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SHORT DURATION RAINFALL FORECASTING MODELING THROUGH ANNS

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Abstract: Present research paper is articulated the application of Artificial Neural Networks (ANNs) in the field of rainfall forecasting. Research shows ability of ANNs for daily rainfall forecasting. Two Different combinations of weather parameters, one day lag and previous moving average week as case I and Case II respectively has been prepared to generate nonlinear relationship. There are single and multi-hidden layer ANNs generated by increasing and decreasing of hidden layer(s) and Processing Element (PE) by trial and error method. Developed models are selected based on mainly two basics criteria least Mean Square Error along with higher Correlation Coefficient and low Value of Akaike Information Criteria(AIC). Different models were developed and tested by using two input dataset. Models were trained and tested using last 30 (1979-2008) years and 5 (2009-13) year of weather parameter respectively. Result showed that multi hidden layer model ANN Model (7-4-1-1) of case II has good Correlation Coefficient (0.93) and least Mean Square Error (0.001) which was selected as best among four models. It clearly revealed that monsoon depends on long term of weather parameter. It unveils that it does not necessary have more number of Processing Element (PE) and more number of hidden layer(s) which always give good result. Sensitivity analysis revealed that wet bulb temperature is most sensible parameter followed by mean temperature, dry bulb temperature, relative humidity, evaporation, rainfall, and wind velocity.

Key words*: rainfall forecasting, ANN$_S$, previous day, moving average week, weather parameter, BPNN, validation, sensitivity*

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INTRODUCTION

Water is essential for all life. Rainfall is vital resources of fresh water. It is also one of the prime requirements for agriculture, industrial production, domestic and re-creation. Components of precipitation, resolved into soil moisture and groundwater, are the prerequisites for biomass production and social development in dry areas. Rainfall is cheap and prime source of fresh water. Per capita availability of water is reducing at alarming rate. It shows serious issue of water stress. India occupies only 3.28 million sq. km geographical area which supports 17% of the population and 20 per cent livestock population of world from 2.4 per cent of the land area and 4% of water resources of the world. The farming is the backbone of Indian agriculture contribute 14.2 per cent share in total GDP. It shows that the water is essential for growth of agricultural and allied sectors.

Artificial Neural Networks (ANNs) are biologically inspired computer programs designed to simulate the way in which the human brain processes information. ANNs gather their knowledge by detecting the patterns and relationships in data and learn (or are trained) through experience, not from programming. An ANN is formed from hundreds of single units, artificial neurons or processing elements (PE), connected with coefficients (weights), which constitute the neural structure and are organised in layers [2]. Rainfall forecasting is tough and nonlinear process. ANNs found to be better in terms rainfall predictions [16]. ANNs were applied for flood forecasting, evaporation study, rainfall runoff relationship, tide forecasting, ground water level forecasting, river stage forecasting, stream flow forecasting, drought forecasting and spring discharge [1]. ANNs have been widely used for rainfall or precipitation forecasting in monsoon season [6-7] [10] [12] [20]. Multi regression and ANNs are useful for long term rainfall forecasting using large scale climate modes [11]. Short term rainfall prediction models useful for real time flood forecasting [17]. Back propagation algorithm gave better result for river stage forecasting [18]. [21] developed FFNN ANN Model for monthly rainfall forecasting next to 5 to 10 year in Johor state, Malaysia. Rainfall becomes more precise where the Rainfall is main source of water for Indian agriculture where 68 % (86 Mha) of a total land are under rainfed area. Contribution of Rainfall in the month of June, July and September is decreasing for few sub-divisions while increasing in August for other subdivision in India. Many researchers have developed accurate rainfall prediction models by artificial neural networks since last decade [8]. On an average, the rainfed regions in India such as Western Rajasthan, eastern Rajasthan, Gujarat, western Uttar Pradesh, Tamil Nadu, Kashmir and Andhra Pradesh are most vulnerable to droughts, suffering once in every three years [16] where rainfall forecasting become more important.

MATERIAL AND METHODS

The study area is the Udaipur city of Rajasthan, India located at latitude and longitude 24°58'*N* and 73°68'*E*, respectively. The elevation of gauging station is at 598 m above the mean sea level.

Data acquisition and pre analysis. The depth of rainfall and its distribution in the temporal and spatial dimensions depends on many variables, such as pressure, temperature, wind speed and direction [10]**.** Model improved forecasting monthly flow of the Mississippi River in USA by providing proper inputs [15]. Meteorological data (i.e. Wet bulb Temperature, Dry bulb Temperature, Relative Humidity, Wind Velocity, Mean Temperature, Evaporation and Rainfall) collected for the period from the month May 25th to October 30th for the year 1979 to 2013 were subjected to Pre-analysis and formulation of the data base. Thus the total number of data for each year's period comes out to be 153. Data from 1979-2008 were used to formulate and validate and data from 2009-13 were used to forecast and check the error. Weather data has been collected from weather observatory station of College of Technology and Agriculture, Maharana Pratap University of Agriculture and Technology, Udaipur.

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. Fig. 1 and Fig. 2 are Single Hidden layer and Multi Hidden Layer respectively.

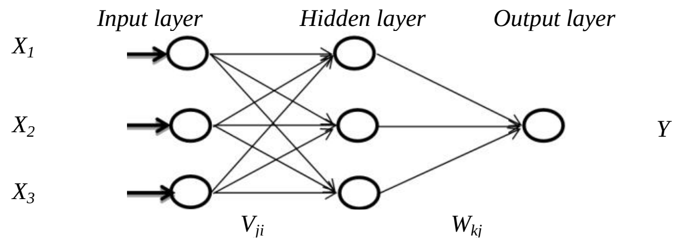

Figure 1. Single idden layer in neural Network

As shown in Fig. 1, X_1 and X_2 represent the inputs of the network, and the connection between the neurons, represented by lines, is quantified by their weights, which are shown in the V_{ji} and W_{kj}, and Y is the output from single hidden layer ANN.

In the Fig 2, inputs are shown by X_1, X_2 and X_3 and V_{ji} represents the connection weight from the jth node in the preceding layer to ithnode. 'Y' is the observed output of the network.

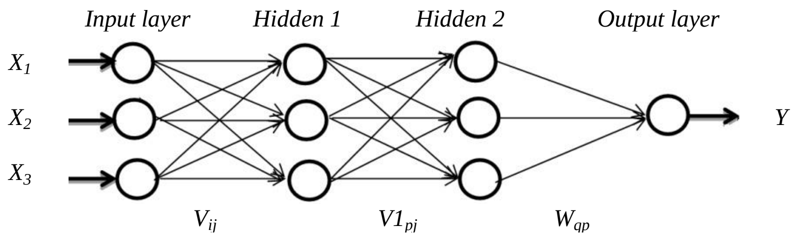

Figure 2. Multi Hidden layer(s) neural Network

Back-propagation training algorithm. Back-propagation training algorithm is the most commonly used supervised algorithm for training the multi hidden layer ANN [18]. An ANN which used back-propagation algorithm for its training is also called back-propagation ANN. In back-propagation ANN, information is processed in the forward direction from the input layer to the hidden layer(s) and then to output layer. The objective of a back-propagation network is to find the weights that approximate target values of output with a selected accuracy. The least mean square error method, along with the generalized delta rule, is used to optimize the network weights in back-propagation networks. The gradient descent method along with the chain rule of derivatives is employed to modify the network weights. It requires a continuous, differentiable and non-linear function on the ANN to compute output from each neuron.

The input data are multiplied by the initial weights, then the weights inputs are added by simple summation to yield the net input to each neuron.

$$Net = \sum_{i=1}^{N} V_{ji} X_i \tag{1}$$

where:
X_i [-] - input to any neuron,
V_{ji} [-] - weighted matrix from j^{th} layer to i^{th} layer,
N [-] - number of inputs,
Net [-] - net for j^{th} neuron.

The net of neuron is passed through an activation or transfer function to produce output form a neuron.

$$O = \frac{1}{1 + \exp\left(-Net\right)} \tag{2}$$

where:
O [-] - output signal form i^{th} neuron.

After error between the output of the network and the target output are computed at the end of each forward pass, and is summed over as follows:

$$E = \sum_{i=1}^{N} \frac{1}{2} (O_i - D_i)^2 \tag{3}$$

where:
E [-] - total error,
O_i [-] - observed output,
D_i [-] - target output.

The weight values are originally initialized randomly for all the connection weights in the network. During the back-propagation of error signal at output neuron, the weights are modified according to the following equations:

$$V_{ji}\,(n+1) = V_{ji}(n) + \Delta V_{ji}(n) \tag{4}$$

$$\Delta V_{ji}(n) = \eta(\delta_i)\big(O_j\big) + \alpha \Delta V_{ji}\,(n-1) \tag{5}$$

where:
$\Delta V_{ji}(n)$ [-] - change in weight V_{ji} at n^{th} iteration,
$\Delta V_{ji}\,(n-1)$ [-] - change in weight V_{ji} at $n\text{-}1^{th}$ iteration,
$V_{ji}(n)$ [-] - weight V_{ji} at n^{th} iteration,
$V_{ji}(n+1)$ [-] - updated value of weight V_{ji} at (n^{th}) iteration,
O_j [-] - output from j^{th} neuron in the output layer,

α [-] - momentum constant,
η [-] - learning constant.

The value of δ_i for output neuron is given by:

$$\delta_i = O_i(1 - O_i)(D_i - O_i) \tag{6}$$

where:
O_i [-] - output from the network,
D_i [-] - target value of the output,
δ_i [-] - error signal term of the output layer.

In the output layer, the target outputs are known, in the hidden layers, target values are not known. Therefore, the back-propagation algorithm uses the sum of the error signals of all the neurons of the succeeding layers to calculate error signals of any neuron 'j' in the hidden layer.

$$\delta_i = O_i(1 - O_i)\sum_p \delta_p W_{qp} \tag{7}$$

Where p runs over all the neurons in the subsequent layers and $\delta_p$in the error signal term corresponding to subsequent layer of p. The value of δ_i is then substituted in the Eq. 5. This procedure is repeated until the selected accuracy is achieved.

Activation function. The output from a neuron is calculated through the use of an activation function. The basic characteristics of the sigmoid function are that it is continuous, differentiable and is monotonically increasing. The sigmoid function is shown in Fig. 3.

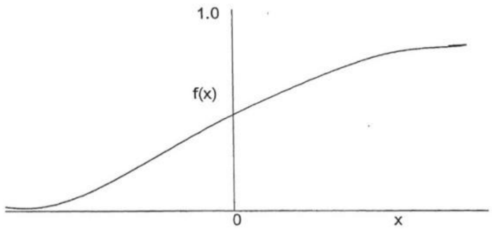

Figure 3. Sigmoid function

The sigmoid function can be represented by the following equation.

$$f(x) = \frac{1}{1 + exp\,(-ax)} \tag{8}$$

where:
a [-] - slope parameter.

The output from sigmoid function is always bounded within 0 to 1 and input to the function can vary between $-\infty$ to $+\infty$.

The most popular and successful technique for selecting the appropriate number and size(s) of the hidden layer(s) is trial and error method. A number of networks with one or two hidden layers are trained with different combinations of hidden neurons and a network is selected that yields the minimum Mean Square Error (MSE) and maximum

Correlation Coefficient (CC). It is important that the size of the network should be small as possible.

Development of ANNs Model Single & multi hidden layer(s) Neural Network Case I & Case II: In this case the observed time series of Wet bulb Temperature, Dry bulb Temperature, Relative Humidity, Mean Temperature, Evaporation, Wind Velocity and Rainfall of previous days and previous moving average week were taken as the input variables in case I and Case II respectively and current day rainfall as the output variable for both case I and Case II for single and multi-hidden layer(s). Levenberg–Marquardt learning algorithm and sigmoid logistic activation function have been used for prediction of annual precipitation [4]. Let the observed values of wet bulb temperature, dry bulb temperature, mean temperature, relative humidity, wind velocity, evaporation and rainfall represented as $Tw_{i,j}$, Td_{ij}, $T_{i,j}$, $RH_{i,j}$, $V_{i,j}$, $E_{i,j}$ *and* $P_{i,j}$ respectively for j^{th} day of the i^{th} year $(i = 1,2,\ldots,M \text{ and } j = 1,2,\ldots,N)$.

The functional form of the models can be represented as:

$$P_{i,j} = f(Tw_{i,j-1}, Td_{i,j-1}, T_{i,j-1}, RH_{i,j-1}, V_{i,j-1}, E_{i,j-1}, P_{i,j-1}) \tag{9}$$

Sensitivity analysis were carried by adding and removing weather parameter one by one then model were formulated and validated for the best identified model ANN (7-4-1-1). Performance evaluations of the models were carried through visual observation based on the graphical comparison between observed and predicted values of rainfall. There were also statistical and hydrological indices used for testing the goodness of fit for comparison between observed and predicted values of rainfall.

RESULTS AND DISCUSSION

There were so many Artificial neural network generated for case I and case II, out of them only four best model were shown for each case having highest correlation coefficient (cc) and lower Mean square error (MSE) value as given in table 1.

Table 1. Performance evaluations of developed ANNs Models during training & testing period

Performance indices	*Case I (One day ahead)*				*Case II (Moving average week)*			
	Training		*Testing*		*Training*		*Testing*	
	7-12-1	*7-6-6-1*	*7-12-1*	*7-6-6-1*	*7-11-1*	*7-4-1-1*	*7-11-1*	*7-4-1-1*
MSE	*0.009*	*0.004*	*0.003*	*0.001*	*0.007*	*0.005*	*0.002*	*0.001*
NMSE	*0.62*	*2.69*	*0.54*	*0.68*	*0.15*	*0.35*	*0.39*	*0.29*
CC	*0.84*	*0.82*	*0.81*	*0.80*	*0.92*	*0.94*	*0.90*	*0.93*
AIC	*-31715*	*-24845*	*-4819*	*-4965*	*-30625*	*-27114*	*-4914*	*-5096*
MDL	*-31545*	*-24480*	*-4754*	*-4847*	*-30444*	*-27003*	*-4762*	*-4923*
% ERROR	*52.15*	*24.14*	*36.18*	*22.12*	*66.87*	*51.40*	*39.69*	*36.09*
CE	*83.55*	*85.60*	*80.65*	*79.75*	*92.59*	*96.74*	*86.62*	*88.45*
EV	*26.15*	*28.94*	*17.14*	*18.05*	*15.40*	*13.06*	*8.42*	*5.34*

Qualitative performance was carried through Statistic Indices and Hydrologic indices. Statistics indices and hydrologic indices shows network 7-4-1-1 as best model

(CC 0.93 and MSE 0.001) followed by 7-11-1 (CC= 0.90 and MSE=0.002), 7-12-1 (CC=0.81 and MSE=0.003) and 7-6-6-1 (CC=0.80 and MSE= 0.001). The network 7-4-1-1 shows 7 inputs, 4 Neurons (processing elements) for first hidden layer, 1 neuron for second hidden layer and 1 output (Rainfall). Value of different statistics indices like Mean Square Error (MSE), Normalise Mean Square Error (NMSE), Correlation Coefficient (CC), Akaike's Information Criterion (AIC) and Minimum Description Length (MDL), Percent Error (% ERROR) and value of Hydrologic indices Volumetric error and Coefficient of Efficiency (CE) of different ANNs were as given in the table 1.

The Fig. 4 shows that there is close agreement between Observed and Predicted Rainfall of ANNs network of 7-4-1-1 followed by 7-11-1, 7-12-1 and 7-6-6-1 of case I and case II respectively during the testing period (2009-2013).

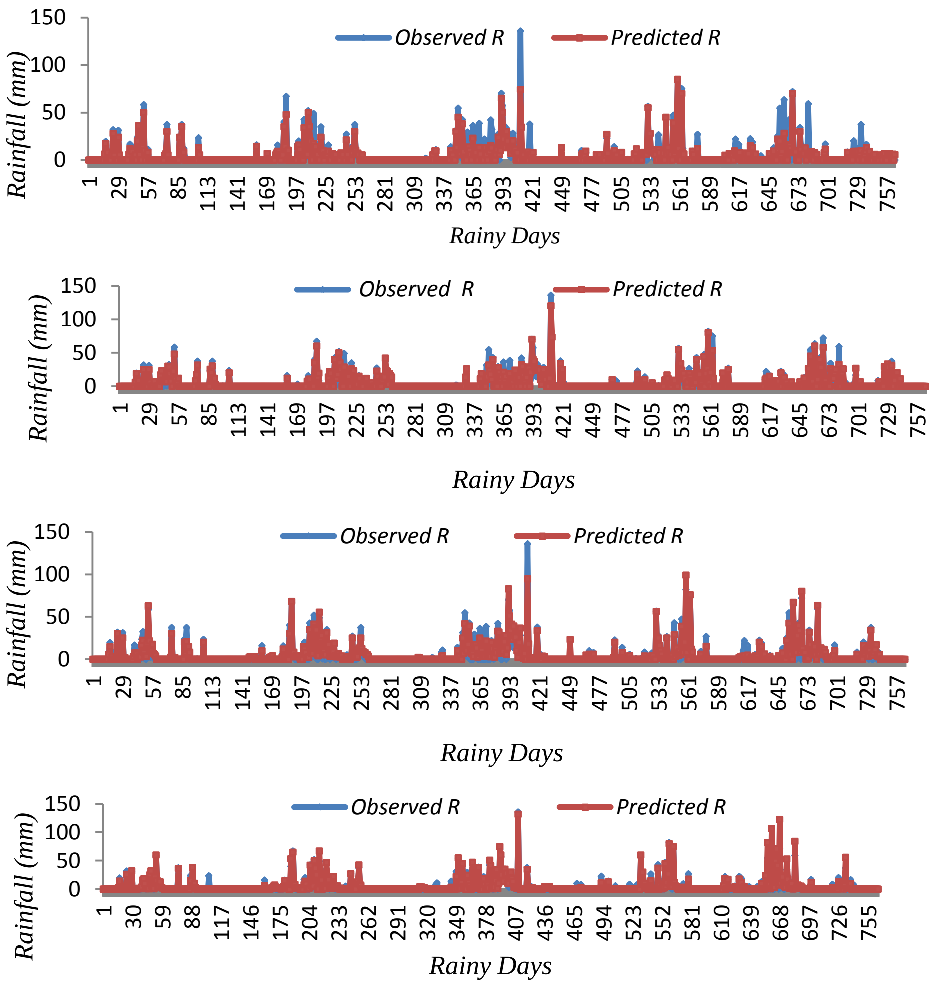

Figure 4. Observed and Predicted Daily rainfall of ANN model 7-12-1,7-6-6-1, 7-11-1 and 7-4-1-1 (top to bottom) during for testing period (2009-13)

It revealed that Rainfall forecasting is carried through previous moving average week weather parameter gives good result as compare to that of previous day. So occurrence of rainfall depends on long term weather parameter. Sensitivity was carried out for the Best ANN model 7-4-1-1 as shown in fig. 5. It shows that Wet bulb Temperature is most sensible parameter followed by Mean Temperature, Relative Humidity, Dry bulb Temperature, Evaporation, Rainfall and Wind Velocity.

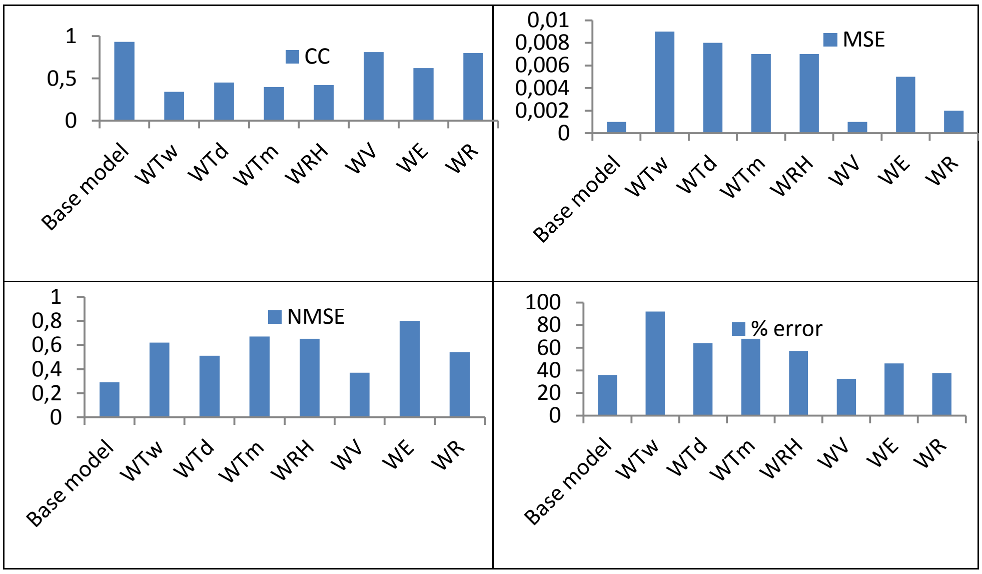

Figure 5. Performance of sensitivity analysis of base ANNs (7-4-1-1) model

CONCLUSIONS

Based on the performance indices of Artificial Neural Networks (ANNs) 7-4-1-1and 7-11-1 show better than networks 7-6-6-1, 7-12-1 of single and multi-hidden layer of case II and case I respectively. It clearly indicates that the rainfall forecasting depends on long term weather parameter. It also noted that more number of Processing Element (PE) and higher number of hidden layer does not give always best result. Sensitivity analysis of Artificial Neural Network 7-4-1-1 revealed that Wet bulb Temperature is most sensible parameter followed by Mean Temperature, Relative Humidity, Dry bulb Temperature, Evaporation, Rainfall and Wind velocity. Visual observation, statistical and hydrological indices were showed that ANN (7-4-1-1) can be useful for rainfall forecasting for Udaipur.

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KRATKOROČNA PROGNOZA PADAVINA MODELIRANJEM KROZ ANNS

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Sažetak: U radu je predstavljena aplikacija Veštačke Neuronske Mreže (ANNs) u oblasti prognoze padavina. Istraživanje pokazuje mogućnost ANNs za dnevnu prognozu padavina. Dve različite kombinacije vremenskih parametara, jednodnevni pomak i prethodna pokretna srednja nedelja kao Slučaj I i Slučaj II, redom, bile su pripremljene da se generiše nelinearna zavisnost. Postoje jedan i više skrivenih slojeva ANNs generisanih povećanjem i smanjenjem skrivenih slojeva i Elementom za obradu (PE) metodom probe i greške. Razvijeni modeli su izabrani na osnovu dva kriterijuma, najmanja srednja kvadratna greška zajedno sa koeficijentom korelacije i kriterijumom donje vrednosti Akaike informacije (AIC). Različiti modeli su razvijeni i testirani upotrebom dva ulazna seta podataka. Modeli su isprobani i testirani upotrebom poslednjih 30 (1979-2008) godina i 5 (2009-13) godina vremenskih parametara, redom. Rezultat je pokazao da je model više skrivenih slojeva ANN Model (7-4-1-1) slučaja II imao dobar koeficijent korelacije (0.93) i srednju kvadratnu grešku (0.001) i bio je izabran kao najbolji od svih modela. Jasno je pokazao da monsun dugoročno zavisi od vremenskih parametara. On otkriva da ne mora da ima veći broj elemenata obrade (PE) i veći broj skrivenih slojeva koji uvek daje dobar rezultat. Analiza osetljivosti pokazuje da je temperature vlažnog termometra najosetljiviji parameter, a za njim sledi srednja temperatura, temperatura suvog termometra, relativna vlažnost, evaporacija, padavine i brzina vetra.

Ključne reči*: prognoza padavina, ANN_S, prethodni dan, prosečna nedelja, vremenski parameter, BPNN, validacija, osetljivost*

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