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Research Article

Maximum Daily Rainfall Simulation by using Artificial Neural Network (Case Study: Saravan-Iran)

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Abstract: Increases in greenhouse gases over the last century have caused abnormalities in the general circulation of the atmosphere. These abnormalities lead to changes in severity of climate phenomenon's in different parts of the globe. This study aimed to simulate the maximum daily rainfall in Saravan using Artificial Neural Network (ANN). To do this, maximum 24-h rainfall of different months was obtained from synoptic station of Saravan and data of climate indicators from 1986 to 2010 obtained from NOAA website. The effective climate indicators were identified using stepwise method. The data were normalized in the range of 0.1 to 0.9 and the data were applied with 80 to 20 combinations for training data and simulation to neural network model. The used networks were back propagation and Radial Basis with Levenberg-Marquardt training algorithm which created by different combinations of inputs, number of hidden layers and the number of neurons. After creation of mass models; it was found that the chosen network model, Radial Basis, has a better function. This model, with 2 hidden layers of 12 neurons, 0.9578 determination coefficients and less error, presented more acceptable performance in the prediction stage. Comparing the results of chosen ANN and regression models showed that ANN model can accurately predict the daily maximum precipitation. It was found, that the monthly precipitation, maximum and minimum monthly relative humidity, tropical pattern of the South Atlantic Index with 7 months delay and nino1+2 Index with 10 months delay play the main role in daily maximum precipitation in Saravan.

Keywords: Artificial neural network, daily maximum precipitation, saravan, simulation

INTRODUCTION

The Occurrence of heavy precipitation causes the flow of a large amount of water and sometimes devastating floods which is led to many damages. Heavy precipitation in dry regions leaves destructive effects due to low vegetation. Because of existing proper vegetation causes the improvement of soil permeability conditions and also acts against the runoff flow as a cause of friction and delays the runoff movement. Therefore, poor vegetation along showery precipitation causes soil erosion, destruction of buildings and communication structures, loss of agricultural lands, water sources degradation, etc. Therefore, providing a method for simulating the time of heavy precipitation is so essential. Using neural networks in this regard as a new approach in climate studies is of high importance. Much research has been done on precipitation. Trimble (1990) for study on and three-day rainfall maxima for central and southern Florida exploited of frequency analysis. Bremaud and Pointin (1993) indicated that to predict showery precipitation in a scale of less than one kilometer, radar data were used to track pluvial convective cells. Investigating the results emphasized a more relative efficiency in the conducted method compared with other methods. Lee *et al*. (1998) for estimation rainfall in Switzerland exploited from the ANNs model. That comparison with the observed data revealed that RBF networks produced good predictions while the linear models poor predictions. Maeda *et al*. (2001) exploited from the ANNs for prediction of precipitation in Kanto and Chubu areas in eastern Japan. Results of these two evaluations show that our method can adequately predict for the subsequent hour and is a practical tool for reducing snow hazards. Manton *et al*. (2001) has been studied role of climate change trends in extreme daily rainfall in Southeast Asia and the south pacific. Pathak (2001) daily rainfall maxima studied of central and south Florida. Rajurkar *et al*. (2002) for estimation rainfall-runoff process in catchment of the Narmada River in Madhya Pradesh (India) used from the ANN.

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The present model provides a systematic approach for runoff estimation and represents improvement in prediction accuracy over the other models studied herein. Grimes *et al*. (2003) with using from satellite data and ANN estimated real-time rainfall of Zambia in central Africa. Gong *et al*. (2004) daily precipitation changes perused in the semi-arid region over northern China. Rajurkar *et al*. (2004) exploited for modeling rainfall-runoff process ANN. Most importantly, the substitution of the previous day's runoff, by a term that represents the runoff estimated from a linear model and coupling the simple linear model with the ANN may prove to be very much useful in modeling the rainfall-runoff relationship in the non-updating mode. Riad *et al*. (2004) used neural network and classic regression model to predict rainfall-runoff process. The obtained results emphasize more accuracy of neural network. used neural network to estimate precipitation and temperature in Shiraz in that the neural network could predict more accurately the precipitation and temperature in Shiraz. Doing a synoptic study of precipitation mechanism in Southeast of Iran, three major mechanisms of precipitation in this area were identified. Waylen and Michael (2005) coincidence of daily rainfall events perused in liberia, costa rica and tropical cyclones in the caribbean basin. Gaume *et al*. (2006) studied short-term precipitation with Dimension Method. CDM analysis showed that rainfall time series is not chaotic and composed of independent variables by predicting precipitation and drought of catchment'sin Urmia Lake using time series method. Kumarasiri and Sonnadara (2006) by using the ANN forecasted short term and long term rainfall in Colombo of Sir Lanka. The success rates and rainfall trends within the monsoon seasons were also studied and presented. Regalado and Jose (2006) for maximum rainfall intensity analysis in Spain used l-moments. Bustami *et al*. (2007) exploited from the ANN toward Precipitation and Water Level Predictions of Bedup River. Results show that ANN is an effective tool in forecasting both missing precipitation and water level data, which are utmost essential to hydrologists around the globe. Nadarajah and Dongseok (2007) for estimation maximum rainfall in South Korea used from Gumbel distribution. Teschl *et al*. (2007) used neural network model to improve the measurement of precipitation by radar sensors. The results showed that these networks have a high accuracy (Hung *et al*., 2008) for rainfall forecasting in Bangkok, Thailand assisted from ANN model. Based on these study results, it is recommended that the developed ANN model can be used for real-time rainfall forecasting and flood management in Bangkok, Thailand. Deka *et al*. (2009) Distribution of Annual Maximum Rainfall analyzed in North-East India. Yoshioka *et al*. (2009) studied nitrogen concentration and rainfall phosphate in different years in Matsue, Japan. The results showed that maximum concentration of current phosphors occurs in spring rainfall and the maximum nitrogen concentration occurs in winter rainfall. Bergaoui (2010) maximum daily rainfalls analyzed in Tunis that results of this study are interesting: they help to diagnostic the behavior of the network of storm drainage and reduce the impact of these events during flooding periods. Charaniya and Dudul (2010) assist from the ANN model for daily rainfall prediction in Nagpur of Indian. Weerasinghe *et al*. (2010) with using ANN forecasted daily precipitation in the dry zone of Sri Lanka. Dutta *et al*. (2011) estimated rainfall intensity in Shriharikota using Doppler climate radar data and neural network model. El-Shafie *et al*. (2011) for rainfall forecasting Alexandria in Egypt used from ANN. That feed forward neural network model has shown better performance than the multi regression model. Khalili *et al*. (2001) by using ANN forecasted daily rainfall of Mashhad in northeast Iran. Results showed that ANN able own tenuous prediction of daily rainfall. Nastos *et al*. (2011) used neural network to predict maximum and minimum intensity of rainfall in Athens. The predictions results of neural network out of precipitation intensity of Athens for the next four months were acceptable. Wu and Chau (2011) for the modeling rainfall-runoff in the two watersheds from China used of artificial neural network coupled with singular spectrum analysis. Results show that MANN does not exhibit significant advantages over ANN. Chadwick and David (2012) by using from ANN estimated multispectral in the over Africa. It appears that multispectral data add more value to rainfall estimates at high-resolution scales than at averaged time scales, where the cloud microphysical information that they provide may be less important for determining rainfall totals than larger-scale processes such as total moisture advection aloft.

The purpose of this research is the simulation and prediction of maximum daily precipitation in Saravan so that the conditions require for the conversion of heavy precipitations will provide an opportunity for development with an appropriate preparation to reduce the effects damaging effects of these precipitations. Management of floods due this cloudburst can obtained design of agriculture development. Also prediction of cloudburst occurrence decreased that loss outturn.

MATERIALS AND METHODS

Saravan pre-province is located in the eastern part of Iran near Pakistan and bordered with Khash, Iran shahr and Saravan cities (Fig. 1). The climate characteristics of Saravan are shown in Table 1 that confirms the arid climate conditions of the area. As is clear, a precipitation more than 10 mm falls per day in less than 4 days in the year. The highest daily rainfall is almost 50 mm. This is while the average annual precipitation is about 107 mm.

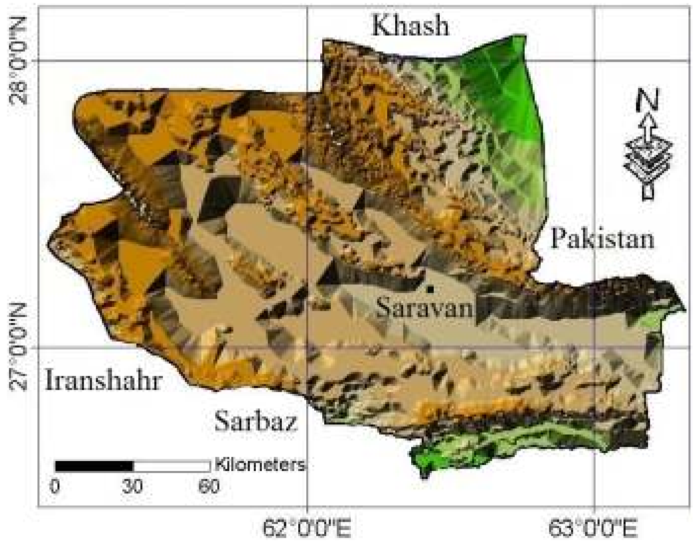

Fig. 1: Geographical location of Saravan township

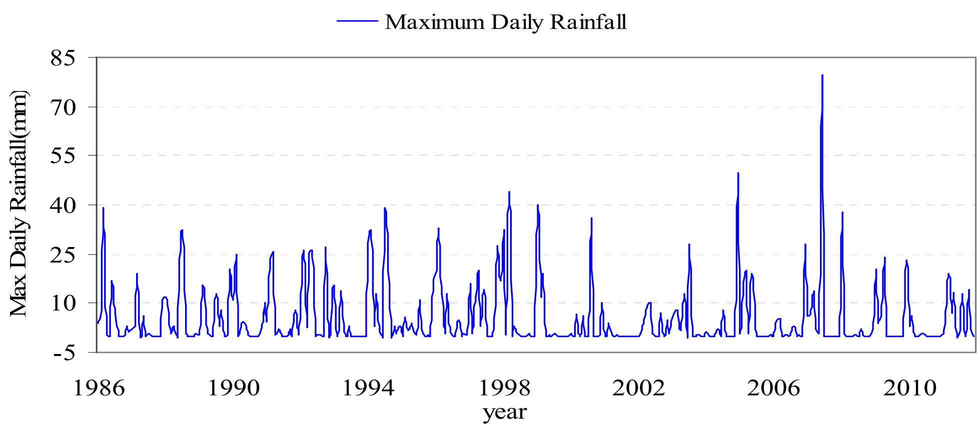

Fig. 2: Graph of maximum daily rainfall in Saravan (1986-2010)

Table 1: Climatic characteristics of the study area

Variable	Value	Variable	Value
Average of minimum temperature	14.5	No. of days with minimum temperature equal 00 and below	12.4
Average of maximum temperature	29.5	Monthly total of precipitation in mm	107.3
Average of mean daily temperature	22	Greatest daily of precipitation in mm	49.8
Temperature records lowest	-7	No. of days with precipitation equal to or greater than 10 mm	3.9
Temperature records highest	44.6	No. of days with precipitation	26.8
Average of relative humidity %	28	No. of days with thunder storm	19.7
Average of maximum relative humidity %	48	No. of days with snow or sleet	0.2
Average of minimum relative humidity %	15	Average of wind speed in knots	6
No. of days with maximum temperature equal 30 and above	190.1	Fastest wind direction and speed in knots: direction 40-speed	43
No. of days with maximum temperature equal 00 and below	0	No. of cloudy days (7-8) /8	12.8
No. of days with minimum temperature equal 21 and above	105	Monthly total of sunshine hours	3416.1

Table 2: Statistical characteristic of maximum daily rainfall Saravan (1986, 2010)

Parameters	Value	Parameters	Value
Mean	5.650	Range	79.70
Median	0.400	Precipitation of less than 10 mm	79.33%
Standard deviation	10.306	Precipitation is 10 to 20 mm	10.67%
Variance	106.227	Precipitation is 20 to 30 mm	6%
Skewness	2.828	Precipitation more than 30 mm	4%

Table 3: Correlation of selected input with maximum daily precipitation Saravan

Variable	Correlated with the maximum rainfall	Variable	Correlated with the maximum rainfall
Monthly precipitation	0.908	Nino1+2 with 10 months delay	0.204
Minimum monthly humidity	0.503	Tsa with 7 month delay	-0.118
Maximum monthly humidity	0.547	-	-

To simulate daily maximum rainfall in Saravan, variables of monthly precipitation, maximum, minimum and mean temperature as well as monthly relative moisture and climate indicators along with time delay as input were used. The cause to use monthly time span is a very small number of rainy days and also lack of climate indicators data in daily timeframe. The duration of statistical period is 25 years (1986-2010) which was confirmed at the 99% confidence level of homogenized data using flow testing? The statistical data of maximum daily precipitation has been shown in Table 2. Also, the time series of daily maximum precipitation in Saravan during the statistical period has been shown in Fig. 2.

The variable affecting daily maximum precipitation in Saravan was determined using stepwise method is SPSS environment (Table 3). Data were applied to neural networks with 80 to 20 combinations for training and prediction data. To increase the efficiency of neural network, data were normalized in 0.1-0.9 range (Sajikumar and Thandaveswara, 1999):

$$N_i = 0.8 * \left[\frac{X_i - X_{min}}{X_{max} - X_{min}}\right] + 0.1 \tag{1}$$

NINO 1+2 indicator with a 10 month delay and TSA indicator with a 7 month delay were chosen among 19 indicators. NINO 1+2 indicator is related to the extent amount of the temperature in Pacific Ocean in eastern tropical areas which involves the range of between 0-10° south and 80-90° west. The tropical pattern of the South Atlantic Ocean or TSA refers monthly mean abnormalities of water temperature of Atlantic Ocean from the tropical region to 20° of southern latitude and 10-30° western longitude.

Artificial neural networks: An artificial neural network is an interconnected group of artificial neurons that has a natural property for storing experiential knowledge and making it available for use. The artificial neuron uses a mathematical or computational model for processing of information based on a connectionist approach to computation, akin to a human brain. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network. Learning in ANN is similar to biological systems, involving adjustments to the synaptic connections that exist between the neurons. Learning often occurs by example through training or exposure to a trusted set of input/output data where the training algorithm iteratively adjusts the connection

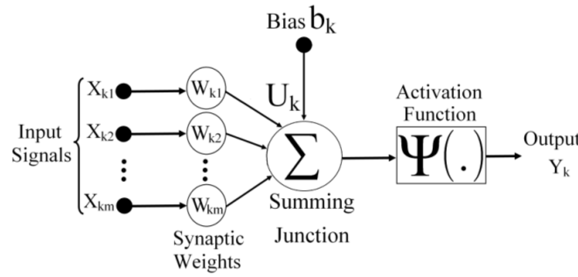

Fig. 3: Modeling a simple neuron (Kumarasiri and Sonnadara, 2006)

weights (synapses) and these connection weights store the knowledge necessary to solve specific problems (Hung *et al*., 2008).

The fundamental processing element of an ANN is an artificial neuron. Just like the natural neuron in human brain, it can receive inputs, process them and produce the relevant output. A simple mathematical model can be used in explaining a neuron quantitatively (Fig. 3). The stimulus functions used here are linear, radbas and hyperbolic tangent Eq. (2) to (4):

$$f(x) = \begin{cases} 0 \; if \; x < 0 \\ 1 \; if \; x \geq 1 \end{cases} \tag{2}$$

$$radbas(n) = e^{-n^2} \tag{3}$$

$$\varphi(U) = tanh\left(\frac{U}{2}\right) = \frac{1 - exp\,(-U)}{1 + exp\,(U)} \tag{4}$$

The networks used in this study are the type back propagation and Radial Basis ones. Back propagation network is a multilayer network with non-linear stimulus function and Widrow-Hofflearning rule. It also uses for the approximate functions and to find a relationship between input and output and classifying them based on determined ways by the designer (Fig. 4). Radial Basis networks need more neurons than the back propagation networks, but they need less time for designation than back propagation networks. When the networks' inputs are high, they have the best efficiency (Fig. 5).

Training neural networks is done based on the minimum error (mse) and maximum correlation value (Aksoy and Dahamshed, 2009). To train network, Levenberg-Marquardt algorithm has been used which follows error back propagation rule. This algorithm tries to reduce calculations using lack of Hessian matrix calculation. Matrix Hessian is computed as follows:

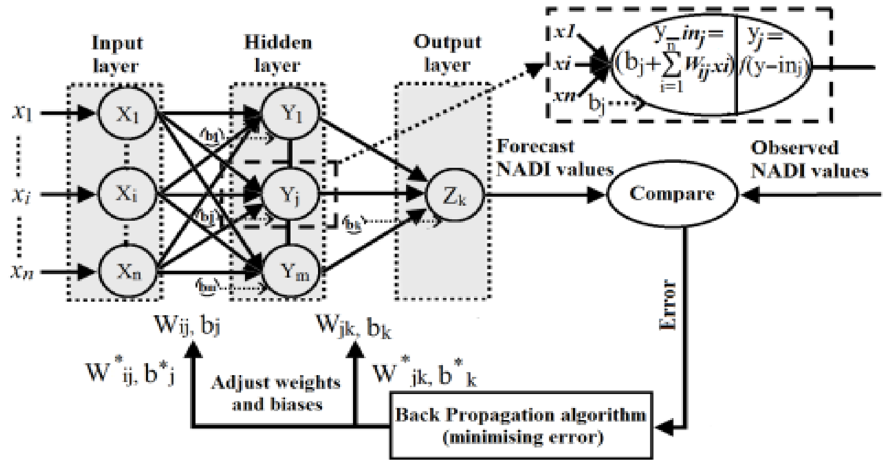

Fig. 4: Multilayer feed forward network with error back propagation training algorithm (Barua, 2010)

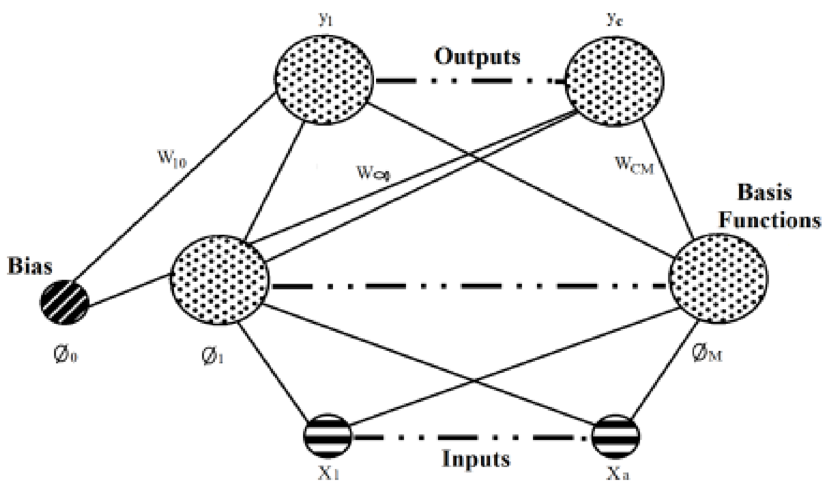

Fig. 5: Architecture of a RBF neural network (Lee *et al*., 1998)

$$H = JTJ \tag{5}$$

The slope is calculated as follows:

$$g = J_e^T \tag{6}$$

where,

J: Jacobian matrix and involves the first derivations of the network errors with respect to weights and biases

e: The network's vector error

Jacobian matrix is estimated by BP standard techniques and has fewer complexities than Hessian matrix. Levenberg-Marquardt algorithm uses the following approximation to calculate Hessian matrix:

$$X_{k+1} = X_k - [J^T J + \alpha I]^{-1} J^T + e \tag{7}$$

where,

X : The weight of neural network

J : The Jacobian of criterion matrix of network performance which must be minimum

α : A number that controls training process

e : The residual error vector

The calculation of neural networks in feed forward is as follows:

$$Net_{pi} = \sum W_{ij}\, a_j + b_i \tag{8}$$

where,

a_{pj} : The output layer of previous layer

W_{ij}: The weight of related layers

b_i : The amount of bias

This relation is linear which F (Net_{pj}) is calculated after it. In fact, F is a stimulus function which is non-linear in hidden layers and linear in output layers. During a training process, i.e., finding the weights and suitable biases to predict, a regressive algorithm for training is required which is Back Propagation method (BP) calculated as follows:

$$\Delta W_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} \quad (9)$$

$$E = \sum_i (obs_i - pre_i)^2 \quad (10)$$

In that ΔW is added to W_{ij} in that η is the rate of training and function.

In this study, multivariate regression method as well as the results of neural network model was used for maximum prediction of daily precipitation in Saravan to determine the performance of these networks by comparing its results with neural network. Multivariate regression model is can be calculated as follows:

$$Y = \beta + \alpha x_1 + \alpha x_2 + \ldots + \alpha x_n \quad (11)$$

Also, besides the results of neural network model, multivariate regression method was used in this study to predict maximum daily precipitation in Saravan in order to determine the performance of these networks by comparing its results with neural network. Multivariate regression model can be calculated as follows:

$$MAE = \frac{\sum_{k=1}^{k} |x_k - y_k|}{k} \quad (12)$$

$$R^2 = \frac{\sum_{k=1}^{k} x_k y_k}{\sqrt{\sum_{k=1}^{k} x_k^2 \sum y_k^2}} \quad (13)$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^{k} (x_k - y_k)^2}{k}} \quad (14)$$

In the above equation,
X_k : The observational amounts
Y_k : The predicted amounts
K : The number of data

DATA ANALYSIS AND DISCUSSION

After forming multiple models in terms of the number of inputs, the number of layer and neurons, it was found that monthly precipitation inputs in Saravan, maximum relative monthly moisture in Saravan, minimum relative monthly moisture in Saravan and TSA climate indicators with 7 months delay and NINO 1+2 indicator with 10 months delay have the most important effects on the maximum daily precipitation of Saravan. The results of neural network modeling shows that 15 models in back propagation networks and 10 models in Radial Basis have more accurate simulation than the maximum rainfall in Saravan (Table 4 and 5).

Results of back propagation simulations show that most models have a very good performance and perform simulation with high accuracy. Although there are trivial differences in the results that shows a better performance of a model than the other one. BP15 model with 0.9996 determination coefficients and the lowest error had the best performance among 15 chosen models in training stage.

Results of other models in this stage were also very good. The highest determination coefficient belongs to BP8 model in the amount of 0.9735 in the prediction stage. However, BP4 model with root mean square of 2.8704 and mean absolute error of 0.3706 have the best performance than the other ones in terms of the lowest amount of error. Therefore, given the closeness of models in terms of the amount of coefficient determination, BP4 model had the lowest error and is chosen as the selected model of back propagation model.

In Radial Basis, RBF 10 model produced the highest determination coefficients (0.9958) and the lowest error in training stage. In this stage, most models are highly accurate and RBF4 model has a very good performance in prediction stage and produced the highest amount of determination coefficients (0.9678) and the lowest amounts of error than the other models.

Table 4: Results of selected models of back propagation neural network

	Train			Test			
Models	R^2	RMSE	MAE	R^2	RMSE	MAE	No neuron
BP1	0.9894	0.9938	0.0641	0.9372	7.3053	0.9431	12-1
BP2	0.9894	0.9921	0.0640	0.9374	5.6752	0.7327	15-1
BP3	0.9896	0.9858	0.0636	0.9360	3.9326	0.5077	25-1
BP4	0.9908	0.9593	0.0619	0.9500	2.8704	0.3706	12-12-1
BP5	0.9906	0.8870	0.0573	0.9391	3.8528	0.4974	15-15-1
BP6	0.9942	0.7377	0.0476	0.9541	5.4060	0.6979	18-18-1
BP7	0.9930	0.8166	0.0527	0.9339	4.1948	0.5416	20-20-1
BP8	0.9896	0.9841	0.0635	0.9753	4.3249	0.5583	8-8-8-1
BP9	0.9928	0.9491	0.0613	0.9539	3.7038	0.4782	12-12-12-1
BP10	0.9898	0.9748	0.0629	0.9397	4.4378	0.5729	15-15-15-1
BP11	0.9934	0.8603	0.0555	0.9294	5.7688	0.7447	10-10-10-10-1
BP12	0.9930	0.9334	0.0603	0.9524	6.9176	0.8931	12-12-12-12-1
BP13	0.9928	0.9442	0.0609	0.9401	7.1511	0.9232	15-15-15-15-1
BP14	0.9974	0.5115	0.0330	0.9337	3.2003	0.4132	18-18-18-18-1
BP15	0.9996	0.2674	0.0173	0.9314	4.6552	0.6010	20-20-20-20-1

Table 5: Results of selected models of radial basis neural networks

	Train			Test			
Models	R^2	RMSE	MAE	R^2	RMSE	MAE	No neuron
RBF1	0.9894	0.9943	0.0642	0.9383	7.9242	1.0230	12-1
RBF2	0.9898	0.9776	0.0631	0.9218	8.8786	1.1462	15-1
RBF3	0.9896	0.9916	0.0640	0.9436	4.9448	0.6384	18-1
RBF4	0.9896	0.9814	0.0633	0.9578	2.5739	0.3323	20-1
RBF5	0.9902	0.9393	0.0606	0.9481	6.0317	0.7787	25-1
RBF6	0.9898	0.9891	0.0638	0.9327	3.2215	0.4159	30-1
RBF7	0.9910	0.9138	0.0590	0.9283	7.2032	0.9299	35-1
RBF8	0.9906	0.9452	0.0610	0.9229	4.0856	0.5275	8-8-1
RBF9	0.9894	0.9957	0.0643	0.9243	6.6936	0.8641	12-12-1
RBF10	0.9958	0.7454	0.0481	0.9266	3.4202	0.4416	15-15-1

Table 6: Comparison of selected models of neural networks and regression

	Train			Test		
Models	R^2	RMSE	MAE	R^2	RMSE	MAE
BP4	0.9908	0.9593	0.0619	0.9500	2.8704	0.3706
RBF4	0.9896	0.9814	0.0633	0.9578	2.5739	0.3323
Regression	-	-	-	0.8911	3.4059	0.1966

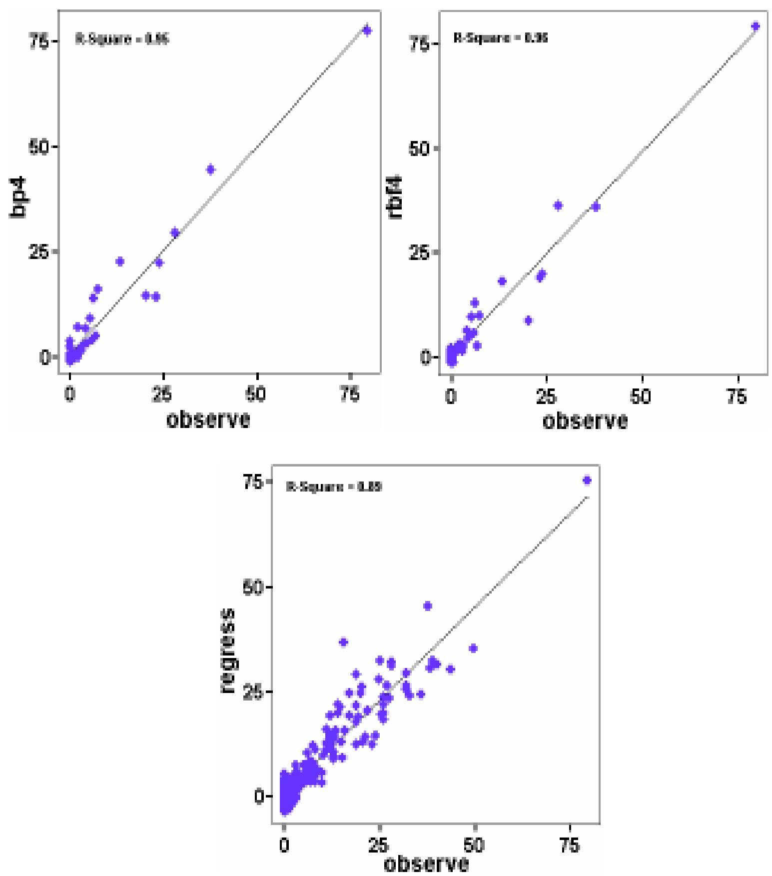

Fig. 6: Scatter diagram of actual and predicted values of the neural networks and regression model

Accordingly, Radial Basis was chosen as the preferred model. Results of selected neural network models and regression model have been shown in Table 6.

Results of Table 5 show that Radial Basis has a high accuracy than the back propagation network as well as a multivariate regression model to predict daily precipitation in Saravan. The distribution diagram of the actual and simulated amounts in the selected neural network models and regression model in Fig. 6 show that neural network model has a high accuracy for maximum daily rainfall simulation in Saravan. The real

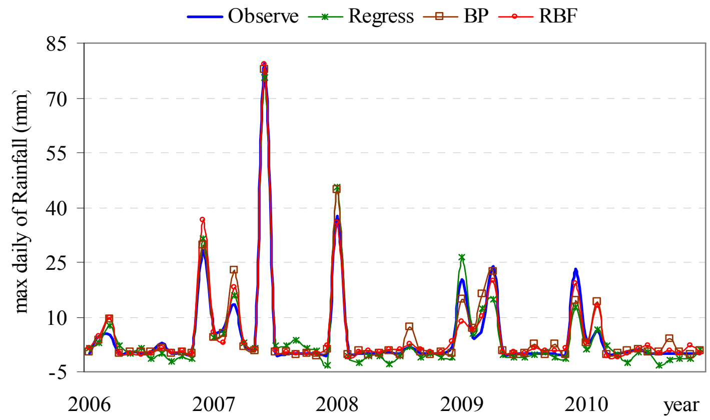

Fig. 7: Comparison of maximum daily rainfall in the neural networks and regression model

and simulated amounts of maximum daily rainfall in Saravan have been shown in Fig. 7 in that it shows that neural network model has simulated well the maximum precipitation in Saravan.

CONCLUSION

In this study, the maximum daily rainfall in Saravan was predicted and simulated using Radial Basis neural network model and back propagation model. The results obtained in these models were compared with regression method in order that the accuracy of the network is specified. Having been analyzed output model of neural networks and regression model, the following results were obtained:

- Monthly precipitation variables, Saravan monthly maximum relative humidity, minimum monthly relative of humidity climate indicators in Saravan and TS Aclimate indicators with 7 months of delay and NINO1 +2 with 10 months delay have the greatest effect on the maximum daily rain fall in Saravan.
- RBF4 model with a hidden 20 neuron layer, 0.9578 determination coefficients, 2.5739 root mean square and 0.3323 mean absolute errors in prediction stage were chosen as the most efficient model for a maximum prediction of daily precipitation in Saravan among the selected models in the two types of neural networks.
- The results comparison of the chosen model of neural network and regression model shows that neural network model predicts maximum daily precipitation in Saravan with a higher accuracy.
- Increasing input variables have not many effects in improving the results of models. Also, normalizing data in 0.1-0.9 range causes the improvement of the results obtained in neural network model.
- In back propagation networks, increasing the number of layers with respect to the volume of input data and lower neuron causes the improvement of this network's performance while more neurons along with a lower layer in Radial Basis networks cause the improvement of the mode's results.

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