly rainfall with almost same prediction efficiency.
3. For daily rainfall model structure of 5-8-8-1 with Levenberg-Marquardt & Tahn Axon, and model structure 5-10-10-1 with Levenberg-Marquardt & Sigmoid Axon performed well.
4. In case of weekly rainfall the model structure of 5-10-10-1 was found to be working well in both the cases.



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VITA

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ABSTRACT

Artificial Neural Network technique has been employed to predict daily and weekly rainfall for Nainital station of Uttarakhand, India. The meteorological data from year (2003 to 2013) were used for training of daily and weekly rainfall prediction models and meteorological data from (2014 to 2018) were used for testing of daily and weekly rainfall prediction models. Gamma test was used for the selection of appropriate input variables of daily and weekly rainfall prediction models. The ANN models were trained using multilayer perceptron with one learning rule i.e. Levenberg-Marquardt and two transfer functions viz. Tanh Axon and Sigmoid Axon. The performance of the models was evaluated qualitatively by visual observation and quantitatively using different performance indices viz. Root Mean Square Error, Correlation Coefficient, Coefficient of Efficiency, Percent Bias and Integral Square Error. It was observed that both Tahn Axon and Sigmoid Axon activation functions are capable of predicting the daily and weekly rainfall with almost equal prediction efficiency, for daily rainfall model structure of 5-8-8-1 with Levenberg-Marquardt and Tahn Axon, and model structure 5-10-10-1 with Levenberg-Marquardt and Sigmoid Axon performed well. And, in case of weekly rainfall the model structure of 5-10-10-1 was found to be working well in both the cases for Nainital station of Uttarakhand, India.



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नाम	नीरज जोशी	परिचयांक	५१२२४
षट्मास एवं प्रवेश वर्ष	१९ २०१६-१७	उपाधि	एमटेक; कृषिअभियांत्रिकी
प्रमुख	मृदा और जल संरक्षण अभियांत्रिकी	विभाग	मृदा और जल संरक्षण अभियांत्रिकी
अल्प	शून्य		
शोध का शीर्षक	कृत्रिम न्यूरल तंत्र द्वारा दैनिक और साप्ताहिक वर्षा प्रतिरूपण		
सलाहकार	डॉ देवेन्द्र कुमार		

सारांश

कृत्रिम न्यूरल तंत्र तकनीक के द्वारा नैनीताल स्टेशन के लिए दैनिक और साप्ताहिक वर्षा की भविष्यवाणी करने के लिए नियोजित किया गया है। वर्ष (२००३ से २०१३) के मौसम संबंधी दत्त.सामग्री का उपयोग दैनिक और साप्ताहिक वर्षा पूर्वानुमान मॉडल और (२०१४ से २०१८) के मौसम संबंधी दत्त.सामग्री का उपयोग दैनिक और साप्ताहिक वर्षा भविष्यवाणी मॉडल के परीक्षण के लिए किया गया था। गामा परीक्षण दैनिक और साप्ताहिक वर्षा भविष्यवाणी मॉडल के उपयुक्त इनपुट चर के चयन के लिए प्रयोग किया गया था। एएनएन मॉडल को मल्टीलायर परसेप्ट्रॉन का उपयोग एक सीखने के नियम के साथ प्रशिक्षित किया गया था जैसे लेवेनबर्ग-मार्वार्ड और दो स्थानांतरण कार्यों जैसे। तन एक्सोन और सिग्मोइड एक्सोन। मॉडलों के प्रदर्शन को विजुअल अवलोकन द्वारा मात्रात्मक रूप से मूल्यांकन किया गया था और विभिन्न प्रदर्शन सूचकांक का उपयोग करके मात्रात्मक रूप से मूल्यांकन रूट मीन स्क्वायर त्रुटि सहसंबंध गुणांक क्षमता का गुणांक प्रतिशत बाईस और इंटीग्रल स्क्वायर त्रुटि के द्वारा किया गया था। यह पाया गया कि ताहन एक्सोन और सिग्मोइड एक्सोन सक्रियण कार्य दोनों ही भविष्यवाणी दक्षता के साथ दैनिक और साप्ताहिक वर्षा की भविष्यवाणी करने में सक्षम हैं। दैनिक वर्षा मॉडल संरचना ५-८-८-१ के लिए लेवेनबर्ग-मार्वार्ड और ताहन एक्सोन और मॉडल के साथ लेवेनबर्ग-मार्वार्ड और सिग्मोइड एक्सोन के साथ संरचना ५-१०-१०-१ अच्छी तरह से प्रदर्शन किया। और साप्ताहिक बारिश के मामले में नैनीताल स्टेशन के लिए दोनों मामलों में ५-१०-१०-१ की मॉडल संरचना अच्छी तरह से काम कर रही थी।


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