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APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR SHORT TERM RAINFALL FORECASTING

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Abstract: Accurate rainfall forecasting is very necessary for water resource management. Recently, several modeling approaches have been investigated to perform such forecasting task. In the present study, possibility of forecasting rainfall in Junagadh has been analyzed through feed forward artificial neural network models. The 30 years data has been used for training and testing the *ANN* networks. In formulating the *ANN* based Predictive model, single and double hidden layers network have been constructed. The performance of models have been evaluated using Correlation coefficient, Mean Square Error, Normalized Mean Square Error, Akaike's information criterion, Coefficient of Efficiency and volumetric error, and two best suitable models (7-12-13-1 and 4-6-4-1) have been selected from case I and II for rainfall forecasting in Junagadh. Based on the performance evaluation of the models, two models found suitable for prediction of daily rainfall for the study area.

Key words: artificial neural network, feed forward algorithm, rainfall prediction, back propagation algorithm

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INTRODUCTION

The climate change is expected to affect precipitation and water availability. Gujarat mainland region receives an average annual rainfall of 800 to 2000 mm, while Saurashtra has an average annual rainfall of 400 to 800 mm. The The incidence and distribution of rainfall, particularly in Saurashtra and Kutch regions and in the northern part of Water scarcity and droughts are not new phenomena for the people of Saurashtra. They have always lived with them and thus have treated water as a highly scarce and precious resource. The above facts lead to conclude that the artificial neural network is the most efficient rainfall forecasting methods for bringing the more agricultural productions from the limited land and water resources. Artificial Neural Networks (*ANN*s) are non-linear mapping structures based on the functions of human brain. They are powerful tools for modeling, especially when the underlying data relationship is unknown. The artificial neural network is the most efficient rainfall forecasting methods for bringing the more agricultural productions from the limited land and water resources.

Different scientist over the globe have developed stochastic weather models which are basicallystatistical models that can be used as random number generators whose output resembles the weather data to which they have been fit (Wilks, 1998). Guhathakurta (2006) implemented *ANN* technique to predict rainfall over a state (kerala) of India. Hu (1964) initiated the implementation of *ANN*, an important soft computing methodology in weather prediction. Michaelides *et al.* (1995) compared the performance of *ANN* with multiple linear regressions in estimating missing rainfall data over Cyprus. Singh *et al.* (2012) has developed radial basis neural network (*RBNN*) for Nagwa watershed for simulating monthly surface runoff and sediment yield.. Abbot and Marohasy (2012) used artificial intelligence to 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. Chauhan and shrivastava (2012)developed *ANN* models for estimation of reference crop evapotranspiration with climate data required for Penman-Monteith (*P-M*) method, to test artificial neural networks (*ANN*s) for estimating reference evapotranspiration (*ET0*) with limited climate data (*ET0*) and compares the performance of *ANN*s with P-M method. Nastos *et al.* (2013) developed predictive models in order to forecast rain intensity (mm/day) in Athens, Greece, using Artificial Neural Networks (*ANN*) models. The objectives of the present study were to formulate Artificial Neural Network model with reliable accuracy and validate formulated models for the study area.

MATERIAL AND METHODS

The Main objective of this study is to developed Artificial Neural Networks models for forecasting of monsoon rainfall. This Chapter deals with the location and climate of study area, collection of meteorological data, methodology adopted for rainfall modeling using artificial neural networks models. Procedure used for calibration and validation of the model and various criteria for evaluating performance of the models discussed here.

Descriptions of area. The study area falls in the District of Junagadh (Gujarat), India. The latitude and longitude of the study area is 21.5° N and 70.1° E, respectively. The elevation of gauging station is 60 m above the mean see level. The climate of area is subtropical and semi-arid type with an average annual rainfall of 900 mm and average annual pan evaporation of 6.41 mm/day. May is the hottest month with mean monthly temperature varying between 35 °C to 45 °C and mean monthly minimum temperature varying between 7 °C and 10 °C as observed from the 10 years data collected by meteorological observatory, Krushigadh, *JAU*, Junagadh.

Data acquisition. The daily meteorological data of 30 years (1979 to 1981, 1984 to 1989 and 1991 to 2011) were collected from meteorological observatory of Krushigadh, Junagadh Agricultural University. The Observatory is situated at Junagadh in the "Saurastra" region of Gujarat state of India.

Development of models for study area. The forecasting of rainfall is very complex and non-linear process, which is affected by many factors which inter-related, some of the parameters includes as vapour pressure, relative humidity, wind velocity, dry and wet bulb temperature and mean temperature etc. Models can identify and learn correlated patterns between input data sets and target values. After training, Models can be used to forecast the outcome of new independent data. In this present study Artificial Neural Networks models have been developed for forecasting rainfall on daily basis.

Artificial neural networks (ANNS). Artificial neural networks (*ANN*s) are inspired by the structure of human brain that is well suited for complicated task such as rainfall prediction, rainfall-runoff modeling, river flow modeling etc., in hydrologic systems. This approach is based on the human brain and it is faster compared with its conventional compatriots, flexible in the range of problems it can solve, and highly adaptive to the newer environments. The process of training is an important aspect, and the performance of an *ANN* is dependent on successful training. The training procedure involves the adjustment of connection between weights and threshold values for each of the nodes. The Fig. 1 shows mathematical representation of *ANN* model.

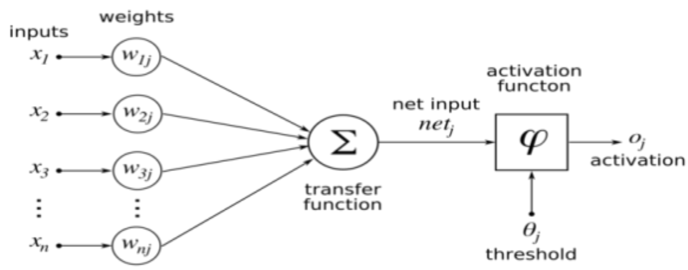

Figure 1. Mathematical representation of neural network

Back-propagation training algorithm. Back-propagation training algorithm is the most commonly used supervised algorithm for training the multi hidden layer *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. 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.

Development of ANN model. In this method, there is a combinations prepared as input of the *ANN* model. The following two cases of the data sets were taken in account for the modeling of *ANN* for rainfall prediction.

Case I: In this case N = 149 days in year and M = 30 years (1979-1981, 1984-1989 and 1991-2011). Let the observed values of vapor pressure, relative humidity, wind velocity, temperature and rainfall represented as $VP_{i,j}$, $RH_{i,j}$, $V_{i,j}$, $T_{i,j}$ and $P_{i,j}$ respectively for j^{th} day of the i^{th} year (i = 1,2,….,M and j = 1,2,…,N).

The functional form of the models can be represented as:

$$P_{i,j} = f(P_{i,j-3}, P_{i,j-2}, P_{i,j-1}, VP_{i,j-1}, RH_{i,j-1}, V_{i,j-1}, T_{i,j-1}) \tag{2}$$

It can be seen from Eq. 2, there are 7 numbers of input and one number of output in this case. Denoting input variables by X_1, X_2,…., X_7 and output by Y, the year wise arrangement of input and output variables is shown in Tab. 3.3. Thus each row of Tab. 3.2 will represent an input-output pair for the development of the artificial neural network model.

Case II: In this case the observed time series of vapour pressure, relative humidity, wind velocity, temperature and rainfall of previous days are taken as the input variables and current day rainfall as the output variable, considering rainfall occurrence period starting from 1st June to 30th October only. In this case N = 152 days in year and M = 30 years (1979-1981, 1984-1989 and 1991-2011). Let the observed values of vapour pressure, relative humidity, wind velocity, temperature and rainfall represented as $VP_{i,j}$, $RH_{i,j}$, $V_{i,j}$, $T_{i,j}$ and $P_{i,j}$ respectively for j^{th} day of the i^{th} year (i = 1,2,….,M and j = 1,2,…,N).

The functional form of the models can be represented as:

$$P_{i,j} = f(VP_{i,j-1}, RH_{i,j-1}, V_{i,j-1}, T_{i,j-1}) \tag{3}$$

It can be seen from Eq. 3.15, there are 4 numbers of input and one number of output in this case. Denoting input variables by X_1, X_2,…., X_4 and output by Y, the year wise arrangement of input and output variables is shown in Tab. 3.3. Thus each row of Tab. 3.2 will represent an input-output pair for the development of the artificial neural network model.

RESULTS AND DISCUSSION

Performance evaluation of model. Qualitative and quantitative evaluation of model is an important task to assess their capability or potential of developed model in simulation of actual circumstances. In the present study the following qualitative and quantitative performance indices were applied to verify the applicability of developed *ANN* model.

Table 1. Performance indicators

Indicator	*Equation*
Mean Square Error (MSE)	$MSE = \frac{\sum_{j=1}^{n}\left(Y_j - Y_{ej}\right)^2}{n}$
Normalized Mean Square Error (NMSE)	$NMSE = \frac{P\ N\ MSE}{\sum_{j=0}^{P}\frac{N\sum_{i=0}^{N} d_{ij}{}^2 - \left(\sum_{i=0}^{N} d_{ij}\right)^2}{N}}$
Correlation Coefficient (CC)	$CC = \frac{\sum_{j=1}^{n}\left\{\left(Y_j - \bar{Y}\right)\left(Y_{ej} - \overline{Y_{ej}}\right)\right\}}{\sum_{j=1}^{n}\left(Y_j - \bar{Y}\right)^2 \sum_{j=1}^{n}\left(Y_{ej} - \overline{Y_{ej}}\right)^2} \times 100$
Akaike's Information Criterion (AIC)	$AIC = 2k + n\ ln\left(\frac{2E}{n}\right)$
Coefficient of Efficiency (CE)	$CE = \left(1 - \frac{\sum_{i=1}^{n}\left(Y_j - Y_{ej}\right)^2}{\sum_{i=1}^{n}\left(Y_j - \bar{Y}\right)^2}\right) \times 100$
Volumetric Error (EV)	$EV = \left[\frac{\sum_{j=1}^{n}\left(Y_{ej} - Y_j\right)}{\sum_{j=1}^{n}\left(Y_j\right)}\right] \times 100$

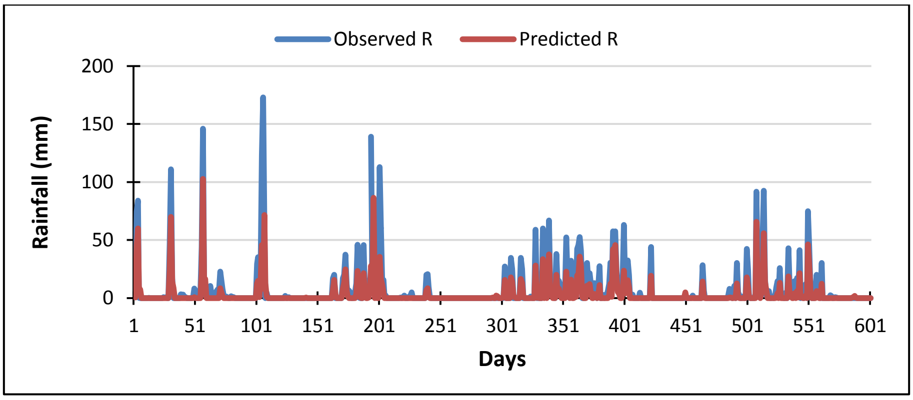

Figure 2. Observed and Predicted daily rainfall using ANN model (7-30-1) during testing period

The performance of the models was evaluated qualitatively and quantitatively by visual observation and employing various statistical indices viz. correlation coefficient, mean square error, normalized mean square error, Akaike's information criterion, co-efficient of efficiency and volumetric error (Tab. 1). The qualitative performance of the single and double hidden layer models (7-30-1), (4-12-1), (7-12-13-1) and (4-6-4-1) are shown in the (Figs. 2, 3, 4 and 5) respectively for the testing periods. In this study, the acceptable limits for the correlation coefficient, mean square error have been considered to be above 75%, and less than 0.01 respectively for quantitative performance of the models. For the comparison of different models, the Mean square error, Correlation coefficient and Akaike's information criterion of different model are calculated (Tab. 2).

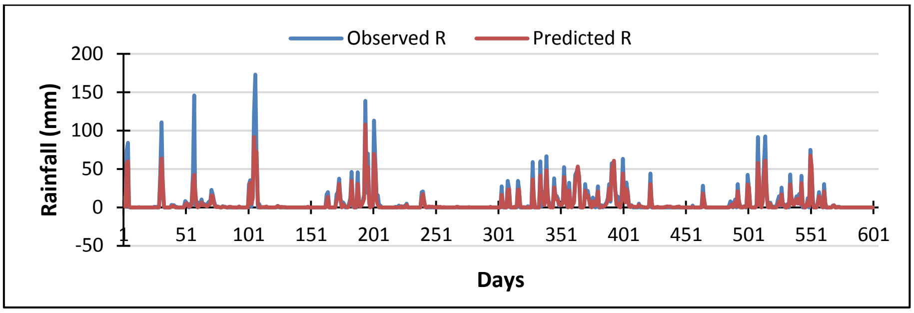

Figure 3. Observed and predicted daily rainfall using ANN model (7-12-13-1) during testing period

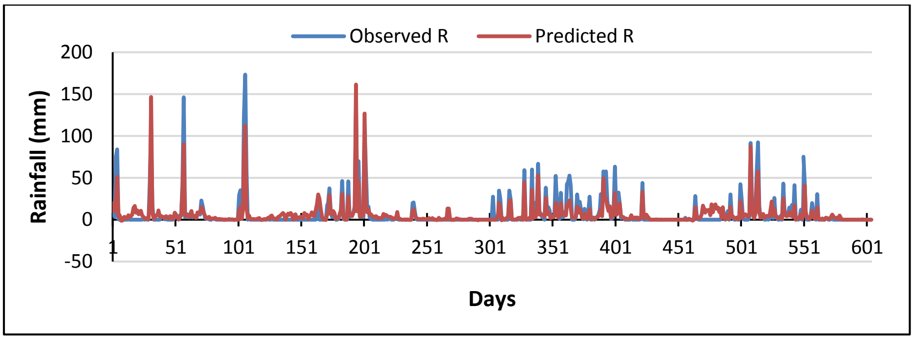

Figure 4. Observed and predicted daily rainfall using ANN model (4-12-1) during testing period

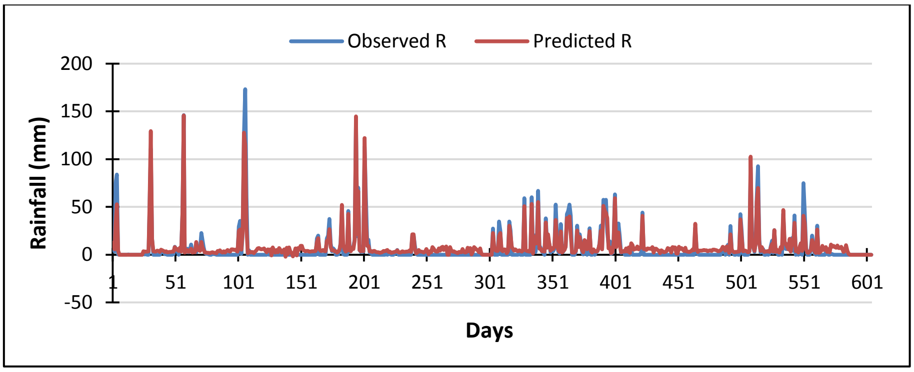

Figure 5. Observed and predicted daily rainfall using ANN model (4-6-4-1) during testing period

Quantitative evaluation. For better appreciation of the model, the predictive effectiveness of *ANN* model is judged on the basis of performance indicators. To judge the predictive capability of the developed model, Correlation Coefficient, Mean Square Error (*MSE*), Normalized Mean Square Error (*NMSE*), Akaike's Information Criterion (*AIC*), Coefficient of Efficiency (*CE*) and Volumetric Error (*EV*) were employed (Tab. 1). The Y_j is observed values, Y_{ej} is the predicted values, $\bar{Y}$ is the mean of observed values, n is the number of observations, P is the number of output processing elements, N is the number of observation in the data sets, *MSE* is mean squared error, d_{ij} is the desired output for observation i at processing element j, E is the sum-square-error, k is the number of parameters.

Table 2. Quantitative performance evaluation of developed models during testing for the best chosen network for ANN

Performance indies	*Single Hidden Layer ANN Network*		*Double Hidden Layer ANN Network*	
	7-30-1	*4-12-1*	*7-12-13-1*	*4-6-4-1*
MSE	*0.0015*	*0.0006*	*0.0008*	*0.0003*
NMSE	*0.43*	*0.37*	*0.40*	*0.29*
CC	*0.80*	*0.89*	*0.89*	*0.95*
AIC	*-3275.82*	*-4250.50*	*-3472.79*	*-4691.61*
CE	*69.7*	*83.48*	*82.5*	*87.1*
EV	*42.14*	*17.34*	*24.7*	*13.54*

Correlation coefficient (CC). The values of correlation coefficient for artificial neural networks models were computed. Based on *ANN* model, the values of correlation coefficient for Junagadh testing of single and double (7-30-1, 4-12-1, 7-12-13-1 and 4-6-4-1) hidden layers networks (2008-2011) of periods are 80.00, 89.00, 89.00 and 95.00 % respectively (Tab. 2). The higher values of correlation coefficient for testing periods show good agreement between observed and predicted values of rainfall. According to the correlation coefficient, the model 4-6-4-1 has better accuracy than the other selected models.

Mean square error (MSE). The mean square error (*MSE*) values between observed and predicted values of rainfall based on developed models of rainfall for single and double hidden layers (7-30-1, 4-12-1, 7-12-13-1 and 4-6-4-1) for testing periods are 0.0015, 0.0006, 0.0008 and 0.0003 respectively (Tab. 2). The lowest *MSE* shows the higher performance of the model and the model 4-6-4-1 has lowest *MSE*.

Normalized mean square error (NMSE). The normalized mean square error (*NMSE*), between observed and predicted values for developed single and double hidden layers models were determined and values so obtained. Based on *ANN*s model, the values of Normalized mean square error of developed models (7-30-1, 4-12-1, 7-12-13-1 and 4-6-4-1) for testing period (2008 to 2011) are 0.43, 0.37, 0.40 and 0.29 respectively (Tab. 2). Among all selected models, the model 4-6-4-1 has the lowest *NMSE*.

Akaike's information criterion. The Akaike's information criterion (*AIC*) is used to measure the tradeoff between training performance and network size. The goal is to minimize this term to produce a network with the best generalization. The values of akaike's information criterion of developed models (7-30-1, 4-12-1, 7-12-13-1 and 4-6-4-1) for testing periods are -3275.82, -4250.50, -3472.79 and -4691.61 respectively (Tab. 2). It can be seen from the performance of the models, the model 4-6-4-1 has greater accuracy as compared to the other models.

Coefficient of efficiency. The coefficient of efficiency of developed single and double hidden layer models for rainfall between the observed and predicted values of rainfall were. Applying the *ANN* model, the values of coefficient of efficiency of models (7-30-1, 4-12-1, 7-12-13-1 and 4-6-4-1) for testing periods are 69.7, 83.48, 82.5 and 87.1 % respectively (Tab. 2). The model 4-6-4-1 has higher value of *CE*. The higher value of *CE* show the good association between observed and predicted rainfall.

Volumetric error. The volumetric error of the model was also assessed by another measure i.e. volumetric error. Using the *ANN* models, the values of volumetric error for single and double hidden layers models (7-30-1, 4-12-1, 7-12-13-1 and 4-6-4-1) for testing period are 32.14, 14.34, 14.70 and 13.54 % respectively (Tab. 2). It is observed that the model 4-6-4-1 has lower *EV* and it shows the higher performance of the model.

CONCLUSIONS

In this work, an attempt has been made to train and validate the artificial neural networks models for monsoon season of Junagadh, Gujarat, India. In order to test these models, the actual rainfall data was collected from Junagadh Agricultural University, Junagadh, Gujarat, India for the period of 2008 to 2011. Two different combinations of the input parameters have been used for predict the rainfall. Four different single and double hidden layers models of artificial neural networks having a less mean square error and high correlation coefficient. The model 4-6-4-1 has lowest *MSE* and higher *CC*. The model 4-6-4-1 has been selected from the four models. It has been proved that *ANN*s provide better accurate forecasting of rainfall. These models based on the individuals parameters like vapour pressure, relative humidity, wind velocity and mean temperature.

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PRIMENA VEŠTAČKIH NEURONSKIH MREŽA ZA KRATKOROČNO PREDVIĐANJE PADAVINA

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Sažetak: Precizna prognoza padavina je neophodna za upravljanje vodenim resursima. Skorije je ispitivano nekoliko pristupa modeliranju postupaka ovakvih prognoza. U ovom istraživanju je analizirana mogućnost predviđanja padavina u Junagadh kroz modele veštačkih neuronskih mreža (*ANN*) direktnih distribucija. Za treniranje i testiranje mreža su korišćeni podaci za period od 30 godina. Pri formulisanju prediktivnog modela, zasnovanog na *ANN*, konstruisane su mreže sa jednostruko i dvostruko skrivenim slojevima. Performanse modela su ocenjivane upotrebom koeficijenta korelacije, srednje kvadratne greške, normalizovane srednje kvadratne greške, kriterijuma Akaike informacije, koeficijenta efikasnosti i zapreminske geške, a dva najprilagođenija modela (7-12-13-1 i 4-6-4-1) su izdvojena iz slučajeva I i II za prognozu kiše u Junagadh. Na osnovu ocene performansi ova dva modela su usvojena za predviđanje dnevnih padavina u ispitivanoj oblasti.

Ključne reči: veštačka neuronska mreža, algoritam direktne distribucije, predviđanje padavina, algoritam učenja sa povratnim širenjem

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