Journal of Environmental Science and Technology

ISSN 1994-7887

Journal of Environmental Science and Technology 6 (1): 16-28, 2013
ISSN 1994-7887 / DOI: 10.3923/jest.2013.16.28

Prediction of Monthly Rainfall for Selected Meteorological Stations in Iraq using Back Propagation Algorithms

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ABSTRACT

Artificial neural network was used for predicting monthly mean rainfall. In order to train the neural network back propagation algorithms had been employed. Rainfall data along the years (1970-2000) measured in four cities (Mosul, Baghdad, Rutba and Basra) in Iraq were used as training and ten years (2001-2010) used for testing. The logistic sigmoid activation function was used for both hidden and output layers. To estimate difference between measured and estimated rainfall values, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and correlation coefficient (R) were determined. According to three statistical indices were calculated to examine the performance of the optimum ANN model, It was found that the optimum model according three among the four considered statistical indices was in Rutba station during December month where the correlation coefficient (R), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Bias Error (MBE) was 0.9998, 0.59, 0.56, -0.56 mm, respectively, these statistical results have shown the ability of the artificial neural network for rainfall prediction.

Key words: Artificial neural network, rainfall prediction, meteorology, artificial intelligence, hydrology

INTRODUCTION

The accurate estimation of monthly rainfall value is very important for agricultural and socio-economic activities. These types of researches serve planning and management of water resource, especially in arid and semi-arid regions like Iraq and neighbor countries which faces terrible water scarcity and experiences difficult in meeting the increasing human and environmental water demand. Since the stream flow, surface water reservoirs but partially also ground water depend basically on precipitation, a good-fit rainfall prediction might be a useful tool to identify these issues. The Artificial Neural Networks (ANNs) became a desirable model in forecasting rainfall (Dooge, 1977; Hao *et al.*, 1980; Jain and Chalisgaonkar, 2000; Smith and Eli, 1995; Cannon and Whitfield, 2002; Silverman, 1999; Navone and Ceccatto, 1994).

It is well-known that the rainfall series have more complex nature compared with river runoff series. The correlation between consecutive rainfall measurements is lower with regard to that of consecutive flow values, for this reason Silverman and Dracup (2000) have employed teleconnection indices and El Niño-Southern Oscillation (ENSO) indicators as input to forecast rainfall values. In contrast, flow prediction based only on previous flows provides quite satisfactory results (Shamseldin, 1997; Dawson and Wilby, 1998; Tokar and Johnson, 1999; Sajikumar and Thandaveswara, 1999; Zhang and Govindaraju, 2003).

Some of the hydrologic problems included the ANN employing for rainfall-runoff modeling (Hsu *et al*., 1995; Smith and Eli, 1995; Fernando and Jayawardena, 1998), scheduling of hydro electric power systems (Saad and Bigras, 1996) and river flow prediction (Karunanithi *et al*., 1994; Zhu and Fujita, 1994). French *et al*. (1992) used the generated rainfall storms to calibrate an ANN model and then generated plausible rainfall sequences that could occur over catchments using a physically based rainfall to validate the ANN. The main advantage of ANN is in cases where intrinsic nonlinearities in the dynamics prevent the development of exactly solvable models, not just in meteorology, all of these criteria are present in the sense that the dynamics are inherently nonlinear and prediction is one of the main goals. ANN has been used successfully to model rainfall in meteorological applications by Xiao and Chandrasekar (1997), they have developed a three-layer perceptron ANN based algorithm for rainfall estimation from reflectivity of radar observations. The present study is an attempt of monthly rainfall prediction by ANNs using previous monthly rainfall measurements. It was aimed to see the rainfall prediction performance of ANNs in the absence of other meteorological parameters.

MATERIALS AND METHOD

Artificial neural network: ANN models are the models which are used for actualizing one or many processes of teaming, relationship, sense brain, generalization and optimization by benefiting from the obtained data (Fausett, 1994). People have studied on human brain for thousands of years and these processes have gained speed with the advent of modem electronics. The first study related with neural network using modem elctronics was done by Wang (2006). In their study, simple neural network s modeled on with electrical cycles. In 1950s, with the advent of the computer technology the developments on artificial neural has gained speed. Firstly with the leadership of IBM research laboratory, Nathaniel Rochester tried to simulate a simple neural network. Although he became unsuccessful first he carried out it in his later attempts (Barto, 2003), he developed MADALINE method. MADALINE is the first neural network model which was adapted from the existed problems in the world This model was used to prevent the echoes which occurred in phone lines and it has still been used for commercial objections. In 1985, American Physics Institution proved that neural network can be used for computer technology (Wang, 2006). Today, ANN is used every part of engineering and the comments on the model is still continuing and companies study on 3 type neurons which are defined as digital, analog and visual.

ANN network may be inspected in two parts any one of which is about its structure and the other is about mathematical functions. In general, ANN structure is formed by the neural cells in the input, hidden and output layers and stormed in according with the linkage among them. In hidden cells, there is an internal processor or a trigger processor called as processor (activation function). Processing of ANN can be thought as internal and external processors which has two mathematical functions. An internal process of ANN is carded out by processors in the hidden layers. External process occurs with the application of the relationship among Myer cells randomly and the reduction of errors to minimum values. These mathematical operations take on the task of ANN learning, being trained, recall and recognition of new information and refresh the network connections (Fausett, 1994).

The aim all the learning algorithm is to obtain the weight of connection which will provide the most appropriate relationship between input and output data. According to the single layer sensor network, the two layers feed forward networks can be eliminate many limits. However, the problems are emerging about sow to change the sheets among the weight connections. In this context, the back propagation algorithm contains a powerful learning process which can be used for ANN models. The essence of back propagation algorithms working process depends on fully and effectively calculations of the changes in ANN which generally occur in sub-systems. This provides the use of the ANN in the learning of information in the complex and nonlinear structure and the relationship among the processor parameters. The architecture of the back propagation algorithm has shown in Fig. 1. Is performed step by step as follows (Fausett, 1994):

- First, the layers and the number of cells in all layers are determined for the purpose of determining ANN's topological structure
- At the later stages, the values of constant parameters are assigned
- The weight connections between layers are determined
- By using the connection weights is assigned with the symbol n measurement number, output vector is obtained for all input vector
- The values are renewed and its starting point is the weight connection between output layer and hidden layer for the purpose of the reversal of the spread of the errors
- For the renewal of the, values, weight coefficients. Firstly it is required the calculation of the error value and derivatives on the basis of weight connection
- Total error value is calculated by using the output values which are given by ANN and expected values
- It is necessary that the derivatives must be taken again according to error relations with the basis of their weights for the purpose of renewal in every weight coefficient

ANN has many applications on hydrology field. There are many successful examples especially on rainfall and runoff models (Fernando and Jayawardena, 1998; Cigizoglu, 2004). Additionally, ANN model is started to be used frequently to determine quality of the water parameters (Newham *et al.*, 2003), To determine evapotranspiration quantity (Keskin and Terzi, 2006), to predict the daily suspended sediment quantity in recent years (Cigizoglu, 2004; Kisi, 2004).

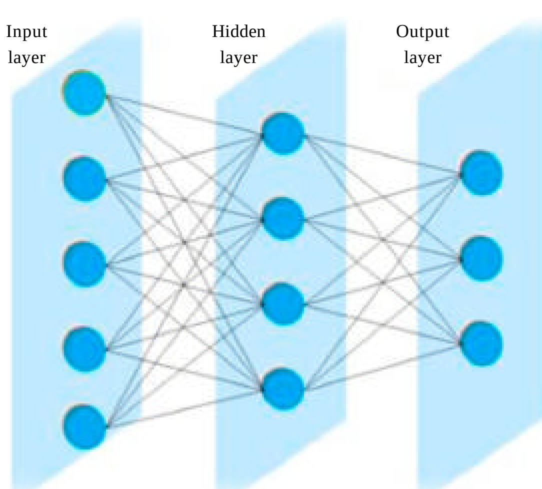

Fig. 1: General ANN structure

Area of study and data processing: The ANN methodology was applied to precipitation predicting in four sites in Iraq (Mosul Baghdad, Rutba and Basra), the study regions map was given in Fig. 2.

In this study, monthly precipitation data for the selected stations were obtained from Iraqi meteorological organization and seismology (IMOS).

The considered period and some statistical description have been shown in Table 1. The data belonging to the period between 1970 and 2000 were used to develop the training part of the ANN model. The remaining years of data (2001-2010) were used to test period.

The missing data ranging between 2.03 to 6.64% from total records of precipitation data, therefore normal ratio method were used to predict the missing data, in this method the missing precipitation values at a site can be estimated from concurrent observations that are located as close to and evenly spaced from the missing data station as possible, known as index station (Gupta, 1989). The normal ratio method is:

$$\frac{P_x}{N_x} = \frac{1}{n}\left(\frac{P_1}{N_1} + \frac{P_2}{N_2} + \frac{P_3}{N_3} + \ldots\ldots\ldots\ldots\ldots\frac{P_n}{N_n}\right) \tag{1}$$

Table 1: Geographical coordinate, measurements periods and monthly precipitation data for considered stations

					Precipitation			
Station	Latitude (N°)	Longitude (E°)	Altitude (m)	Period (year)	Minimum (mm)	Maximum (mm)	Mean (mm)	SD (mm)
Mosul	36.19	43.09	222.6	1970-2010	165.1	577.1	355.10	111.43
Baghdad	33.21	44.26	34.0	1970-2010	57.8	284.1	118.70	48.23
Rutba	33.02	40.17	615.5	1970-2010	23.3	263.8	122.40	62.19
Basra	30.25	47.50	3.1	1970-2010	48.3	296.6	138.02	58.81

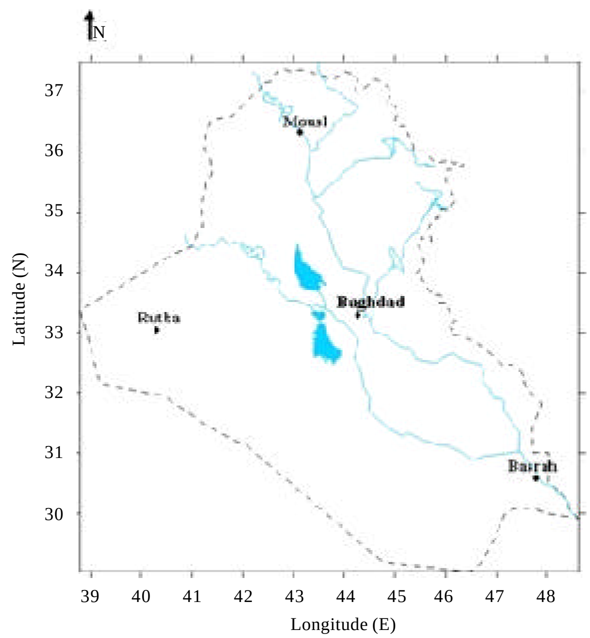

Fig. 2: The map of Iraq with four experimental sites

Where:

P_x	= Missing precipitation for station x
P_1, P_2, P_3, P_n	= Precipitation at neighboring station for the concurrent period
N_x	= Normal long-term precipitation at station x
N_1, N_2, N_3, N_n	= Normal long-term precipitation for neighboring station
n	= Number of observations

The data that is used in present study consist of daily measurements of rainfall. Preprocessing steps for the data were needed due to the huge size of it and also to show the statistical nature of it. The following steps were taken in the preprocessing stage:

- Calculating the monthly average for the rainfall
- Calculating the total rainfall percentage for each month. For (i =1, 2, 3 ………. 12) which represents the months and for (t = 1970, 1971 ……… 2010) which represents the years, then the average rainfall in each month R in each year can be represented as R_{it} For each month the total rainfall that happened through all the years S_i:

$$S_i = \sum_{i=1970}^{2010} R_{it} \tag{2}$$

And the gross total rainfall for all the period G is:

$$G = \sum_{i=1}^{12} S_i \tag{3}$$

So, the total percentage for each month P_i is:

$$P_i = \frac{S_i}{G} \tag{4}$$

- The yearly total rainfall R^y_t where t = 1970, 1971, ... , 2010, are calculated
- Calculating the change in rainfall between every two succeeding years. The change in rainfall is determined for the yearly total rainfall, January and December. This is illustrated in the following equations:
  - For yearly total rainfall at any year t:

$$\Delta^y_i = R^y_{t-1} - R_t^{12} \tag{5}$$

  - For January (i = 1) at any year t:

$$\Delta^1_t = R^1_{t-1} - R_t^1 \tag{6}$$

  - For December (i =12) at any year t:

$$P_1, P_2, P_3, P_n\ \Delta_t^{12} = R^{12}_{t-1} - R_t^{12} \tag{7}$$

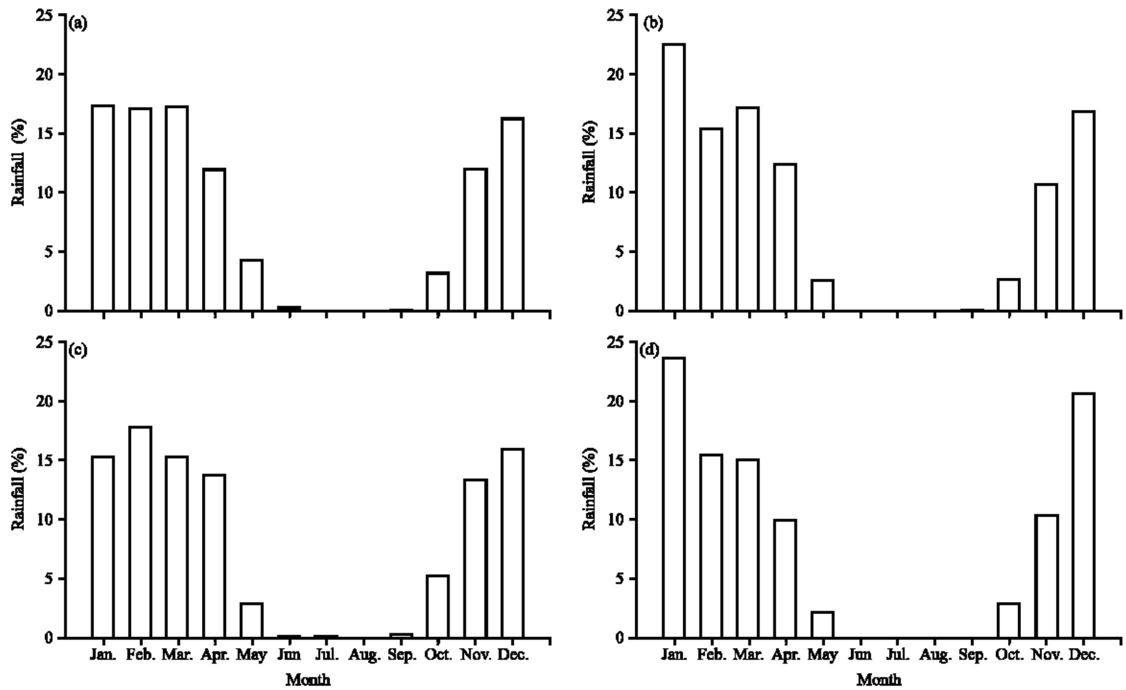

Fig. 3(a-d): Total rainfall of (a) Mosul, (b) Baghdad, (c) Rutba and (d) Basra stations

A corroding to above calculations and in order to choose the months which use in present study, the total percentage for each month was used and two empathizes have been considered. The first was months which have the values more than 15% of total annually rainfall and represented by (January, February, March and December) for all stations and the second was the months which achieves values of rainfall summation more than 60% of the total annually rainfall as shown in Fig. 3.

Evaluation of the predicted results: The reliability of the predictive model was demonstrated by the use of some statistical indices. In order to establish the credibility and generally the capacity of a good prognosis by the trained and tested ANN model, the Root Mean Square Error (RMSE), the correlation coefficient (R) and Mean Square Error (MSE) were used as statistical indices (Willmott, 1982; Schaeffer, 1980; Loague and Green, 1991) and defined as the following:

$$\text{RMSE} = \sqrt{\sum \frac{(m-e)^2}{n}} \tag{8}$$

$$R = \frac{\sum [(m-\overline{m})(e-\overline{e})]}{\sum \sqrt{(m-\overline{m})^2 (e-\overline{e})^2}} \tag{9}$$

$$\text{MSE} = \sum_{i=1}^{n} \frac{(m_i - e_i)^2}{n} \tag{10}$$

where, m is the measured value, e is the estimated value, m, e are the average values of the measured and estimated values respectively and n is the number of the observation, the RMSE is a commonly used measure of the differences between the predicted values by a predictable model and the real-observed values. The RMSE was used as a single measure that indicates the ability of the model prediction and has the same units as the predicted value. The smaller the numerical value of RMSE was, the closer the real values were to the predicted values by the model.

In statistics, the correlation coefficient (R),The main purpose is the prediction of future outcomes on the basis of other related information. It is the proportion of the variability in a data set that is accounted by statistical model. It provides a measure of how well future outcomes are likely to be predicted by the model.

RESULTS AND DISCUSSION

Table 2 shows the values of the statistical indices of reliability, such as RMSE, MAE, MBE and R, for the four examined stations and for each particular case of prediction as monthly and yearly basis. In the result of the training procedure, it can be seen in Table 2 that the MAE value ranged from 0.46 to 2.23 mm differ from the actual value for the long-term monthly rainfall, while the RMSE values ranged from 0.59 to 2.72 for the monthly rainfall. For the long-term monthly rainfall, the maximum MAE values were found for march in Mosul and Baghdad meteorological stations. On the other hand, the best results were found to be 0.011 and -0.069 mm in Rutba meteorological stations for January and December months respectively. The maximum correlation coefficients (R)

Table 2: The root mean square error (RMSE), mean absolute error (MAE), mean bias error (MBE), correlation coefficient (R) Values for testing procedure

Duration	RMSE	MAE	MBE	R
Mosul station				
January	2.6432	2.1700	-0.0362	0.9980
February	2.4557	1.8200	-0.3925	0.9977
March	2.7299	2.2300	-0.2642	0.9982
December	2.1513	1.8800	-0.5724	0.9982
Yearly	6.2738	4.3900	0.9888	0.9984
Rutba station				
January	0.5947	0.4609	0.0119	0.9984
February	0.8121	0.7220	0.0311	0.9981
March	0.8883	0.7371	-0.0901	0.9976
December	0.6632	0.5173	-0.0693	0.9989
Yearly	3.9676	2.6011	0.4358	0.9980
Baghdad station				
January	1.2440	0.6712	0.2347	0.9983
February	1.0830	0.5853	-0.2017	0.9989
March	4.4303	2.2107	0.5965	0.9953
December	0.7798	0.5417	-0.1373	0.9983
Yearly	3.9950	2.8313	1.0310	0.9975
Basra station				
January	1.3098	0.9962	-0.4449	0.9976
February	1.9311	1.6801	-0.7291	0.9967
March	1.2876	1.1090	-0.4488	0.9983
December	1.6686	1.4023	0.0915	0.9970
Yearly	3.1537	2.1468	-0.0461	0.9985

between the measured and predicted value for the long-term monthly rainfall were found to be 0.9989 and 0.9953 in Rutba and Baghdad meteorological stations for testing stag, respectively.

In Table 3 it can be seen that the MAE value ranged from 0.56 to 2.90 mm differ from the actual value for the long-term monthly rainfall, while the RMSE values ranged from 0.5978 to 3.56 for the monthly rainfall. For the long-term monthly rainfall, also as obtain in the training procedure the maximum MAE values were found for March in Mosul and Baghdad meteorological stations. On the other hand, according to MBE statistical indicator the more accurate results were found to be 0.1397 and -0.1109 mm in Rutba and Baghdad meteorological station for March and February months, respectively. The maximum correlation coefficients (R) between the measured and estimated values for the long-term monthly rainfall were found to be 0.9998 in both Rutba and Basra meteorological stations and 0.9917 for Baghdad station. Finally from Table 3 we can concluded that the optimum results for yearly and monthly basis was found at Rutba station also another significant point in this study, as seen in Table 3, the performance of the testing the network estimations with the measurement values were drawn for all target stations in order to indicate the performance of the ANN method and the diagrams are presented in Fig. 4-7, from these figures it can be seen that the results of the predicted monthly rainfall values in all tested months and the largest errors according RMSE and MAE was founded in Mosul station especially in January, February and march months where the values of the mentioned statistical indicators

Table 3: The root mean square error (RMSE), mean absolute error (MAE), mean bias error (MBE), correlation coefficient (R) Values for testing procedure

Duration	RMSE	MAE	MBE	R
Mosul station				
January	3.1638	2.2222	0.8475	0.9985
February	3.5248	2.4186	-1.1457	0.9952
March	3.1695	2.9045	1.2564	0.9971
December	2.6150	2.3026	-0.7891	0.9985
Yearly	7.3279	5.8103	4.4224	0.9982
Rutba station				
January	0.6491	0.5962	0.4270	0.9993
February	2.0983	1.7411	-0.5927	0.9922
March	0.7734	0.6155	0.1397	0.9986
December	0.5978	0.5605	-0.5605	0.9998
Yearly	1.0329	0.9112	-0.6594	0.9997
Baghdad station				
January	1.1001	0.6901	0.1577	0.9988
February	0.6602	0.5956	-0.1109	0.9988
March	3.5655	2.3468	1.2184	0.9917
December	0.8533	0.5809	0.4411	0.9981
Yearly	4.0407	3.3575	0.6824	0.9938
Basra station				
January	1.8216	1.4308	0.4014	0.9976
February	1.9241	1.6751	0.9842	0.9949
March	1.7414	1.4581	1.0210	0.9998
December	1.4768	1.3098	-0.1461	0.9961
Yearly	1.1609	0.9132	-0.7994	0.9998

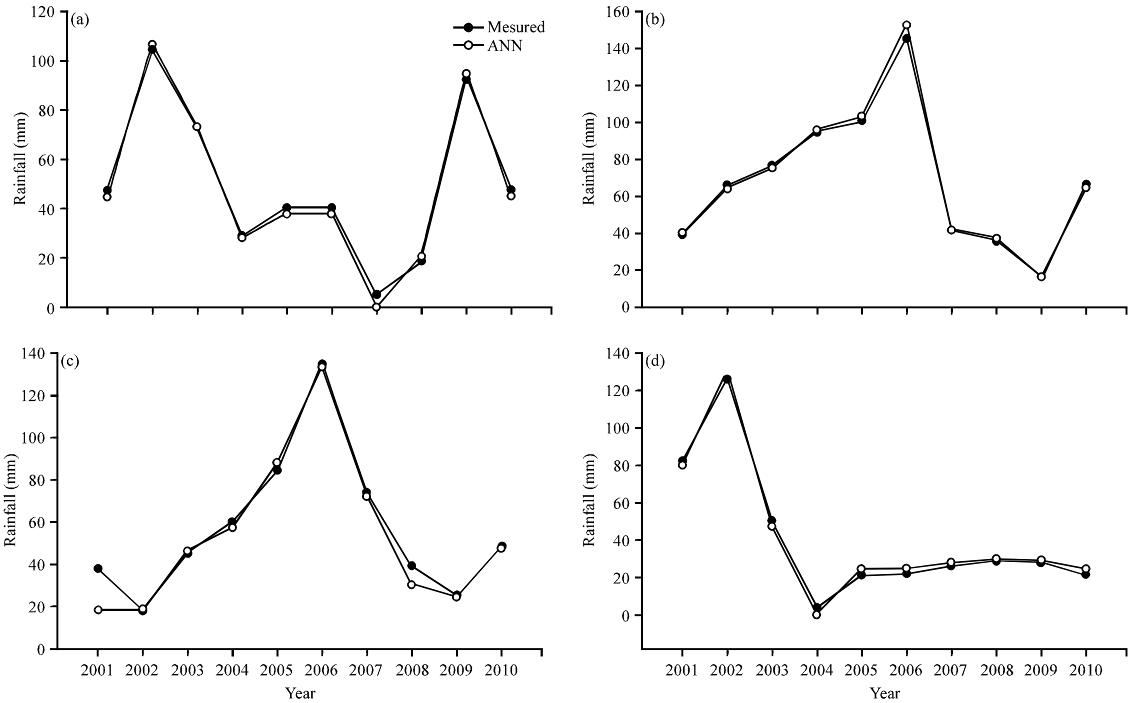

Fig. 4(a-d): Comparison between measured and ANN estimated values of Mosul station rainfall happened in (a) December, (b) January, (c) February and (d) March

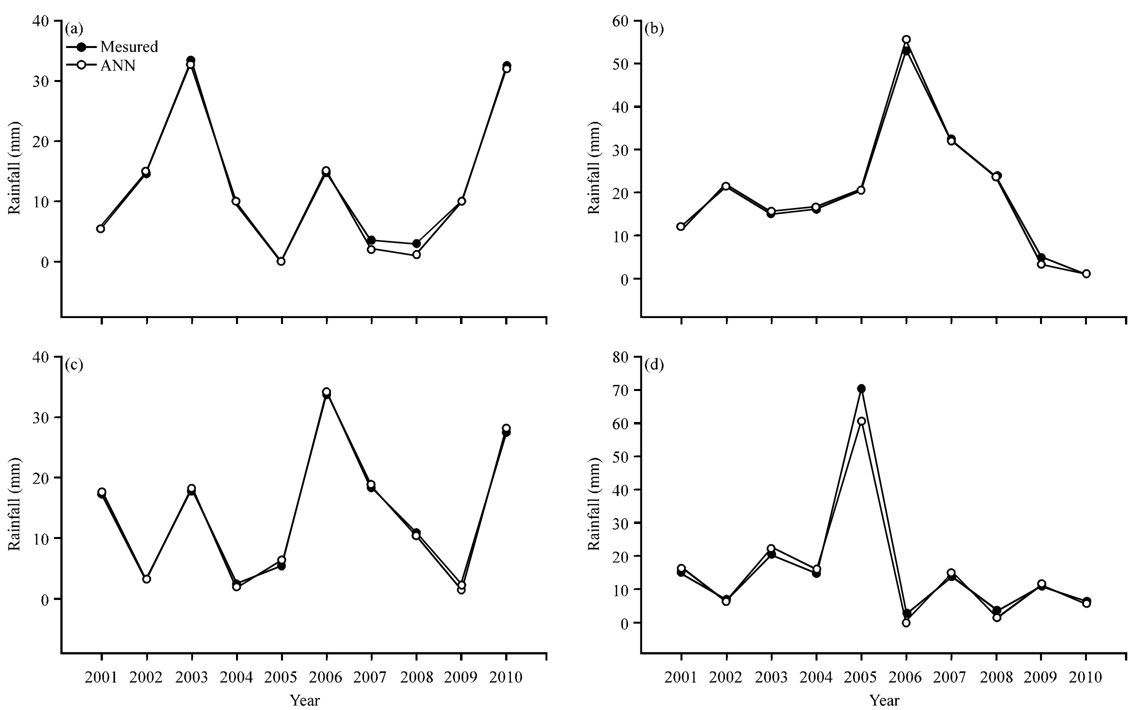

Fig. 5(a-d): Comparison between measured and ANN estimated values of Baghdad station rainfall happened in (a) December, (b) January, (c) February and (d) March

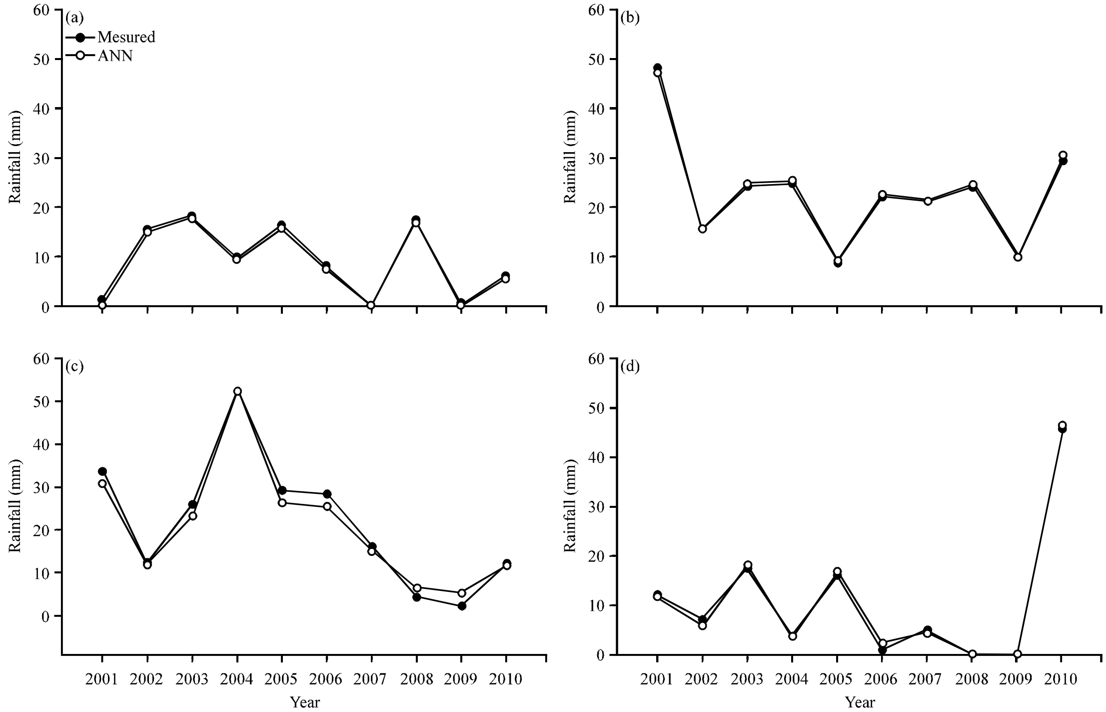

Fig. 6(a-d): Comparison between measured and ANN estimated values of Rutba station rainfall happened in (a) December, (b) January, (c) February and (d) March

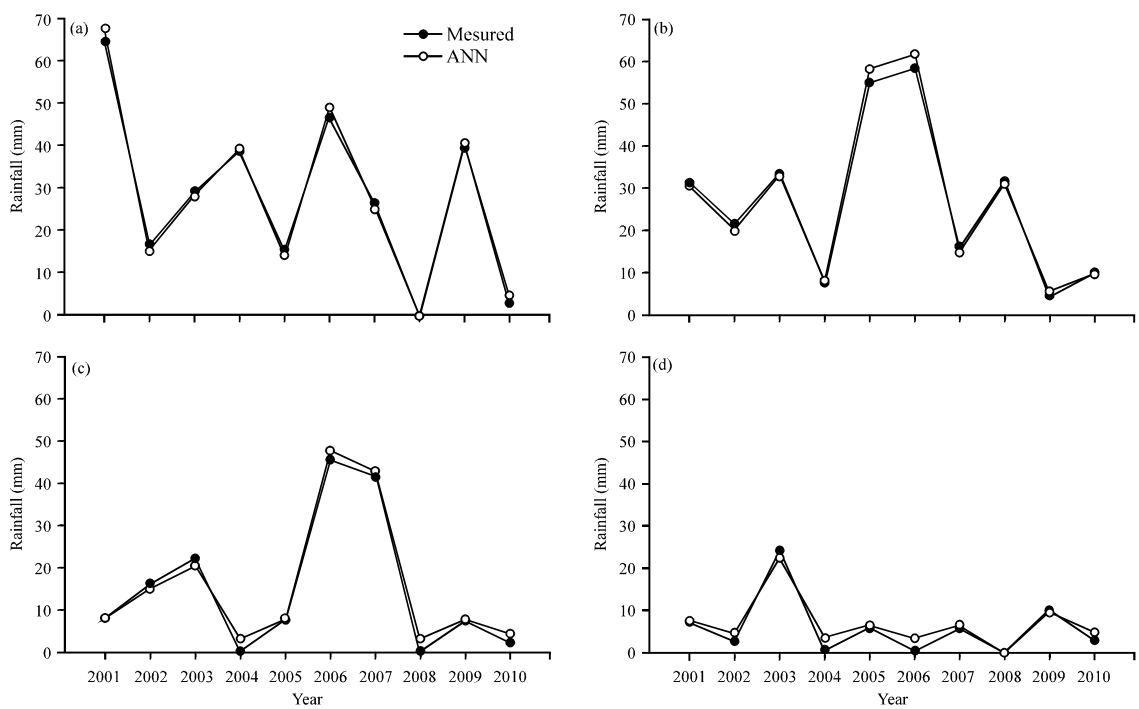

Fig. 7(a-d): Comparison between measured and ANN estimated values of Basra station rainfall happened in (a) December, (b) January, (c) February and (d) March was ranged between 3.16-3.52 mm for RMSE and 2.2-2.9 mm for MAE. In general it can be seen from the Fig. 4-7 that the results of estimation have fairly close agreement with the corresponding measurements for all stations. Errors obtained in these models are very well within acceptable limits.

Comparing the results of present research to those carried out by Morid *et al.* (2007) and also Mishra *et al.* (2007) indicates that although the study area of the present research has been located in a hyper arid climate condition where rainfall amount and distribution is extremely variable but the obtained predictions are quite acceptable. In Morid *et al.* (2007) the best prediction had the R was 0.96 for the lead time of 6 months, in an area where mean annual precipitation varies from 430 to 120 mm (in different stations), however they have mentioned efficiency of ANN in precipitation prediction which is in support with the present study. About the results of Mishra *et al.* (2007) the highest R for the predictions with 6 months lead time has been 0.94 and recommended that ANN is an efficient tool for rainfall prediction which is in support with the findings of present study. Study area of Mishra *et al.* (2007) is Kangsabati catchment in India with mean annual precipitation of about 1268 mm. However, in the present study where mean annual precipitation is about 600 mm and for prediction lead time of 12 months the highest R for the predictions is about 0.99 (by all proposed ANN models) which shows the higher quality of predictions in comparison to all mentioned studies. It is quite clear that normally as lead time increases the accuracy of predictions decreases and also in humid climate conditions the variability of precipitation decreases and therefore in general the accuracy of predictions increase. Hung *et al.* (2009) used ANN for rainfall forecasting in Bangkok, according to the results, it was stated that ANN forecasts have had superiority over the local traditional model. Therefore, the findings of the research are also in support with the results of this study. In addition, the results taken by Wong *et al.* (2003), Bustami *et al.* (2007), Gholizadeh and Darand (2009), Hopfield (1982) and Tektas (2010) are all in support with the findings of this research recommending good performance of ANN tools for precipitation prediction. Finally it can be concluded that the ANN technique can successfully predict the long-term monthly rainfall of any location in Iraq using the past period measurements.

CONCLUSION

It is believed that global warming has attracted considerable attentions of scientists in recent years. Global warming lead to changes in rainfall patterns, a rise in sea level and a wide range of impacts on plants, wildlife and humans. Due to this reason, the importance of rainfall predictions has been increased all over the World. In present study, ANN_s were applied to predict the long-term monthly rainfall at different locations in Iraq. The previous year's monthly rainfall was used as an input data for this approach, Finally the results from present study evidently prove that ANN models developed are reliable to predict monthly rainfall values and produce very high accuracy of rainfall estimation at considered stations in Iraq, Also this study has initiated a new approach in water resources management in Iraq particular, in areas where present rainfall data are absent. It can be concluded that the ANN method seems a powerful tool in predicting the long-term monthly rainfall of any location in Iraq employing the previous rainfall measurements.

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