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Full Length Research Paper

Artificial neural network technique for rainfall forecasting applied to Alexandria, Egypt

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Two rainfall prediction models were developed and implemented in Alexandria, Egypt. These models are Artificial Neural Network ANN model and Multi Regression MLR model. A Feed Forward Neural Network FFNN model was developed and implemented to predict the rainfall on yearly and monthly basis. In order to evaluate the incomes of both models, statistical parameters were used to make the comparison between the two models. These parameters include the Root Mean Square Error RMSE, Mean Absolute Error MAE, Coefficient Of Correlation CC and BIAS. 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. The MLR model revealed a humble prediction performance. The linear nature of MLR model estimators makes it inadequate to provide good prognostics for a variable characterized by a highly nonlinear physics. On the other hand, the ANN model is a nonlinear mapping tool, which potentially is more suitable for rain (nonlinear physics) forecasts. More detailed studies are necessary due to uncertainties inherent in weather forecasting and efforts should be addressed to the problem of quantifying them in the ANN models.

Key words: Neual network, multi regression, rainfall forecasting, Alexandria city.

INTRODUCTION

Accurate forecasting of rainfall has been one of the most important issues in hydrological research, because early warnings of severe weather, made possible by timely and accurate forecasting can help prevent casualties and damages caused by natural disasters. In the last years, researchers have begun to investigate the potential of Artificial Neural Networks ANN as a tool for simulation of behavior of systems that are governed by nonlinear multivariate, generally unknown, interconnections within a noisy, less-controllable physical environment. A significant growth in the interest of this computational mechanism has occurred since Rumelhart et al. (1986) developed a mathematically rigorous theoretical framework for neural networks. Since then, ANNs have found increasing use in diverse disciplines ranging over perhaps all branches of engineering and science (ASCE 2000a, b; Maria et al., 2005). Such methods motivate the researchers to utilize in several applications. For example, El-Shafie et al. (2010a) reported an application of utilizing Adaptive Neuro-Fuzzy Inference System ANFIS for under water tracking Global Positioning System (GPS) sonobouy. In addition El-Shafie et al. (2010b) introduced the Radial Basis Function Neural Network (RBF-NN) model for predicting the creep in masonry.

Researchers in hydrology have shown serious interest in this computational tool only during the last decade. The prediction of Indian summer monsoon rainfall (ISMR) on a seasonal time scales has been attempted by various research groups using different techniques including artificial neural networks. Sahai et al. (2000) have used

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ANN in a time series approach with the presumption that, ISMR is not only related to previous seasonal mean ISMR values but also with the previous monthly mean (June, July, August and September) rainfall values. A feed forward neural network with back propagation algorithm was used in this study. Sahai et al. (2000) have for the first time, shown that monthly rainfall during the monsoon season can be predicted with sufficient lead time and good skill. Artificial neural networks can be used to predict the seasonal and monthly mean rainfall over the whole of India, using only rainfall time series as inputs. Various verification statistics have shown that prediction skill is good. Since only the previous five years monthly and seasonal mean rainfall values were used to predict next year values, these predictions have much longer lead time (8 months) compared to conventional statistical methods that use teleconnection parameters. There is also useful skill for a two year lead time. This indicates that, it may be possible to develop a suitably configured neural network for predicting monsoon rainfall on suitably defined regional scale.

Bodri and Cermak (2000) 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. In the present work, Bodri and Cermak (2000) have evaluated the applicability of neural networks for precipitation prediction and presented some preliminary results. The results show that relatively simple neural networks, with an adequate choice of the input data, can achieve reasonably good accuracy. The specific structure of the network input which is able to generate adequate patterns of precipitation generates a question whether this configuration has some identifiable relationship to the physics of precipitation process. Recently, the authors already developed Artificial Intelligent (AI) model for inflow forecasting at Aswan High Dam utilizing Adaptive Neuro-Fuzzy Inference System (ANFIS), Mutli-Layer Perceptron Neural Network MLPNN and Radial Basis Function Neural Network (RBFNN), (El-Shafie et al., 2007; El-Shafie et al., 2008; El-Shafie et al., 2009; El-Shafie et al., 2010c). In fact, those models showed very good potential for providing relatively high level of accuracy for inflow forecasting at AHD. Valverde et al. (2005) have used an artificial neural network to construct a nonlinear mapping between output data from a regional ETA model and surface rainfall data for the region of Sao Paulo State, Brazil. The objective of this study is to evaluate a methodology for rain forecast in Sao Paulo State using ANN and numerical weather prediction NWP model outputs. In order to analyze the ANN performance, a multiple linear regression MLR model was also developed. The ANN used in this study, namely the multi-layer Perceptron, commonly referred to as feed forward network with resilient propagation RPROP learning (French et al., 1992; Halff et al., 1993).

In conclusion, an analysis of two statistical models developed for rainfall forecast in the Sao Paulo State, Brazil, shows that an ANN has a better performance than an MLR model. The MLR model revealed a strong bias in predicting rainfall for periods when no rain was observed. Nevertheless, the MLR model succeeded in forecasting rain when it did occur. In fact, the linear nature of MLR model estimators makes it inadequate to provide good prognostics for a variable, characterized by a highly nonlinear physics. On the other hand, the ANN model is a nonlinear mapping tool, which potentially is more suitable for rain forecasts. The analyzed study cases suggest that, ANN provide better results than the ETA model regarding the statistical criteria used.

Kumarasiri and Sonnadara (2008) carried out a forecasting for the daily occurrence and annual depth of rainfall for a single meteorological station in the city of Colombo which is the commercial capital of Sri Lanka situated in the wet zone of the western coast of the island. The main objectives of the present study are to forecast the rainfall occurrence of the following day (one-day-ahead), and the rainfall depth of the following year (one-year-ahead). Using neural networks based on weather parameters measured at ground level. Two models were developed based on the feed-forward back-propagation neural network architecture and the outputs of the models were compared with the exact observations. The results of this study show that, the one-day-ahead forecasting network is successful in forecasting the rainfall occurrence of the next day with a success rate of 74.3%. The one-year-ahead forecasting network is highly successful in forecasting the annual rainfall depth of the next year, with a success rate of 80.0%. The feed-foreward neural network Artificial neural networks have been found to be a powerful tool for solving different problems in a variety of enginnering applications ranging from pattern recognition to system optimization. It has been recently applied to problems of water resources research and practice. This research focuses on the application of neural networks to rainfall modeling, particularly forecasting.

The main objective of this study is the development of an artificial neural network for rainfall forecasting for yearly and monthly basis. This general objective includes:

1. Developing a multi-layer feed foreward neural network (FFNN) and equiping it with a backpropagation training function for accurate and reliable rainfall forecasting.
2. Developing a multi-linear regression MLR model and implement it as an alternative method for forecasting rainfall.
3. Comparing the ANN and the MLR results for rainfall forecasting.
4. Furthermore, stastical models have been developed

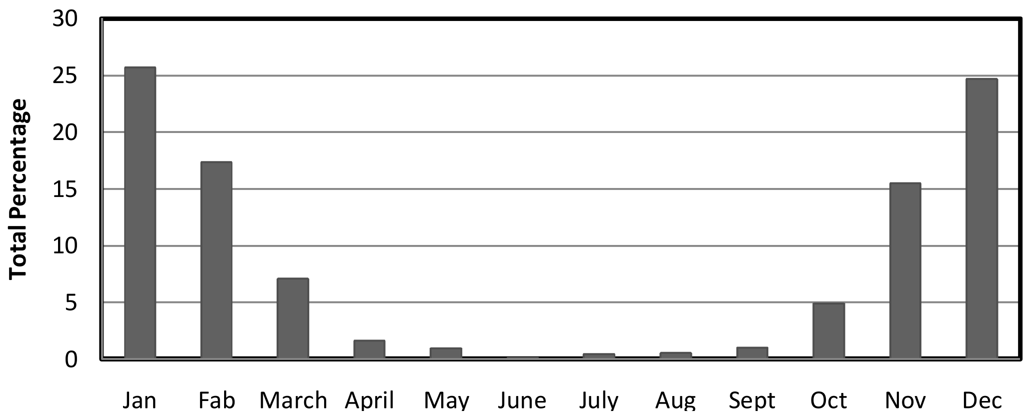

Figure 1. Total rainfall percentages.

independently for this data set and is used in comparative study.

MATERIALS AND METHOD

Alexandria is a semi-desert, characterized by hot dry summers, moderate winters and very little rainfall. It has only two seasons 1) a mild winter from November to April and 2) a hot summer from May to October. The difference between the seasons is a variation in daytime temperature and changes in prevailing wind. Average annual temperature ranges between minimum of 14°C in winter and maximum of 30°C in summer. Alexandria is one of the wettest areas of Egypt, which has an average annual precipitation of about 200 mm, which is more compared to nation's annual average precipitation rate 80 mm. Most of the rainfalls occur along the coastal area and it decreases. The development of the models is based on a set of hydrological time series. The series consist of daily readings of maximum and minimum temperatures, rainfall and wind speed. These readings were taken in Alexandria province, Egypt, from 1957 to 2009 .

In this present study, meteorological data for Alexandria, Egypt have been collected for the period from 1957 to 2009. A feed forward network equipped with back propagation algorithm was adopted, to forecast the total rainfall for the next year and to forecast the total rainfall for the next January and next December. Additionally, predictions with multiple linear regression MLR model were compared to those of ANN. In order to evaluate the rainfall forecast a statistical analyses were performed.

Data preprocessing

As mentioned before, the data that is used in this study consist of daily measurments of rainfall, maximum and minimum temperature. Preprocessing steps for the data were needed due to the huge size of it and also to show the statistcal nature of it. The following steps were taken in the preprocessing stage:

1. Calculating the monthly average for the rainfall and the temperature.
2. Calculating the total rainfall percentage for each month. For (i=1, 2, 3… 12) which represents the months and for (t=1957, 1958… 2009) 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 is

$$S_i = \sum_{t=1957}^{2009} R_{it} \tag{1}$$

And the gross total rainfall for all the period G is

$$G = \sum_{i=1}^{12} S_i \tag{2}$$

So, the total percentage for each month P_i is

$$P_i = \frac{S_i}{G} \tag{3}$$

1. Figure 1 shows the total percentage for each month. In order to classify the months to categories, the total percentage for each month was used. The first category includes month with more than 20% (January and December), and the second category with less than 20% (February to November). Since the percentage of rainfall for January and December together, first category, represent more than 50% of the total percentage, the monthly basis forecasting in this study included only these two months.
2. Considering only the winter season, the yearly total rainfall R_t^y and the yearly average temperature T_t^y, where t=1957, 1958,…,2009, are calculated.
3. 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:

i) For yearly total rainfall at any year t:

$$\Delta_t^y = R_{t-1}^y - R_t^y \tag{4}$$

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

$$\Delta_t^1 = R_{t-1}^1 - R_t^1 \tag{5}$$

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

$$\Delta_t^{12} = R_{t-1}^{12} - R_t^{12} \tag{6}$$

Artificial neural network

The type of network used in the present study falls into the most popular class that of the layered feed-forward network with synchronously operating neurons. In feed forward networks of the back-propagation type, neurons in a given layer do not connect with each other, and do not take inputs from subsequent layers or layers before the previous one. A problem is presented to the network as an array of real values, each element of which is entered to a different neuron in the input layer. The input neurons transmit these values across the links to the next (hidden) layer of neurons. On each link, the weight W_{ij} was used to multiply transmitted values. The weighted values converging at a neuron in the hidden layer are summed up along with a weighted bias b_j associated with that neuron. The result is then put through a transfer function to generate a level activity for the neuron. The activation levels of the hidden neurons are then transmitted across their outgoing links to the neurons of the output layer. As before, these values are weighted during transmission across the links, and then summed up at the output neuron and put through an activation function. The level of activity generated at the output neurons is the network's solution to the problem presented at the inputs. This process can be formalized into a set of simple algebraic equations. For any hidden neuron *j*, the level of activity h_j can be described by the following equation:

$$h_j = f\left(\sum_i W_{ij} I_i + b_j\right) \tag{7}$$

Where transfer function *f* is a sigmoid function, I_i are activity levels generated for neurons in the previous layer *i*, W_{ij} represents the weight from neuron *i* in some layer to neuron *j* in the next layer and b_j is the weighted bias associated with neuron *j*.

It is assumed that the network does not have any a priori knowledge about the problem. So at the beginning, the network weights are initialized with a set of random values. The network is learned (trained) with repeated sets of input patterns. The feed-forward operation calculates an output for each input and then compares it with the correct output. The error *E* of the neural network is defined as:

$$E = \frac{X_p - X_a}{X_a} \times 100\% \tag{8}$$

Where X_p is the predicted rainfall and X_a is the actual rainfall. In the case of prediction accuracy, classification was done at the 20% error bound on the percentage error. Thus, if the rainfall prediction were within ±20% of the actual observations, they were considered as successful prediction. The physical processes determining the structure and variability of the rainfall are complex and the character and strengths of connection among them are not clearly known. Therefore, it is not possible to predict the overall behavior of the rainfall by the models developed on the basis of selecting a few parameters because there are many more parameters which could be added to the list.

However, in order to safeguard against over fitting, that would jeopardize the validity of the regression relationship in the independent data set, it has been found effective to limit the input to very few (two to three) of the most promising predictors. So, the prediction of the rainfall depends on the change in the rainfall and the temperature, whose physical mechanisms and cause and effect relationship is not yet clear (Sahai et al., 2000). Figure 2 provides a visual representation of the complete feed-forward network architecture that is used in this study. The neural network has been used to predict the rainfall on yearly basis and monthly basis, January and December. Generally, the prognostic variables consist of a pair of input;

$$(\Delta_t^y, T_t^y), (\Delta_t^1, T_t^1) \ or \ (\Delta_t^{12}, T_t^{12})$$

While the output will be the amount of rainfall for the next year, next January or next December, $(R_{t+1}^y, R_{t+1}^1, R_{t+1}^{12})$, respectively.

Yearly basis rainfall forecasting

The number of neurons used in the input and output layers are fixed by the nature of the problem being modeled. However a configuration of hidden neurons for a given problem is more flexible. Here, a network with one input layer, three hidden layers and one output layer was implemented and tested. The architecture of the neural network is (2, 10, 7, 6, 1) which represents the number of the neurons in each of the input, hidden and output layers. This architecture showed the best potential within a short training and testing period, and was considered. Table 1 summarizes the properties of the hidden layers.

Monthly basis rainfall forecasting

Utilizing the same previous approach, an ANN was developed to predict rainfall for the next January and December. The input vector comprised of the change in rainfall and the monthly average temperature for both months. For January forecasting, a network with one input layer, three hidden layers and one output layer was implemented and tested. The architecture of the neural network is (2, 8, 5, 4, 1) which represents the number of neurons in each of the input, hidden and output layers. While for December forecasting, it consists of one input layer, three hidden layers and one output layer. The architecture of the neural network is (2, 8, 9, 5, 1). Tables 2 and 3 summarizes the properties of the hidden layers for January and December networks. All the three networks were trained with the data for a period of 43 years, from 1957 to 1999, using the error back propagation algorithm, and were tested for a separate data set of 10 years from 2000 to 2009. During the training period, a limit of 2500 epochs and a training mean square error of 10^{-4} were set. The weights were updated after each sweep. The training was stopped when the mean square error reached the predefined limit or the maximum epoch was reached, whichever came first.

Multi-linear regression

MLR is probably the most widely used method in hydrology for developing models to predict climate variables. Generally, the

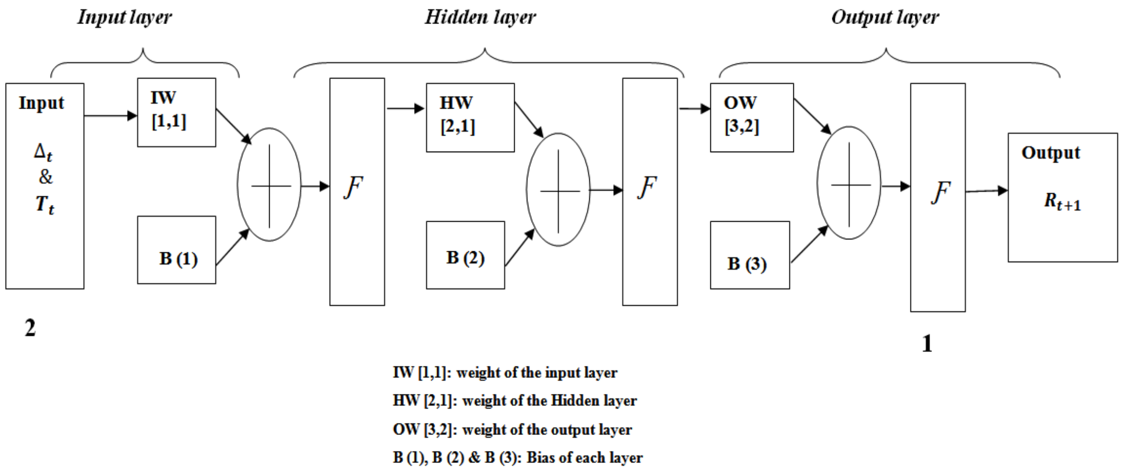

Figure 2. The applied feed forward neural network architecture.

Table 1. Hidden layer properties – yearly basis network.

Layer	Neurons	Transfer function
Hidden layer 1	10	tan sigmoid
Hidden layer 2	7	tan sigmoid
Hidden layer 3	6	Log sigmoid

Table 2. Hidden layers properties – January network.

Layer	Neurons	Transfer function
Hidden layer 1	8	Tan sigmoid
Hidden layer 2	5	Log sigmoid
Hidden layer 3	4	Log sigmoid

Table 3. Hidden layers properties – December network.

Layer	Neurons	Transfer function
Hidden layer 1	8	Tan sigmoid
Hidden layer 2	9	Tan sigmoid
Hidden layer 3	5	Log sigmoid

predictor variables consist of a pair of input $(\Delta_t^y, T_t^y), (\Delta_t^1, T_t^1)\ or\ (\Delta_t^{12}, T_t^{12})$. While the predictants will be the amount of rainfall for the next year, next January or next December, $(R_{t+1}^y, R_{t+1}^1, R_{t+1}^{12})$, respectively.

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:

$$y_i = b_o + b_1 X_{i,1} + b_2 X_{i,2} + \cdots + b_k X_{i,k} + e_i \quad (9)$$

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

$$\hat{y}_i = \hat{b_o} + \hat{b_1} X_{i,1} + \hat{b_2} X_{i,2} + \cdots + \hat{b_k} X_{i,k} \quad (10)$$

Where the variables are defined as in equation (8) except that "^" denotes estimated values.

Performance evaluation for ANN and MLR models

For inter-comparisons between actual versus predicted rainfall using the ANN and MLR models, four basic statistical parameters were used: mean error (BIAS), mean absolute error (MAE), root-mean-square error (RMSE), and the correlation coefficient (CC), which are, in this order, expressed by

$$BIAS = \frac{1}{N}\sum_{i=1}^{N}(X_i - X_i') \quad (11)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|X_i - X_i'| \quad (12)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - X_i')^2} \quad (13)$$

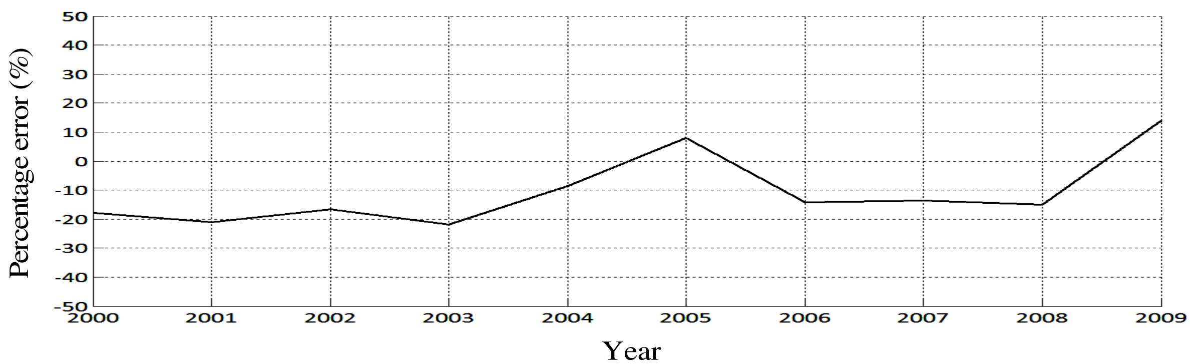

Figure 3. Percentage errors between the observed and the predicted yearly rainfall 2000-2009.

and

$$CC = \frac{\sum_{i=1}^{N}(X_i - \hat{X})(X_i' - \hat{X}')}{\sum_{i=1}^{N}(X_i - \hat{X})^2 \sum_{i=1}^{N}(X_i' - \hat{X}')^2} \quad (14)$$

Where N is the total number of forecast outputs, X_i is the i^{th} rainfall forecasts by ANN or MLR models, and X_i' is the corresponding i^{th} observation. $\hat{X}'$ and $\hat{X}$ are the averages for the observed and predicted values respectively. For a good prediction, the correlation coefficient should be near 1 and the RMSE, MAE and BIAS values small.

RESULTS AND DISCCUSION

A feed forward neural network with back propagation algo-rithm was implemented and tested for the purpose of yearly basis rainfall forecasting. The input data were the change in the yearly rainfall and average tempera-ture. A supervised learning technique was used by intro-ducing the observed yearly rainfall to the network. The network was trained with data of 43 years start from 1957 to 1999. To test the accuracy of the network a 10 years data, 2000 to 2009, were introduced to the network for the first time. The output of the network is the predicted yearly rainfall. On the other hand, a multi-linear regression MLR model was also implemented to predict the rainfall on yearly and monthly basis.

Yearly basis forecasting

During the training period, a limit of 2500 epochs and a mean square error MSE of 10^{-4} were set. Here, the network stopped the training when it reached the designed limit at 428 epochs. The overall prediction came successful with a percentage error between ±20%. Figure 3 shows the percentage error for the testing data set.

It was observed that the network underestimated the yearly rainfall for the testing data set. The maximum deviation from the observed was 45 mm at 2001. As a comparison between the observed and the predicted yearly rainfall using ANN. Alternatively, MLR model has estimated the forecasted rainfall. The maximum deviation from the observed value is equal to 89 mm at 2004. Figure 4 plots the results of the ANN and MLR models and compares them with the observed values.

Monthly basis forecasting

ANN and MLR models were implemented and tested for the purpose of rainfall forecasting for January and December. The results are presented and discussed here.

Predicting the rainfall for January

The input data that have been introduced to ANN were the change in rainfall and the average temperature for January. The total rainfall for January was introduced to the network as the observed values. The network stopped the training when it reached the designed MSE 10^{-4}, at a number of epochs was equal to 70. The neural network showed an outstanding result in predicting the rainfall for January with a percentage error range between ±10% (Figure 5). The network estimated the rainfall with very small deviation from the observed; the maximum deviation is equal to 5.9 mm which can be seen at 2009. While the MLR models' maximum deviation from the observed value was 32 mm at 2009. Figure 6 represents the forecasts from ANN and MLR model and compare them with the observed data.

Predicting the rainfall for December

Here, the ANN stopped the training when it reached the designed MSE, 10^{-4}, at a number of epochs was equal to 70. The ANN prediction was successful for all the years as the percentage error range between ±20%. Figure 7

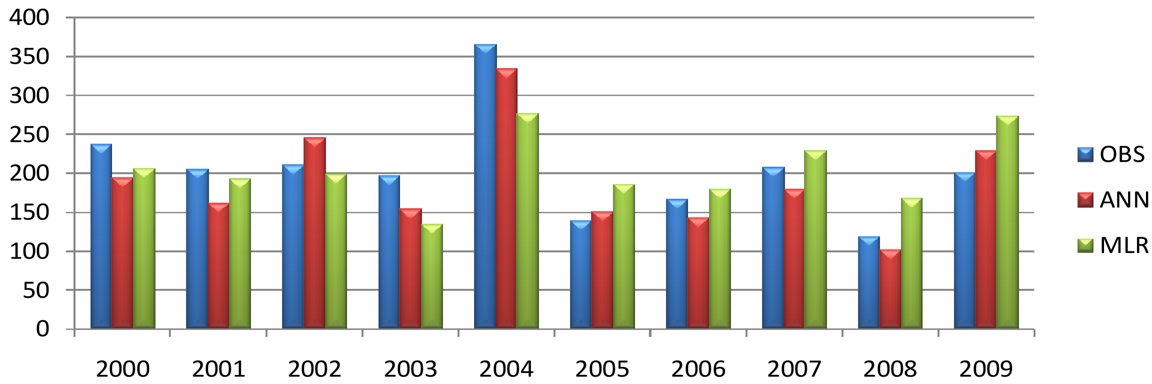

Figure 4. Plot of observed versus predicted yearly rainfall using ANN and MLR 2000-2009.

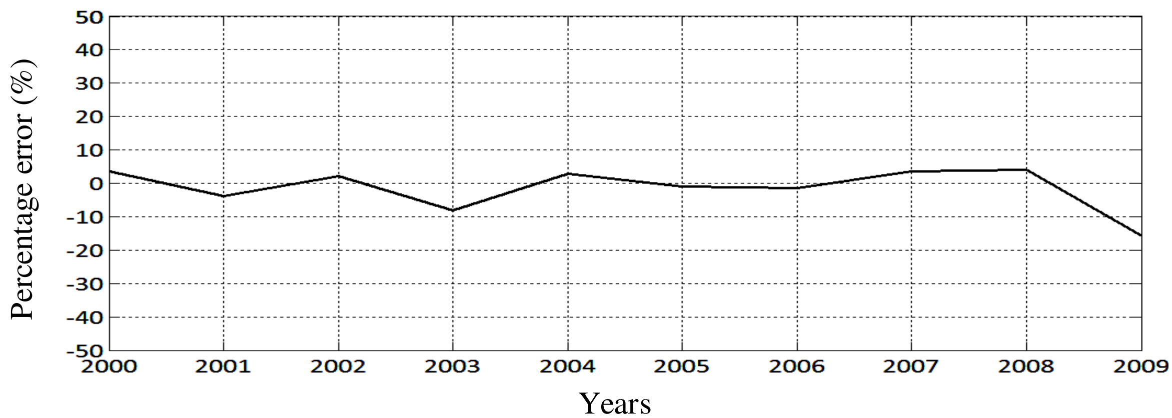

Figure 5. Percentage errors between observed and predicted rainfall for January 2000-2009**.**

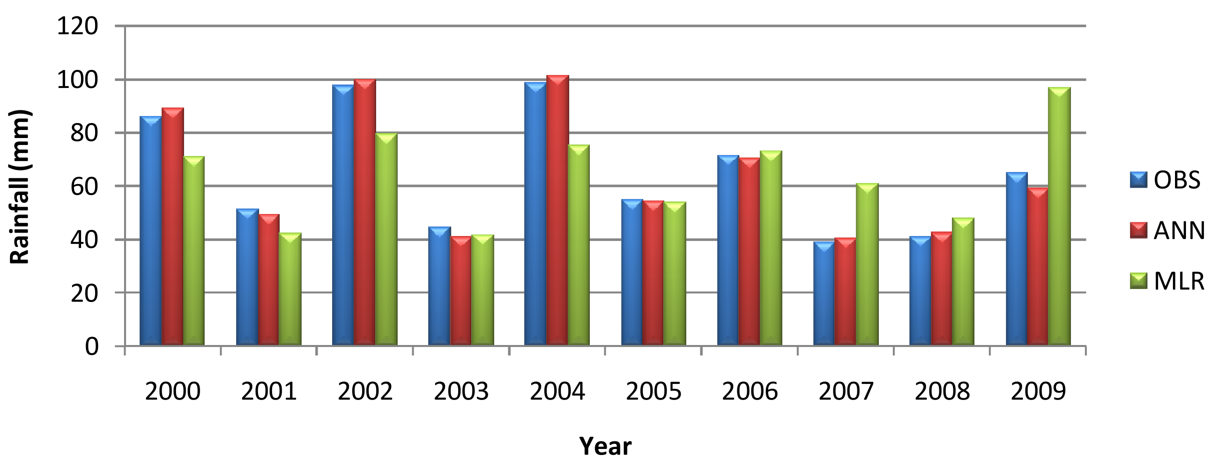

Figure 6. Observed versus predicted January rainfall using ANN and MLR 2000-2009.

shows the percentage error for the testing data set (2000 to 2009). The network estimated the rainfall with very small deviation from the observed; the maximum deviation was equal to 16 mm which can be seen at 2001. While the MLR model has estimated the rainfall with a maximum deviation from the observed value was 44 mm at 2004. Figure 8 represents the forecasts from ANN and MLR models and compare them with the observed data.

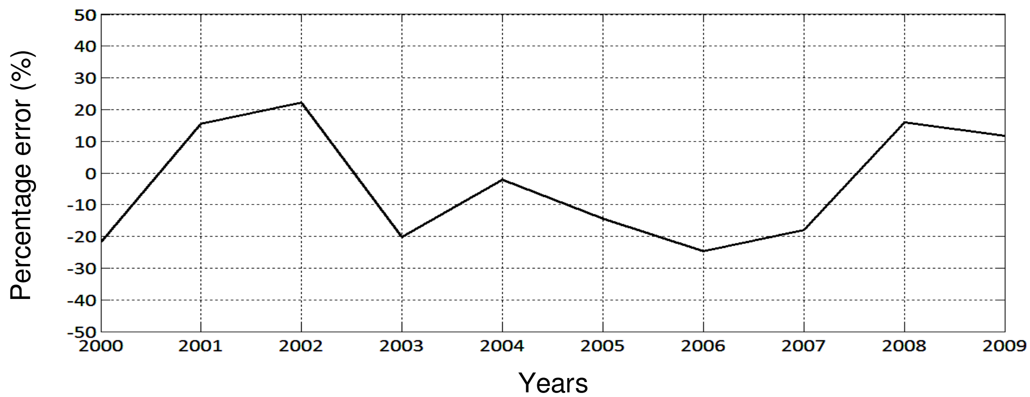

Figure 7. Percentage errors between the observed and the predicted rainfall for December 2000-2009.

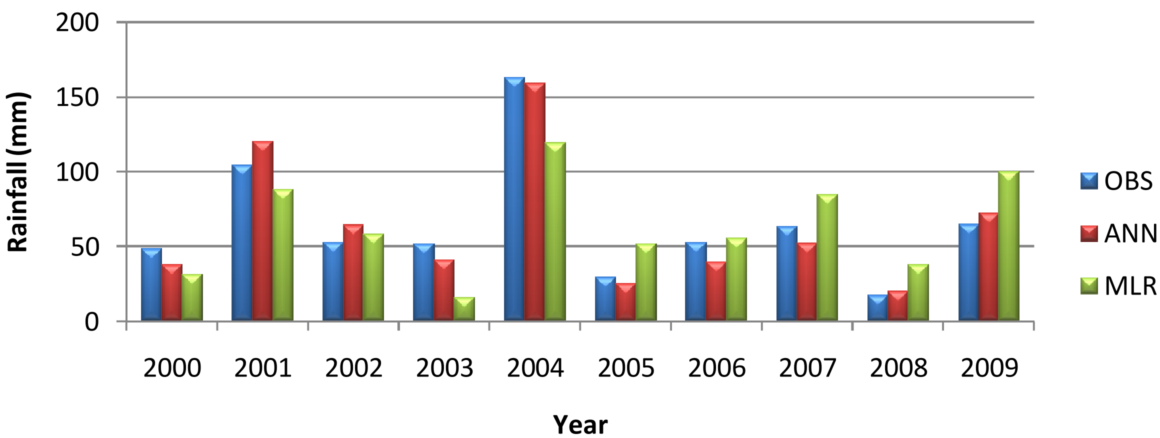

Figure 8. Plot of observed versus predicted December rainfall using ANN and MLR 2000-2009.

In order to taste the accuracy of the ANN and MLR forecasts, scatter diagrams were plotted. The diagrams show the observed versus predicted yearly rainfall. The more perfectly the models were fitted the data, the closer the points fall on the straight line the closer R^2 value to 1.

In yearly basis forecasting, the coefficients of determination R^2, obtained from ANN and MLR, were equal to 0.811 and 0.416 respectively. From Figure 9, it can be seen that both models had the ability to predict the extreme values, maximum and minimum values. However, the ability of ANN model to predict the mid-range values was better than the ability of MLR model, as the clusters in ANN diagram are closer to the straight line than the clusters in MLR diagram. In monthly basis forecasting, the coefficients of determination R^2 for January, obtained from ANN and MLR, were equal to 0.987 and 0.432 respectively. While R^2 for December, obtained from ANN and MLR, were equal to 0.945 and 0.586 respectively. Figure 9 represents the scatter diagrams for yearly and monthly basis forecasting models.

For inter-comparisons between actual versus predicted rainfall using the ANN and MLR models, four basic statistical parameters were used: mean error (BIAS), mean absolute error (MAE), root-mean-square error (RMSE), and the correlation coefficient (CC). For a good prediction, the correlation coefficient should be near 1 and the RMSE, MAE and BIAS values small. Table 4 shows the RMSE, BIAS, MAE and CC values for the yearly and monthly basis forecasting using ANN and MLR models. In Table 4, the BIAS value for yearly and December from MLR are higher than the values that were obtained from ANN, this is because each forecast can be positive or negatively biased, individual forecast errors may cancel each other out. For this reason, the BIAS alone is not enough to indicate the forecast accuracy. It can be seen from Table 4 that both ANN and MLR models underestimated the forecast rainfall. Although, MAE values for ANN and MLR, are relatively high, the ANN model gave a smaller value for MAE than the MLR model. The ANN model shows a smaller value for RMSE compared to those in MLR model. Also, the ANN outstanding performance was emphasized in the values of coefficient

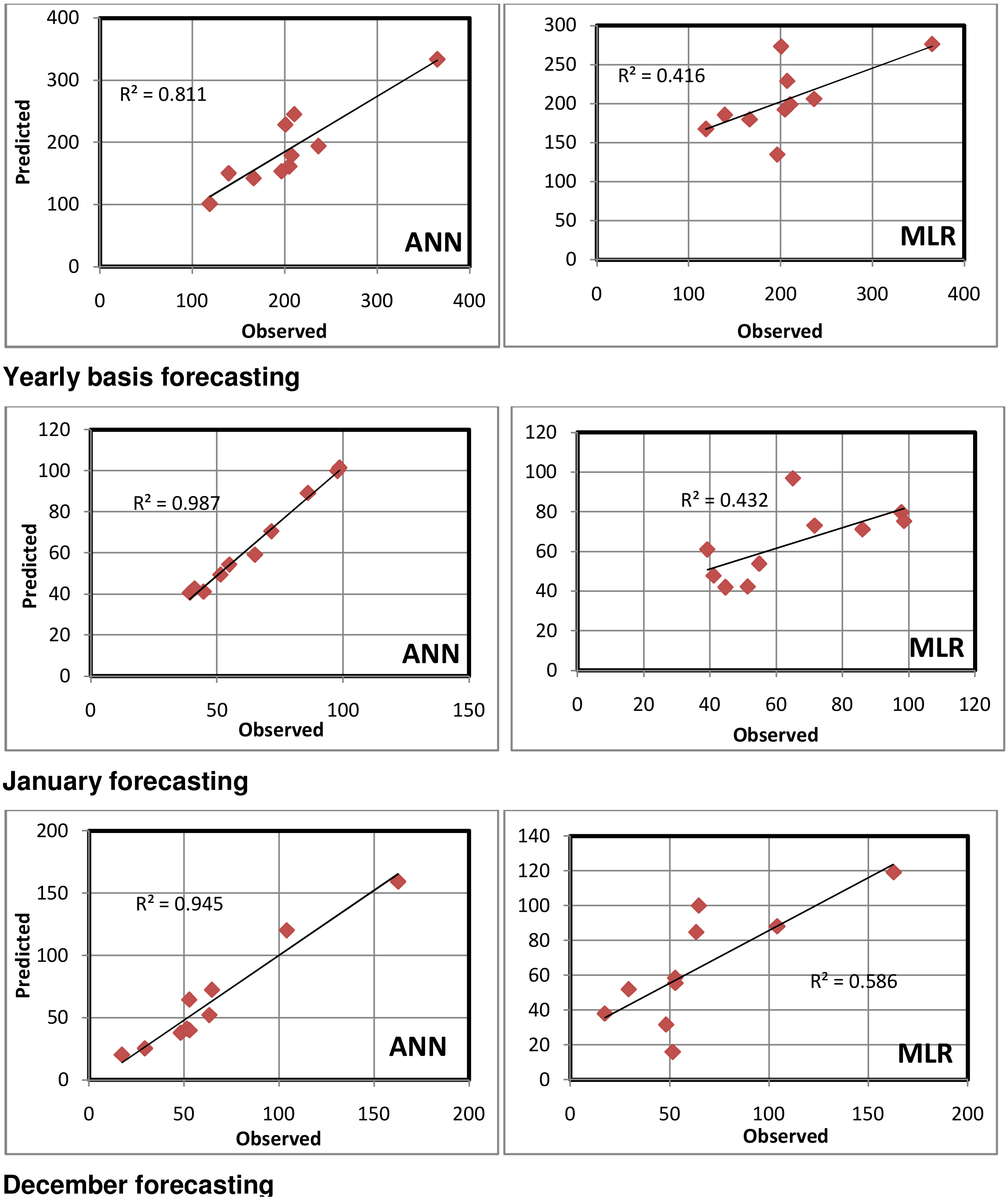

Figure 9. Scatter diagram showing the relations between the observed and the predicted rainfall on yearly basis and monthly basis.

of correlation CC that determined for ANN and MLR. The CC values for ANN were much higher than those for MLR model.

Generally, a low BIAS accompanied by a low RMSE and MAE indicates a good forecast. However, a good forecast may have a low BIAS and high MAE and RMSE values (if the forecast values are poorly correlated with observations) or a relatively high BIAS value but a

Table 4. Comparison between ANN and MLR.

	ANN			MLR		
	Yearly	**January**	**December**	**Yearly**	**January**	**December**
RMSE	32.04	2.83	10.04	48.32	16.50	25.23
BIAS	-15.46	-0.19	-1.48	-0.30	-0.78	-0.49
MAE	30.31	2.42	9.11	40.75	13.11	21.96
CC	0.90	0.99	0.97	0.65	0.66	0.77

relatively low MAE and RMSE values (if the forecasts are well correlated with observations). In general, the application of neural network in rainfall forecasting is promising. However, the proposed ANN model approaches are still lacking appropriate method for searching the optimum ANN architecture. In addition, preprocessing of the data is an essential step for time series forecasting model and requires more survey and analysis that could lead to better accuracy in this application. The optimal selection of the key parameter still requires to be achieved by augmenting the ANN model with other optimization model such as genetic algorithm or particle swarm optimization methods. On the other hand, the variable selection (input pattern) in ANN model is always a challenging task due to the complexity of the hydrologic process. Some other advanced ANN model, namely; Dynamic Neural Network (DNN) that considers the time-dependent interrelation-ship between the input and output pattern could be investigated and might provide better forecasting model. Furthermore, more robust input pattern selection approaches (e.g. systematic searching of optimal or near optimal variable combination in DNN with ensemble procedure) can be explored and may lead to important new methods for monthly inflow forecasting in hydrological processes.

Conclusion

An analysis of two statistical models developed for rainfall forecast on yearly and monthly basis in Alexandria, Egypt shows that an ANN has a better performance than an MLR model. The MLR model revealed a humble prediction performance. The linear nature of MLR model estimators makes it inadequate to provide good prognostics for a variable characterized by a highly nonlinear physics. On the other hand, the ANN model is a nonlinear mapping tool, which potentially is more suitable for rain (nonlinear physics) forecasts. The analyzed study cases suggest that, ANN provide better results than the MLR model regarding the statistical criteria used to make the comparison between ANN and MLR models. However, the comparison is reasonable since the aim of this study is to obtain a more specific rainfall forecast using the available data. The final results suggest that, the ANN model could be an important tool for local rain forecasting, although not replacing the forecasters' experience, but complementing it with extra information thus rendering his (her) task less arduous.

It is true that more detailed studies are necessary due to uncertainties inherent in weather forecasting and efforts should be addressed to the problem of quantifying them in the ANN models (Maier and Dandy, 1996). The probabilistic forecast is one way to quantify these weather uncertainties (Krzysztofowicsz, 2001). In order to improve the prediction skill of the ANN model, additional data are needed to be assimilated by the model, such as satellite image and a much longer observed rainfall time-series. In this context, data pre-processing could be applied to these datasets, such as the wavelet analysis that would reduce the size of ANN input data.

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