Prediction Of Monthly Rainfall In Kirkuk Using Artificial Neural Network And Time Series Models

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Abstract

One of the major problems in water resources management is the rainfall forecasting. With the effect of rainfall on water resources as a foregone conclusion, more accurate prediction of rainfall would enable more efficient utilization of water resources and power generation. On the other hand, climate and rainfall are highly non-linear and complicated phenomena, which require non-linear mathematical modeling and simulation for accurate prediction. One of the non-linear techniques being recently used for rainfall forecasting is the Artificial Neural Networks (ANN) approach which has the ability of mapping between input and output patterns without a prior knowledge of the system being modeled. In this study, three rainfall prediction models were developed and implemented based on past observations such as time series models based on autoregressive integrated moving average (ARIMA),Artificial Neural Network ANN model and Multi Linear Regression MLR model. A Feed Forward Neural Network FFNN 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 Errors(RMSE). The data set that has been used in this study includes monthly measurements for the rainfall, mean temperature, wind speed and relative humidity from year 1970 to 2008 for Kirkuk station. The models were trained with (25 years) of monthly rainfall data. The ANN, ARIMA and MLR approaches are applied to the data to derive the weights and the regression coefficients respectively. The performances of the models were evaluated by using remaining (13 years) of data. By comparing R^2 values (0.91, 0.85, and 0.823) of the models, the study reveals 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.
Keywords; rainfall , artificial neural network, time series models

التنبؤ بالأمطار الشهرية لمدينة كركوك باستخدام الشبكات العصبية الاصطناعية ونماذج السلاسل الزمنية

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الخلاصة :

واحدة من المشاكل الرئيسية في إدارة الموارد المائية هو التنبؤ بسقوط الأمطار ومع تأثير الأمطار على موارد المياهبات امراً" مهما التنبؤ الدقيق للأمطار لغرض التمكين من الاستخدام الأمثل للموارد المائية وتوليد الطاقة. من ناحية اخرى تعتبر الامطار من الظواهر غير الخطية المعقدة والتي تتطلب النمذجه الرياضية غير الخطية لغرض التنبؤ بها. واحدة من التقنيات غير الخطية المستخدمة حديثا" للتنبؤ بسقوط الإمطار هي الشبكات العصبية الاصطناعية (ANN) التي تمتلك القدرة على التنبؤ بنمط العلاقة بين المدخلات والمخرجات دون معرفة مسبقة للنموذج المراد تمثيله. في هذه الدراسة، تم تطوير ثلاثة نماذج للتنبؤ بهطول الأمطار اعتمادا" على بيانات سابقه وهذه النماذج هي نموذج السلاسل الزمنية على أساس متوسط الانحدار الذاتي المتكامل المتحرك (ARIMA) ونموذج الشبكات العصبية الاصطناعية(ANN)والنموذج الخطي المتعدد(MLR). تم تطبيقا عادة توجيه تغذية نموذج الشبكة العصبية نموذج(FFNN)للتنبؤ بهطول الأمطار على أساس شهري. ومن أجل تقييم النماذج الثلاثة ، تم استخدام المعاملات الإحصائية للمقارنة بين هذه النماذج،وتشمل هذه المعايير معامل الارتباط(R) وجذر متوسط مربعات الأخطاء(RMSE). شملت مجموعة البيانات التي استخدمت في هذه الدراسة القياسات الشهرية لهطول الأمطار، سرعة الرياح، متوسط درجة الحرارة، والرطوبة النسبية خلال الفترة الزمنية منالعام1970 حتى 2008لمحطة كركوك. تم تدريب النماذج مع25 عاما" من بيانات هطول الأمطار الشهرية وتم تطبيق النماذج(ANN، ARIMAوMLR)على البيانات لاستخلاص الأوزان ومعاملات الانحدار على التوالي.أنجز تقييمأداءالنموذجبأستخدام13 سنة المتبقية من البيانات.من خلال مقارنةR^2من النماذج، تم الاستنتاج على أنه يمكن استخدام نموذج(ANN)كأداة تنبؤ مناسبة لقيم سقوط الأمطار، الذي يعتبر أفضل من نموذج(ARIMA و MLR).

Introduction

Accurate information on rainfall is essential for the planning and management of water resources. Additionally, in the urban areas, rainfall has a strong influence on traffic, sewer systems, and other human activities. Nevertheless, rainfall is one of the most complex and difficult elements of the hydrological cycle to understand and to model due to the complexity of the atmospheric processes that generate rainfall and the tremendous range of variation over a wide range of scales both in space and time (French et al., 1992) [1].Thus, accurate rainfall forecasting is one of the greatest challenges in operational hydrology, despite many advances in weather forecasting in recent decades (Gwangseob and Ana, 2001)[2] .

Thus many researchers have conducted long-term rainfall modeling in tropical regions either with the use of linear techniques like Box-Jenkins methods (Mishra & Desai, 2005)[3] or nonlinear techniques like ANN modeling. After publishing the paper of (Box and Jenkins 1976)[4], Box-Jenkins models became one general time series model of hydrological forecasting. These models include: Auto Regressive Integrated Moving Average (ARIMA), Auto Regressive Moving Average (ARMA), Auto Regressive (AR), and Moving Average (MA). However, these models are very useful for forecasting changes in a process (Karamouz and Araghinejad, 2012)[5] . Models of time series analysis (Box-Jenkins models) and ANN models invarious fields of hydrology and rainfall forecasting in irrigation schedule are widely applied, which some of them will be described in the following:-

(Burlando et al., 1993)[6]using ARMA models forecasted short-term rainfall. Hourly rainfall from two gaging stations in Colorado, USA, and from several stations in Central Italy been used. Results showed that the event-based estimation approach yields better forecasts.(Bodri and Cermak, 2000)[7] were evaluated an artificial neural network model for precipitation forecasting. Back-propagation neural networks were trained with actual monthly precipitation data from two Moravian meteorological stations for a time period of 38 years. Predicted amounts are of next-month-precipitation and summer precipitation in the next year. The results show that relatively simple neural networks, with an adequate choice of the input data, can achieve reasonably good accuracy results. (Toth et al., 2000)[8]used the ANN and ARMA models to forecast rainfall. The results show the success of both short-term rainfall-forecasting models for forecast floods in real time.(Luc et al., 2001)[9] predicted rainfall in catchment’s upper Parramatta river in Australia using Multi-Layer Feed-forward Neural Network (MLFN). Their results showed that MLFN has more accuracy in rainfall modeling in comparison to Time Delay Neural Network (TDNN) and Recurrent Neural Network (RNN). While TDNN anticipated to RNN and MLFN through rainfall prediction using large scale continental signals in west of Iran. However, according to the literature, it seems that for rainfall prediction, Multi-Layer Feed-forward Perceptron (MLFP) has more reasonable outputs in comparison to other ANN types which is used in this study.(Ramirez et al., 2005)[10]used artificial neural network technique for rainfall forecasting applied to the Sao Paulo region. The results showed that ANN forecasts were superior to the ones obtained by the linear regression model thus revealing a great potential for an operational suite. Two rainfall prediction models were developed and implemented in Alexandria, Egypt by (El-Shafie et al., 2011)[11]. These modelsare ANN model and Multi Regression MLR model. A Feed Forward NeuralNetwork FFNN model was developed to predict the rainfall on yearly and monthlybasis.The data set that has been used in this study includes daily measurements for the rainfall and temperature and cover the period from 1957 to 2009. The FFNN model has shown better performance than the MLR model. ANN and MLR models were developed to estimate monthly total rainfall (RMT) for Isparta by (Terzi and Cevik, 2012)[12].The rainfall data from Senirkent, Uluborlu, Egirdir, Yalvac and Isparta stations in Isparta, were used to estimate R_{MT}.The results of ANN and MLRmodels were compared with measured rainfall values to evaluate performance of the developed models. Thecomparisons showed that there was a good agreement between the ANN estimations and measured rainfallvalues. (Mahmood, et. al, 2012)[13], was developed ANN model to forecast monthly release water for Haditha dam. Seven different combinations of input variable were trained for release model. It was found that ANNs have the ability to predict the release water with accepted accuracy.

In the present study, a comparative study of rainfall behavior was conducted as obtained by autoregressive integrated moving average (ARIMA), (MLR) and the artificial neural network (ANN) techniques. The aim of apply these models are to develop rainfall estimation models for Kirkuk station, to compare the three models results and to evaluate the potential of ANN for estimating monthly rainfall.

The Study Region And Data

Kirkuk is an Iraqi governorate, located in 236 kilometers (147 mi) north of the capital, Baghdad as shown in **Figure .(1)**. It is located at geographical coordinates are 35° 28' 5" North, 44° 23' 32" East. Kirkuk experiences a hot semi-arid climate with extremely hot and dry summers and cool, rainy winters. A mean annual temperature of 43.2 °Cin the hot month and a mean temperature of 0°C or -3°C in the coldest month, (Iraqi Ministries of Environment and Water Resources Report, 2006)[14].

The observed data for Kirkuk stations used to develop the ANN, ARIMA and MLR models are obtained from the Iraqi State Meteorological Service, Baghdad. These data used to develop models include monthly rainfall observations, air mean temperature, relative humidity and wind speed between 1970 and 2008 years. Air mean temperature, relative humidity and wind speed is given as input data. Monthly rainfall data for Kirkuk are selected to be the desired output data for training and testing.

Fig. (1): Location of Kirkuk

Figure .(2) shows the average monthly rainfall taken over a period from 1970 to 2008 in Kirkuk. There are two peaks of rainfall in January and February months. The average annual rainfall is 31.04 mm with the highest average monthly rainfall of approximately 70 mm observed in January, and the lowest average monthly rainfall of about 0 mm occurring in August and July.

ARIMA Model

Box & Jenkins (1970)[15] developed this forecasting technique which is still very popular among hydrologists. The autoregressive integrated moving average ARIMA(p,d,q) model of the time series {r1, r2,…..} is defined as,

$$\phi (B)\Delta^d r_t = \theta (B) e_t \qquad \text{……………………….. (1)}$$

where r_t and e_t respectively represent mean annual rainfall time series and random error terms at timet. B is the backward shift operator defined by $Br_y = r_{y-1}$ and related to Δ by Δ = 1- B; d is the order of difference. The ϕ (B) and θ (B) of order p and q are defined as

$$\phi (B) = 1- \phi_1 B - \phi_2 B^2 - \text{……………..} \phi_p B^p \qquad \text{…………………… (2)}$$

$$\theta (B) = 1- \theta_1 B - \theta_2 B^2 - \text{……………..} \theta_q B^q \qquad \text{…………………… (3)}$$

where, ϕ_1, ϕ_2, ……$\phi_p$are the autoregressive coefficientsand θ_1, θ_2, …..θ_q are the moving averages coefficients, for more details see (Box and Jenkins, 1976).

In this ARIMA(p,d,q) modeling, the first step is to determine whether the time series is stationary or non-stationary. If it is non-stationary it is transformed into a stationary time series by applying suitable degree of differencing by selecting proper value of d. The appropriate values of p and q are chosen by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the time series.

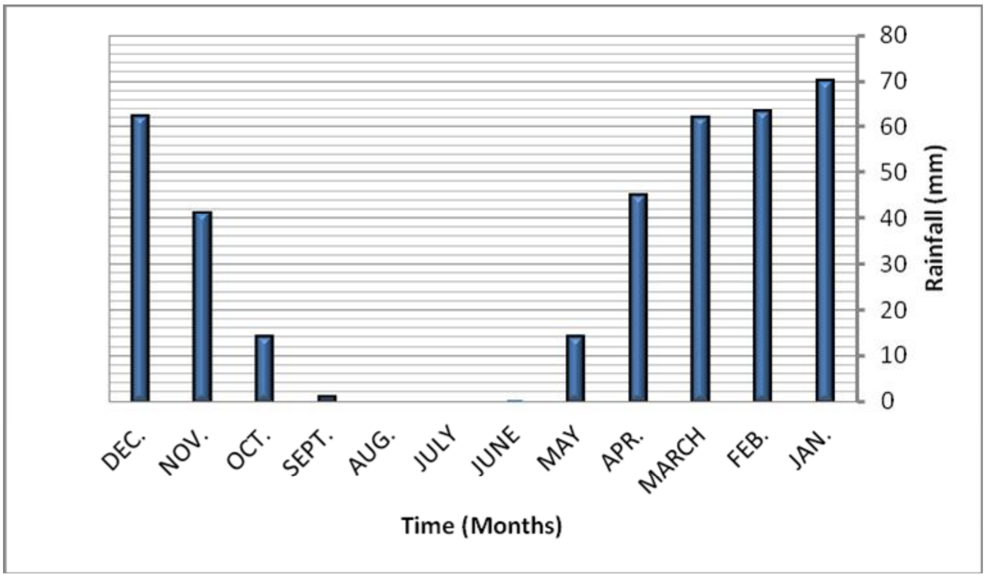


Fig .(2): Average monthly rainfall for Kirkuk

ANN Model

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological neurons systems. As in nature, the network function is determined largely by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between the elements. Commonly, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown in **Figure .(3)**. Here, the network isadjusted based on a comparison of the output and the target, until the sum of square differences between the target and output values becomes the minimum. Typically, many such input/target output pairs are used to train a network. Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector. Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision, and control systems. Today neural networks can betrained to solve problems that are difficult for conventional computers or human beings (Demuth and Beale, 2001)[16].

Feed forward ANNs comprise of a system of neurons, which are arranged in layers. Between the input and output layers, there may be one or more hidden layers. The neurons in each layer are connected to the neurons in a subsequent layer by a weight *w*, which may be adjusted during training. A data pattern comprising the values *xi* presented at the input layer *i*is propagated forward through the network towards the first hidden layer *j*. Each hidden neuron receives the weighted outputs *wijxij* from the neurons in the previous layer. These are summed to produce a net value, which is then transformed to an output value upon the application of an activation function (Imrie et al., 2000)[17]. A typical three layer feed-forward ANN is showed in **Figure .(4).**

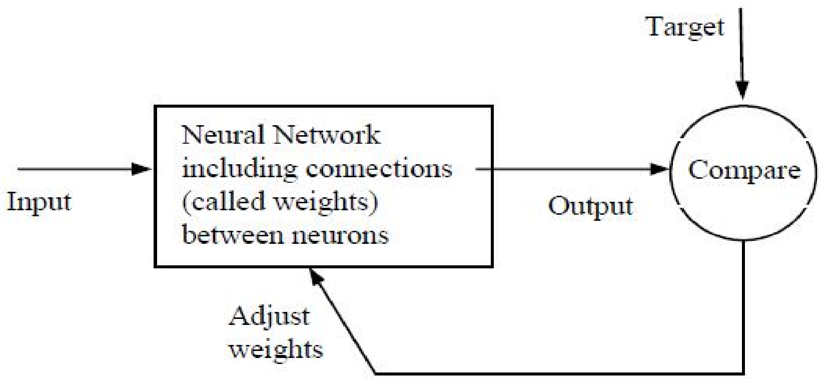


Fig .(3):Basic principle of artificial neural networks.

In **Figure (4),** a typical ANN consists of three layers, namely input, hidden and output layers. Input layer neurons are x_o, x_1,..x_n; hidden layer neurons are h_1,h_2… h_m; and output layer neurons are o_1, o_2… o_k.

A neuron consists of multiple inputs and a single output. The sum of the inputs and their weights lead to a summation operation as:

$$NET_j = \sum_{i=1}^{n} w_{ij} x_{ij} + \theta \qquad \text{...(4)}$$

in which *wij*is established weight, *xij*is input value, θ is bias that additional inputs withunitary connection weights and NET_j is input to a node in layer *j*.

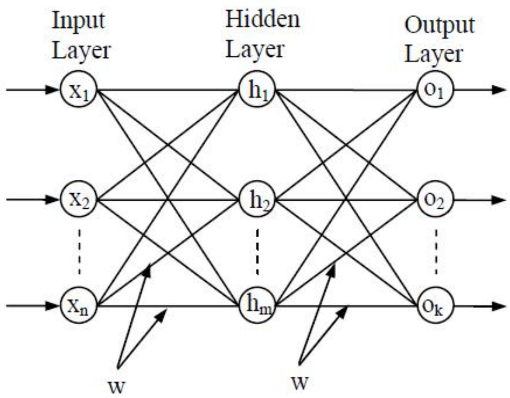


Fig .(4): Atypical Three Layers of Feed-Forward ANN.

The output of a neuron is decided by an activation function. There are a number of activation functions that can be used in ANNs such as step, sigmoid, threshold, linear etc. The sigmoid activation function, f(x), commonly used and applied in this study, can be formulated mathematically as:

$f(x) = 1/[1+ exp(-x)]$ ......…………………(5)

$OUTPUT_j = f\,(NET_j) = 1/[1+ exp(-NET_j)]$ …………………..(6)

The back-propagation learning algorithm is one of the most important historical developments in neural networks. This learning algorithm is applied to multilayer feed-forward networks consisting of processing elements with continuous and differentiable activation functions. Such networks associated with the back-propagation learning algorithm are also called back-propagation networks. Given a training set of input-output pairs, the algorithm provides a procedure for changing the weights in a back-propagation network to classify the given input patterns correctly. The basis for this weight update algorithm is simply the gradient-descent method as used for simple perceptrons with differentiable neurons, (Lin and Lee, 1995)[18].

The input data and the desired output data should be scaled into the range of 0 to 1. The final data preprocessing step is data balancing. Initially random weights between ±0.5 are assigned to each weight as initial guesses. The weights are learned through an iterative process. During learning the weights are updated. When the network learns the training set of patterns well enough it can be used for determining the output values for the pattern with unknown outputs (Test period or prediction period).

For a given input-output pair, the back-propagation algorithm performs two phases of data flow. First, the input pattern is propagated from the input layer to the output layer and, as a result of this forward flow it produces an output pattern with minimum sum of square differences between output and target data. Then the error signals resulting from the difference between output pattern and an actual output are back-propagated from the output layer to the previous layers for them to update their weights, (Lin and Lee, 1995)[18].

Multi-Linear Regression (MLR)

MLR is probably the most widely used method in hydrology for developing models to predict climate variables. Generally, the predictor variables consist of a pair of input. While the predictants will be the amount of rainfall for the next month.

Model Equation

The model expresses the value of a predictant variable as a linear function of one or more predictor variables and an error term:

$$y_i = b_o + b_1 X_{i,1} + b_2 X_{i,2} + \cdots + b_k X_{i,k} + e_i \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Where y_i is a predectant in year i, and $X_{i,k}$ value of k^{th}predictor in the year i. The regression constant is b_o and b_k is a coefficient on the k^{th} predictor. While e_i is the error term.

Prediction Equation

The Model equation is estimated by least squares, which yields parameter estimates such that the sum of squares of errors is minimized. The resulting prediction equation is

$$\widehat{y_i} = \widehat{b_o} + \widehat{b_1} X_{i,1} + \widehat{b_2} X_{i,2} + \cdots + \widehat{b_k} X_{i,k} + e_i \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Where the variables are defined as in equation (7) except that “^”denotes estimated values.

Application And Results

Prior to execution of the model, standardization is done according to the following expression such that all datavalues fall between 0 and 1.

$$X = \frac{X_i - X_{min}}{X_{max} - X_{\min}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Where X is the standardized value of the X_i; X_{max} and X_{min} are the maximum and minimum values in all observation sequence. The main reason for standardizing the data is that the variables are usually measured in different units. By standardizing the variables and recasting them into dimensionless units, the arbitrary effect of similarity between objects is also removed (Sudheer et al., 2002;Romesburg, 1984)[19][20].

In this study, ANN (i, j, k) indicates a network architecture with i, j and k neurons in input, hidden and output layers, respectively. Herein, i runs 2, 4 and 5; j assume values of 2, 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12, whereas k =1 is adopted in order to decide about the best ANN model alternative. The optimum number of neurons in hidden layer is determined using a trial and error method by considering the RMSE and R^2 values for testing data set.

Learning rate and momentum are the parameters that affect the speed of the convergence of the back propagation algorithm. In the mode, the initial weights are chosen randomly from -0.5 to +0.5. After each training iterations/epochs the network is tested for its performance on validation data set [Chattopadhyaya and Debnath, (2009)][21].The training process is stopped when the performance would reach the maximum on validation data set. In this study, stopping criteria is employed10000 epochs for training. A learning rate of 0.001 and momentum 0.1 are fixed for selected network after training and model selection is completed for years 1970 to 1995. The trained networks are used to run a set of test data for years 1996 to 2008.

Two criteria are used to evaluate the adequacy of each model: the coefficient of determination (R^2) and the root mean square error (RMSE). The coefficient of determination,based on the flow forecasting errors iscalculated as, (Steel andTorie, 1960; Wilks, 2006)[22][23]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(R_{i(measured)} - R_{i(model)}\right)^2}{\sum_{i=1}^{n}\left(R_{i(measured)} - R_{mean}\right)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

where n is the number of measured rainfall data, $R_{i(\mathrm{measured})}$ and $R_{i(\mathrm{model})}$ are monthly rainfall measurement and model estimations, respectively, and R_{mean} is the mean rainfall measurements.

The root mean square errors (RMSE) is used to decide the best model and defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(R_{i(measured)} - R_{i(model)}\right)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Where, all parameters have been defined above.

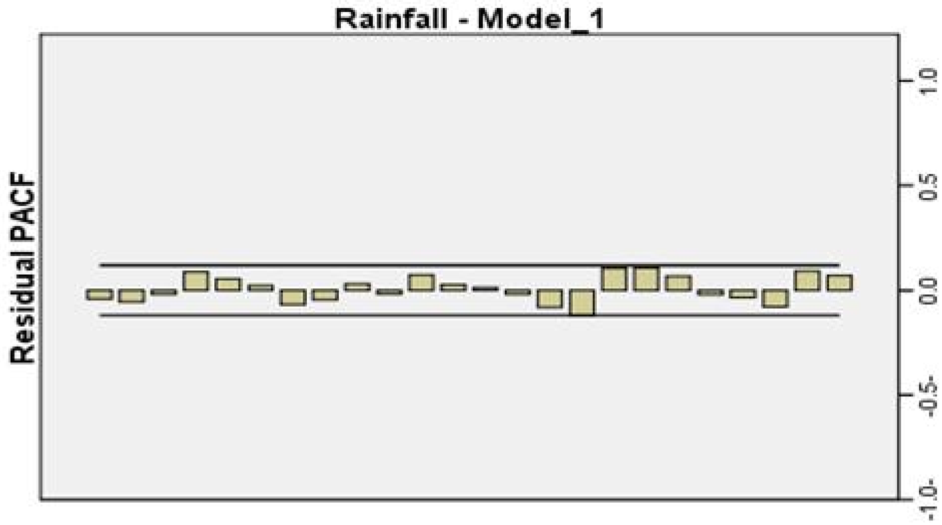
In this study, three models are developed to forecast monthly rainfall for Kirkuk station using the ARIMA, ANN and MLR methods. The best network architectures for artificial neural network model is determined as ANN(4,8,1). The results of the developed ANN with four input parameters ANN (4,8,1) models are compared based on training and testing datasets. Also, ARIMA and MLR models are developed to estimate monthly rainfall for the same input and output variables used in ANN models.

The autocorrelation ACF and partial autocorrelation coefficient PACF for various lags (in year) of monthly rainfall data with 95% confidence level are displayed in **Figures(5 and 6)**, were used for estimating the parameters of ARIMA model. Both the ACF and PACF have two significant terms at lag 1 and 8, the second term at lag 8, indicates that if moving average or autoregressive models are used, they should be of order 8. Following the principle of parsimony, we choose autoregressive model of order1 for fitting the data. Thus, the ARIMA(1 0 0) model is used for present study.

The best-fit network structure is determined according to the model performance criteria for testing data set. The results of statistical analyses for ANN, ARIMA and MLR models are given in **Table (1).** As seen from **Table (1)**, R^2 values, for testing set, of ANN (4,8,1) models are 0.91, ARIMA (1 0 0) models are 0.85 and MLR models are 0.823 respectively. Hence, the ANN (4,8,1) model with four input parameters have the higher R^2 and lower RMSE values than ARIMA and MLR models for testing data set. Therefore, the ANN(4,8,1) model is selected for monthly rainfall estimation in the study region. The performance of the ANN (4,8,1) model suggests that the rainfall could be estimated easily from available rainfall data using ANN approach. This result is of significance in situation where a hydrological model is to be developed with limited data.

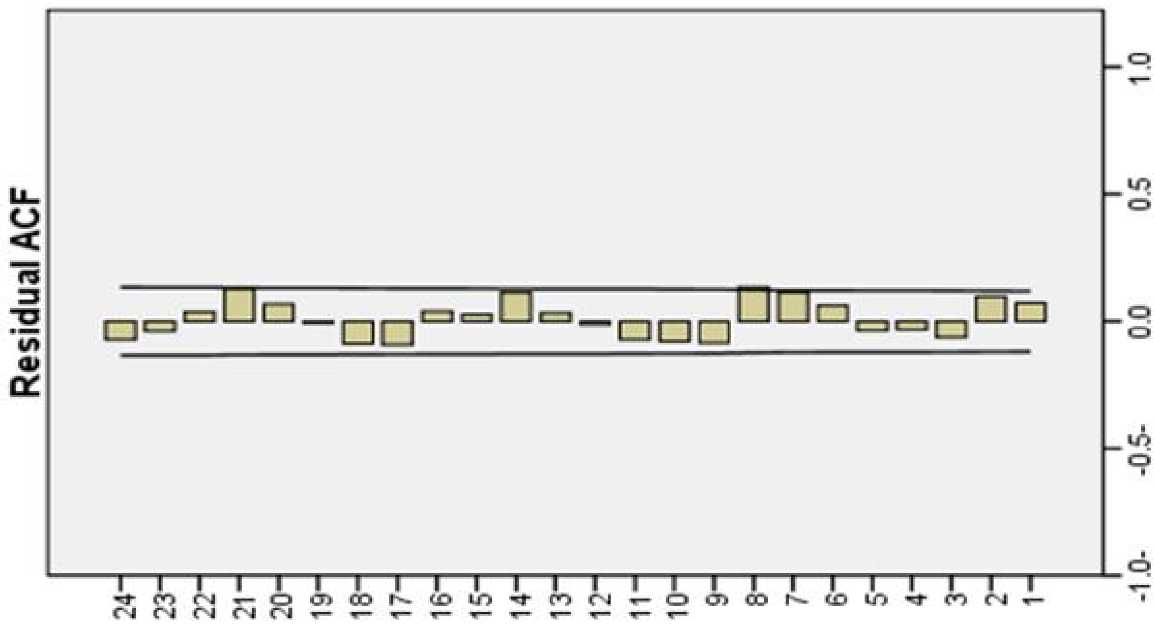
Table (1): The coefficient of determination (R^2) and root mean square errors (RMSE) of ANN ARIMA and MLR models

Techniques	Error measures from monthly rainfall test data set	
	R^2	RMSE
ANN (4,8,1)	0.91	27.278
ARIMA (1 0 0)	0.85	38.120
MLR	0.823	38.543



Lag (year)

Fig. (5): Partial autocorrelation coefficient and time lags of monthly rainfall data



Lag (year)

Fig. (6): Autocorrelation coefficient and time lags of monthly rainfall data

In order to expose the performance of three models, results of the ANN(4,8,1), ARIMA and MLR models are plotted versus rainfall values in **Figure .(7).** The ANN(4,8,1), ARIMA and MLR model comparison plot is around 45° straight line which implies that there are no bias effects.

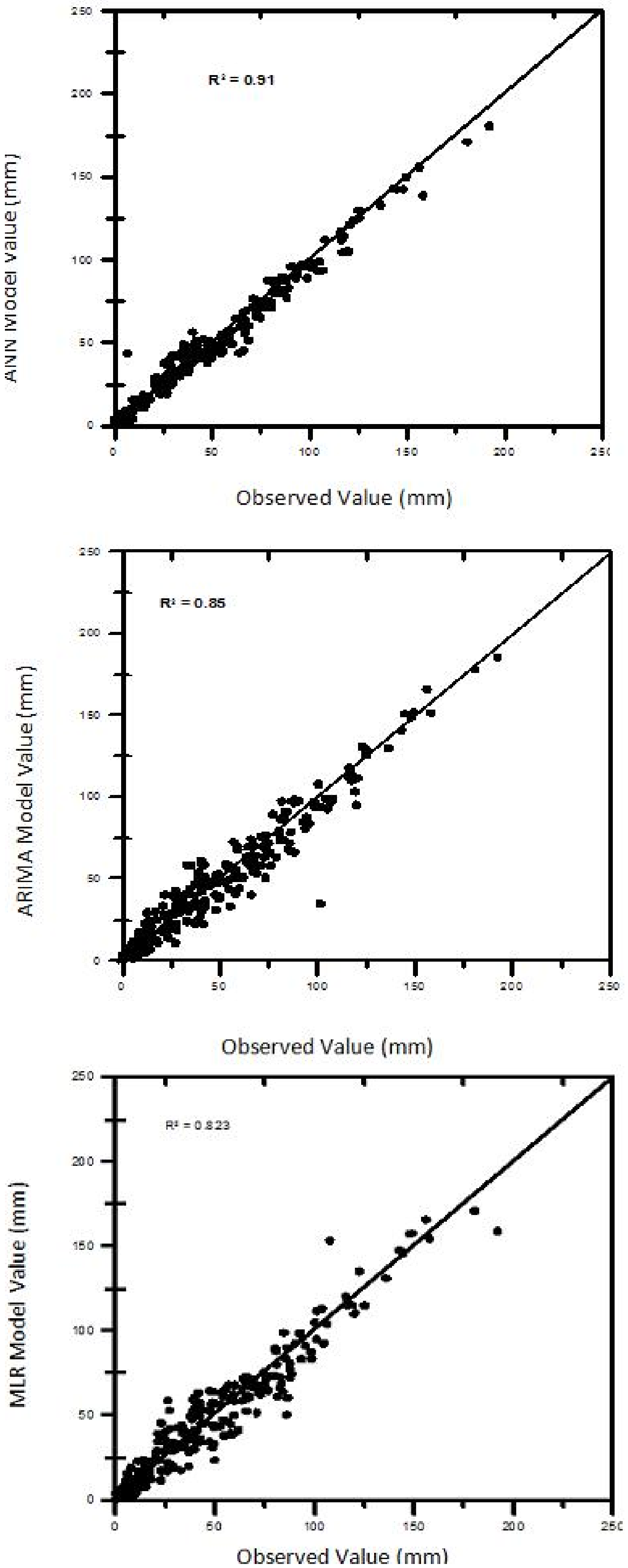


Fig .(7): Comparison rainfall values with ANN (4,8,1), ARIMA and MLR models for testing data set.

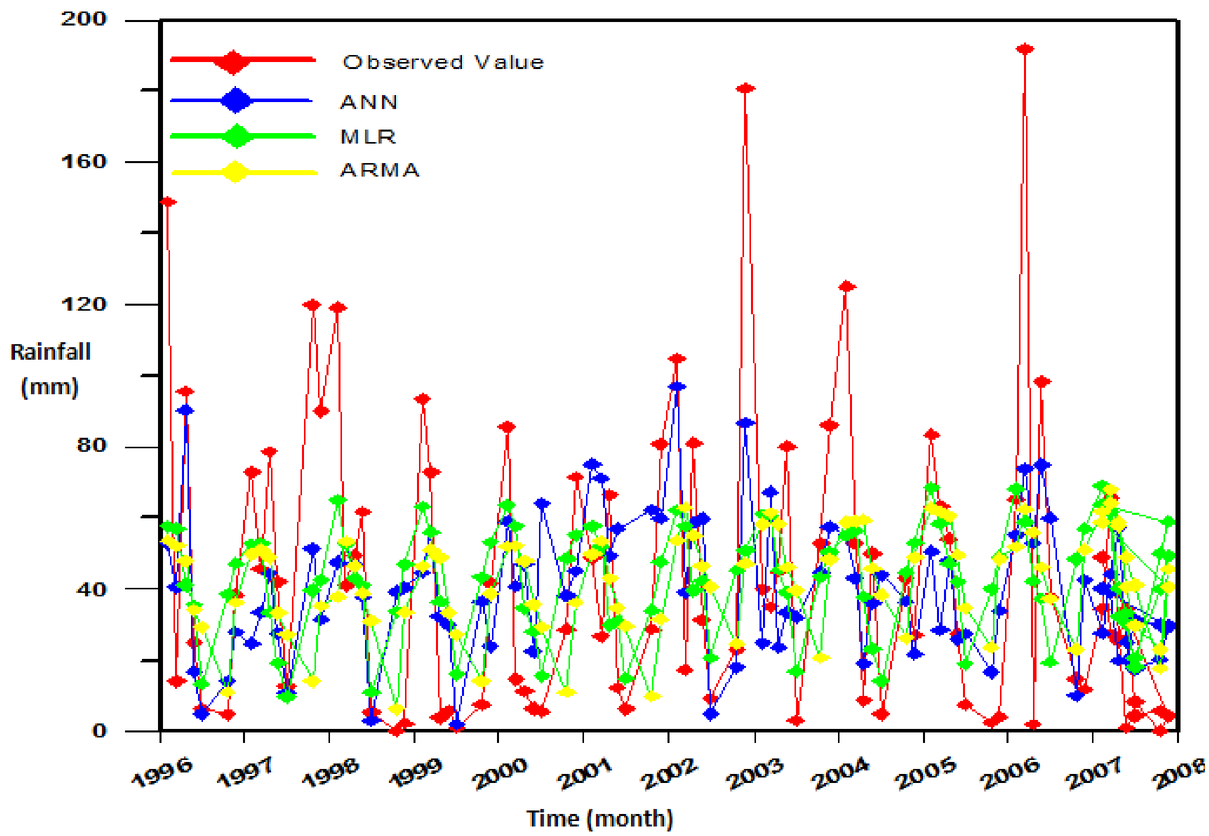


Fig. (8): Modeled and measured rainfall values for testing data set

The results of ANN(4,8,1), ARIMA and MLR model and observed rainfall values are presented in **Figure. (8). Figure. (8)** shows a good agreement between the developed models and measurements of rainfall values.

Conclusions

The estimating of rainfall is of great importance in terms of water resources management, human life and their environment. It can be met with the incorrect or incomplete estimation problems because rainfall estimation is affected from the geographical and regional changes and properties. Also, because the current rainfall models in the literature are specific to the region, they are not directly used and are needed to adapt for study region. For this reason, the various rainfall estimation models have been developed to forecast monthly rainfall for Kirkuk region. A monthly rainfall, air mean temperature, wind speed and relative humidity data spanning over a period of 1970-2008 for Kirkuk station was used to develop and test the models. The developed ANN, ARIMA and MLR models with different input combinations are compared to measured rainfall values. The structure of ANN is achieved by using a Multi-layer feed-forward perception with back propagation algorithm. The present analysis uses four past observations as inputs to neural network model. In all analysis, ANN model with four inputs have higher R^2(0.91) and lower RMSE values (27.278) for testing data set. It is shown that the ANN (4,8,1) model are superior among three models. Comparing the performance of the ANN(4,8,1), ARIMA and MLR models, it can be observed that they are performed in a more similar way. The study reveals that ANN model can be used as an appropriate forecasting tool to predict the rainfall from available data, which is preferable over the ARIMA and MLR models.

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