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Designing Weather Forecasting Model Using Computational Intelligence Tools

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ABSTRACT

Climate changes on Iraq characterized by increasing droughts and desertification cause many environmental problems especially in the last decade. In this study, a model was designed to forecast selected weather variables in Nineveh province which is located in northwestern of Iraq based on artificial neural networks consisting radial basis function, Fuzzy C-Means, and Nonlinear Autoregressive Network with Exogenous inputs. The performance accuracy of this developed model gives very close predicted results with very small statistic errors for predicted period years from 2015 till the year 2050 then the model begins to collapse and its results are irrational. An interface window was designed to be an easy facility to work on this model without any difficulty or complexity. This model is a very useful tool for decision-makers for developing future plans to address the rapid climate changes in the study area.

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Introduction

Weather forecasting can be defined as the application which inserts many scientific technologies to predict the atmosphere status for the future time for specific locations (Sheridan 2002) where forecasted weather variables are very important in addressing future environmental and industrials planning. For forecasting local-scale weather variables, the empirical approaches are used as weather forecasting methods if data are plentiful. Many effects of climate change have become apparent to Iraq; drought is one of them especially in the last previous decade (UNEP 2013). Many factors have contributed to the acceleration of drought in Iraq (USAID 2006; FAO 2014) including irregular migration as a result of successive wars, bad management of water resources and many other reasons. The study area represents the Iraqi agricultural economic center, providing Iraq with significant quantities of wheat and barley crops that are necessary to meet the requirements of the population. The province of Nineveh is in northwestern Iraq between 41° 30′–44° 30′

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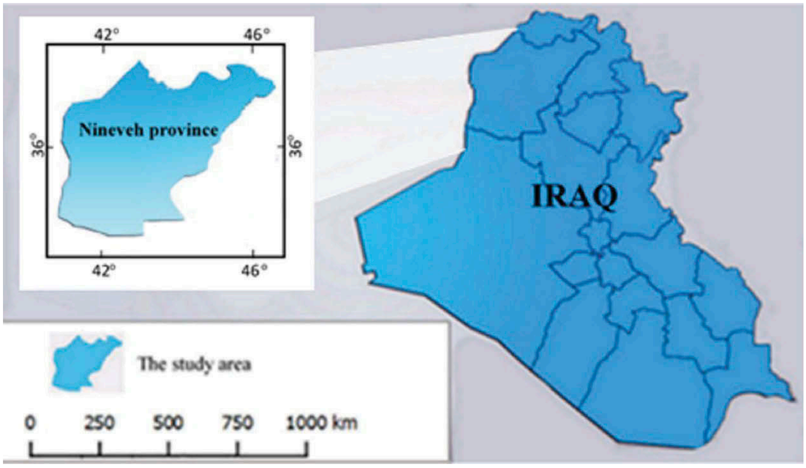


Figure 1. The study area.

longitude and 35° 00′–37° 00′ latitude. It shares a border with Syria and several other Iraqi governorates as given in Figure 1. Nineveh is the third largest province in terms of size. Its total area is 37,323 km^2, which represents 8.6% of the total area of Iraq. The provincial capital is the city of Mosul. The current population of the province is more than 2 million. Winter in Nineveh is mild but not tropical; the average temperature in January is 7°C. The summer in Nineveh is very hot and relentlessly sunny, with possible daytime temperatures of 43°C in July and August; however, air humidity is low. The average rainfall per year is 365 mm concentrated between November and April. Nowadays, climate change negatively impacts all parts of the province with the growing of dust and sand storms phenomenon that sweep the province, causing economic, environmental and psychological damages.

In order to forecast weather variables in a very effective way and to help overcome all climate changes problems in the study area, artificial intelligent procedure represented by artificial neural networks (ANNs) can be used, which have the ability to simulate nonlinear input data and generate artificial mechanism to study the pattern of observed data and train it to predict future weather data. The ANNs are designed mathematical models that simulate the nervous system in the human mind that works as associative memory to resolve real-world problems that need complex calculations. All ANNs have a specific structure that contains layers connected by neurons. These neurons can be defined as important aspects of ANNs where they work as communication lines between the network parts with associated weights (Kosko 1992). A neural network model is a mathematical framework that can be designed to represent the relationships between the data patterns and their changes over time where the successive training and testing steps to obtain the best results (Nayak, Mahapatra, and Mishra 2013).

Related Studies

Many studies have been done on weather forecasting using ANNs. Special interest works are taken on forecasting weather variables but first it is important to define the term forecast; it can be defined as a dynamic filtering methods in which future values are predicted based on the previous values of one or more time series (Deshpande 2012; Farajzadeh, Ahmad, and Saeed 2014). Different ANN procedures have been applied by Hsieh and Tang (1998) for predicting meteorology and oceanography data where they found that these procedures have the ability to analyze these kinds of data effectively and efficiently. Many advantages of ANN procedures explained by Liong and Shan (2010) include nonlinearity analysis, easy data preparation, ability to learn and high accuracy with low statistical errors. In this study, three famous ANNs (radial basis function [RBF], Fuzzy C-Means [FCM] and Nonlinear Autoregressive Network with Exogenous [NARX]) were chosen according to many scientific articles that prove their ability and efficiency to predict future weather data with high performance accuracy.

RBF networks have been successfully applied in function approximation, curve fitting, time series prediction, control and classification problems etc. Many researchers have predicted weather variables by using ANNs of their studies based on different approaches (Abhishek et al. 2012). Therefore, in order to produce efficient and accurate forecasting results, the ANNs were used by Doucoure, Agbossou and Cardenas (2016) for developing weather forecasting model; the model performance accuracy was evaluated and tested using different approaches based on deferent statistical errors. NARX input approach is a powerful class of models for modeling nonlinear systems and specially time series (Lin et al. 1996). The NARX, artificial networks have proved its suitability for long-term prediction (Caswell 2014). In order to forecast daily rainfall (Devi et al. 2016), they adopt different neural network models such as BPN, Cascade-forward Back Propagation Neural Network, Distributed Time-Delay Neural Network and NARX. The forecasting capabilities of all models have been compared where the results show that the use of meteorological variables such as temperature and humidity as input dataset enhances the performance accuracy of these models. Clustering is an important process for extracting useful information from time series datasets. There are different types of clustering paradigms such as FCM that are defined as unsupervised technique based on fuzzy theory that submitted for first time by Bai, Dhavale and Sarkis (2016). FCM is commonly used in wide range of problems that can be solved using this technique like weather forecasting, agricultural engineering and remote-sensing image analysis etc.

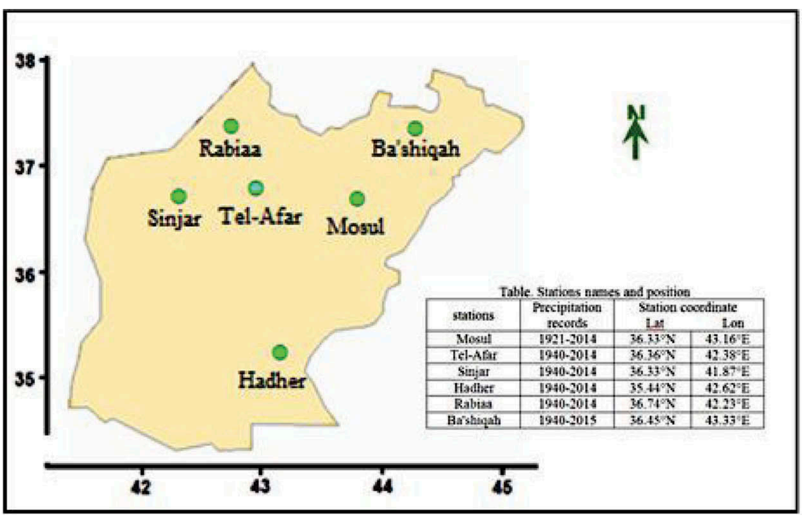
(Ding and Xian 2016). FCM can be classified under classical fuzzy clustering algorithms which is based on an idea of dividing a single dataset or a time series into a number of groups which have specific attributes for each group (Nagahamulla, Ratnayake, and Ratnaweera 2012; Zadeh 1965). The objective of this study is to design and develop an ANN model for weather forecasting using three ANNs approaches RBF, FCM and NARX as a useful tool for addressing future climate changes throughout forecasting weather variables in the study area.

Dataset and Methodology

Dataset Specification and Organization

Ideally the analysis using ANNs need continues time series dataset (Zhang, Patuwo, and Hu 1998). Furthermore, it is logical to insert the weather data records of all meteorological stations within a selected region when designing a weather forecasting model to ensure obtaining realistic results. The study area contains six meteorological stations (Mosul, Tal Afar, Sinjar, Hadher, Rabiaa and Sinjar stations) (Figure 2).

As a result of the difficult circumstances that faced Iraq in general and Nineveh province in particular as a result of wars when it fell under the control of terrorist organizations during the previous 5 years which caused some stations to stop working, it was difficult to obtain accurate weather variables records of all stations. To complete this study, the records dataset of only Mosul station was used to represent all weather data for the entire study area because it has continued records dataset from 1972 to 2017, where



stations	Precipitation records	Station coodinate Lat	Lon
Mosul	1921-2014	36.33°N	43.16°E
Tel-Afar	1940-2014	36.36°N	42.38°E
Sinjar	1940-2014	36.33°N	41.87°E
Hadher	1940-2014	35.44°N	42.62°E
Rabiaa	1940-2014	36.74°N	42.23°E
Ba'shiqah	1940-2015	36.45°N	43.33°E

Figure 2. The distribution of meteorological stations in the study area.

meteorologists that working at this station updated the climate data records even during the war.

Five weather variables records (rainfall, temperature, humidity, wind speed and sun shine) that belong to Mosul station for the period 1972–2017 were used as 540 samples for each variable to train and test the designed neural networks models (Iraqi Meteorological Network Data 2017). Those variables were arranged in an excel file sheet which is imported into the MATLAB workspace (MATLAB R2017a 2017). Due to the lack of available data and to ensure the best results in the training and testing of neural networks, the volume of data has tripled to become 1620 by simply appending it with itself three times. Out of the 1620 samples, 70% samples called the training data that are randomly selected by *nntool* for training ANNs. To measure the popularization of the network, 15% of samples called validation data feed the ANNs as data have not been deal with or seen before. To get an independent measurement of the ANN performance in terms of root mean squared error (RMSE), the rest of the 15% dataset (testing set) was used to accomplish this stage. In this study, one variable (rainfall) has been examined for all designed ANN approaches where the necessary parameters prepared during experimentation. The same technique is followed in designing the rest of the ANNs to suit other variables.

Designed ANNs

Three different neural network approaches, RBF, NARX and FCM, were used to develop different neural network sub-models collected together in one model used for local weather forecasting in the study area. The Neural Network Fitting Tool Box (GUI) available in MATLAB (R2017a) is used to develop the designed ANNs (Qi and Zhang 2001). Many trials and error attempts have been carried out to set up the fit number of hidden layers and best number of artificial neurons to reach optimal performance. RMSE, Mean Absolute Percentage Error (MAPE) and the coefficient of determination (R^2) were used as performance criteria. Furthermore, these three used ANN approaches are shortly described.

A Radial Basis Function Neural Network (RBFNN) is a special type of feeding forward neural network that uses RBF as its activation function to control the behavior of this neural network. RBFNN structure consists of three layers, the first layer is not weighted linear layer that has a role to transmit input data by the neurons into the next layer. The second layer is not weighted nonlinear layer called hidden layer (may be one or more) where in this layer, the hidden neurons process the input data. The number of neurons in the hidden layer must be chosen carefully because they effect on the complexity and capability of the network (Basheer and Hajmeer 2000).

The third layer is the output layer, which can be defined as a weighted nonlinear layer which has a role to producing the output results.

The Nonlinear Autoregressive Network with Exogenous Inputs Neural Network (NARXNN) is a powerful procedure for modeling and predicting time series taking into account the complexity and nonlinearity of time series patterns (Diaconescu 2008). This ANN is classified as feed forward neural network where the input can be feedback using the output results. FCM algorithm is defined as unsupervised technique based on fuzzy theory that was submitted for first time by Li, Cheng, and Lin (2008). FCM can be classified under classical fuzzy clustering algorithms which is based on an idea of dividing a single dataset or a time series into a number of groups which have specific attributes for each group (Fan, Zhen, and Xie 2003).

To gain the best performance model, the model structure is designed in four stages. All sub-models work separately in the first stage called training stage then their results were gathered and fed back to working in second stage also named testing stage where in this stage, the performance accuracy of the all designed sub-models was evaluated. Third stage is prediction stage, where the data records were processed to estimate the predicted data of five weather variables (rainfall, temperature, humidity, wind speed and sun shine). The final stage is called presentation stage where an interface window was designed to be an easy facility to work on this model without any difficulty or complexity. A designed window shows several options to make it easier for the user to work on this model, where the type of weather variables, method of prediction, data record length and prediction period in years can be chosen. Also, this window has the ability to show the tested and forecasted results in tables and figures formats (Figure 3).

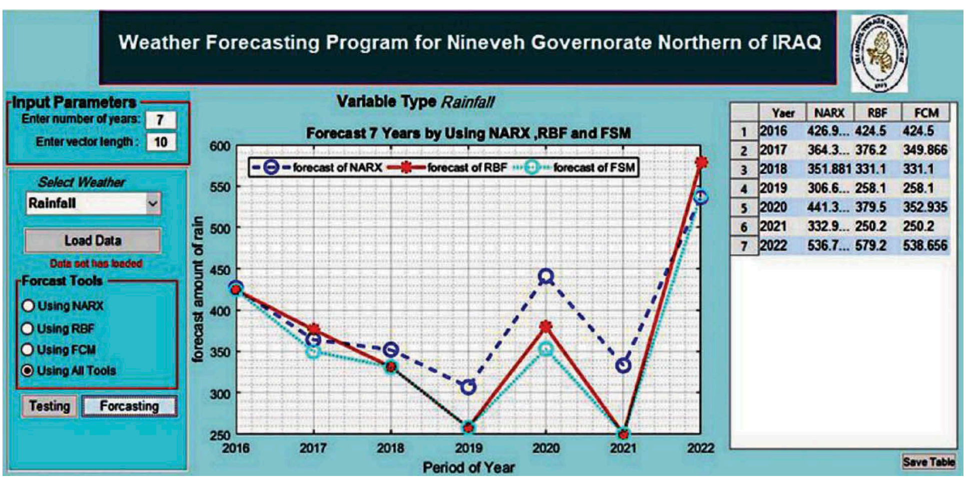


Figure 3. The designed interface window for the develop model.

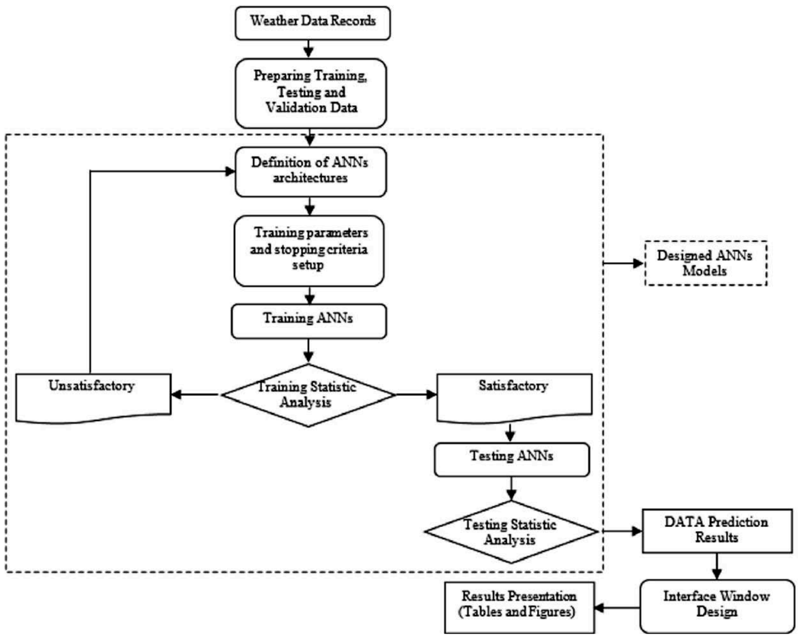


Figure 4. Flowchart designed structure of the developed model.

Figure 4 shows the procedure that was used in this study. Fifteen ANN sub-models were designed as three sub-models for each variable were named where the number of hidden layers and the number of neurons in each sub-model were found by experimentation. The designed sub-models of rainfall variable (RBF-1, NARX-1 and FCM-1) were discussed in detail as an example of all designed sub-models for the rest of the variables (Table 1).

To clarify the names of the sub-models, the arrangement of RBF-1 structure is 10-344-1 as example indicates the number of neurons in the input layer as first number, the second one represents the neurons in one hidden layer and the last number represents the neurons in the output layer. The same format is used to define NARX sub-models. Since FCM sub-models do not contain hidden layers and neurons in their structures, so they will be described as in Table 1. Fifteen sub-models were developed for five variables as three sub-models for each one. The designed sub-models are described in detail as follows:

Table 1. Architectures design of develop ANNs sub-models.

Variables	RBF sub-models	RBF structures	NARX sub-models	NARX structures	FCM sub-models
Rainfall	RBF-1	10-344-1	NARX-1	10-32-4-1	FCM-1
Temperature	RBF-2	10-300-1	NARX-2	10-42-4-1	FCM-2
Humidity	RBF-3	10-266-1	NARX-3	10-34-4-1	FCM-3
Wind speed	RBF-4	10-310-1	NARX-4	10-40-6-1	FCM-4
Sun shine	RBF-5	10-286-1	NARX-5	10-38-4-1	FCM-5

RBF Sub-Models

RBF-1 was discussed in detail as example of the five sub-models illustrated by the following stages below.

Stage one: Excel file as training dataset was prepared to build up RBFNN. To approximate the function of the training dataset, *newrb* function was used to create a RBFNN layers and add neurons to the hidden layer until it meets the specified mean squared error goal. Three arguments must be taken into account to ensure that this function works correctly where the mean squared error goal must be set up; in this study, the goal was set up equal to 0.0000001 and the spread of RBFs was set up as default equal to 1.0. The maximum number of neurons was carefully selected by trial and error to ensure that the network works smoothly without any complication. It was found that the most appropriate number of neurons equals to 344 which gave acceptable results. Epoch, learning rate and the duration of the iteration time are factors affecting on the performance of RBF. Several values are tested for epoch and learning rate where the best values have been set to 1000 and 0.1, respectively.

Stage two: to measure prediction accuracy of the models, the RMSE and the coefficient of determination (R^2) are calculated. According to RBF setup design values, the faster iteration has been achieved in 12 s and reached the epoch 160 geve best performance training obtained RMSE equal 0.0009989 and best R^2 results was 0.99857 (Table 2).

Stage three: represents the output results of the training stage where several results were found in the form of tables and figures. These results illustrate the relationship between the observed and output of training dataset as seen in Figure 5.

NARX Sub-Models

NARX-1 sub-model for rainfall forecasting was discussed in detail as example of the five sub-models. Ten variables are entered as input variables with one exogenous input delay and two feedback delays. This sub-model has 2 hidden layers with 32 and 4 neurons for the first and second layer, respectively. Data were divided into 3 sets out of 1620 samples using the *divide block* function. Excel file as training dataset contains 1134 samples that represents 70% of rainfall record and 30% of data used in both validation and testing trials 486

Table 2. Statistical error parameters of developed RBFNNs sub-models.

Sub-model	Input dataset	RBF structure	R^2	RMSE	Iterations and epochs
RBF-1	Rainfall	10-44-1	0.99857	0.0009989	12 s, reached the epoch 160
RBF-2	Temperature	10-300-1	0.89474	0.0009308	26 s, reached the epoch 240
RBF-3	Humidity	10-266-1	0.89113	0.0009117	16 s, reached the epoch 120
RBF-4	Wind speed	10-310-1	0.95241	0.0009885	20 s, reached the epoch 185
RBF-5	Sun shine	10-286-1	0.99147	0.0009988	14 s, reached the epoch 195

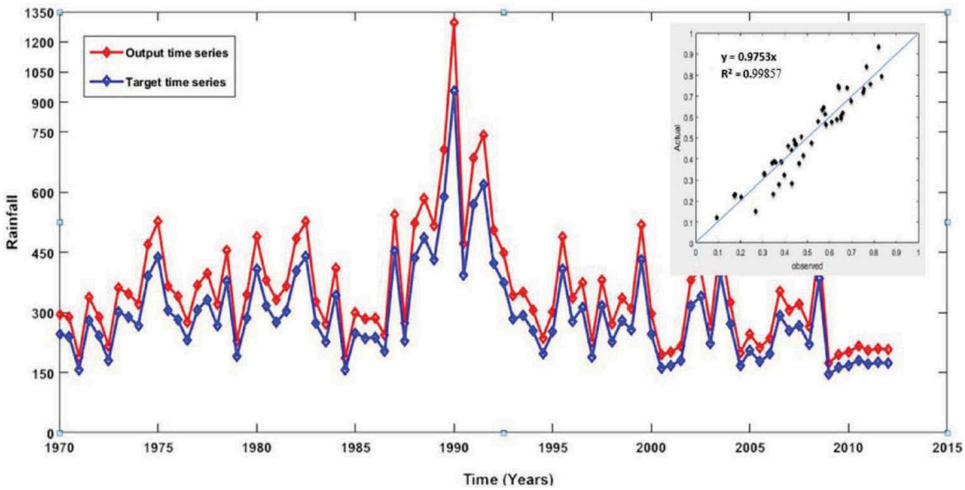


Figure 5. RBF-1 sub-model training results using rainfall dataset.

samples. Neural network learning was limited to a maximum of 1000 epochs. The activation functions in developed NARX sub-models are sigmoid functions, and for more efficient training algorithm *narxnet, closeloop* functions were used to obtain best result. Levenberg–Marquardt as better performance than all other training algorithms is used for training of the network using the *trainlm* function that can be defined as network training function that updates weight and bias values according to Levenberg–Marquardt optimization. The performance of a trained sub-model was evaluated using RMSE and R^2. The average R^2 for training, validation and testing datasets was R^2 = 0.98776 simulated mathematically by function formed as (output = 0.99*T + 0.31), and the root mean squared error was RMSE = 0.000326 as seen in Table 3 and Figure 6.

FCM Sub-Model

FCM-1 sub-model for rainfall forecasting was discussed in detail as example of the five sub-models. In the first stage, the real data will be read and preprocessed to be applied to the prepared fuzzy inference system with input parameters. To design fuzzy inference system structure in MATLAB workspace, *genfis2* function was used (Astakhova, Demidova, and Nikulchev 2015). The input parameters that must interred to generate this function are

Table 3. Statistical error parameters of developed NARX sub-models.

Sub-model	Input dataset	NARX structure	R^2	RMSE	Iterations and epochs
NARX-1	Rainfall	10-32-4-1	0.98776	0.000326	8 s, reached the epoch 230
NARX-2	Temperature	10-42-4-1	0.91411	0.009930	46 s, reached the epoch 520
NARX-3	Humidity	10-34-4-1	0.89987	0.019611	6 s, reached the epoch 180
NARX-4	Wind speed	10-40-6-1	0.85233	0.021711	10 s, reached the epoch 220
NARX-5	Sun shine	10-38-4-1	0.99475	0.000828	16 s, reached the epoch 395

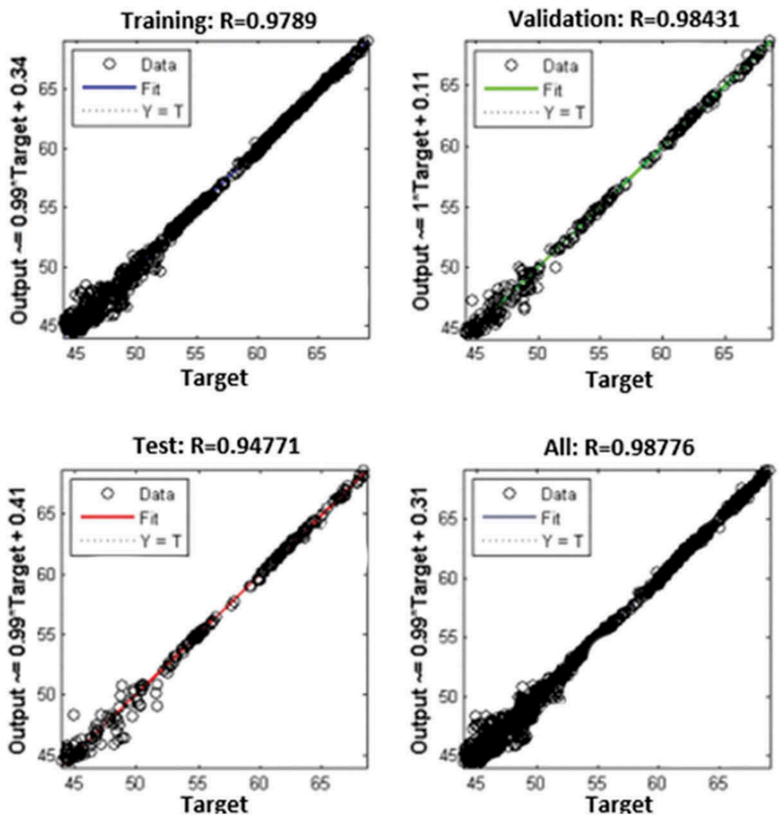


Figure 6. NARX-1 sub-model training results using rainfall dataset.

the input dataset matrix (one dimensional dataset in this study) and the radii as a vector that specifies a cluster center's range of influence in the input dataset where the radii parameters are tuned equal to 0.06 for subtractive clustering. This automatically generates the number of clusters where three clusters were generated. The number of clusters is input to the FCM algorithm as starting point only. The membership functions will be created where the sum of all membership functions must be 1.0.

The generated number of membership function rules was 23. The sub-model is trained using hybrid learning algorithm to identify the membership function parameters of single output where the sugeno-type fuzzy inference systems for fuzzyffication process were adopted to complete training phase. FCM clustering is an iterative process. The process stops when the maximum number of iterations is reached or when the objective function improvement between two consecutive iterations is less than the minimum amount of improvement specified. For this sub-model, the total number of iteration is tuned as default equal to 500. The model stopped when it reach 148 iteration with total objective

Table 4. Statistical error parameters of developed FCM sub-models.

Sub-model	Input dataset	R^2	RMSE	Iterations and epochs
FCM-1	Rainfall	0.98776	0.000784	0.459 s, reached the epoch 148
FCM-2	Temperature	0.91411	0.000930	0.87 seconds, reached the epoch 221
FCM-3	Humidity	0.89987	0.000611	0.91 s, reached the epoch 294
FCM-4	Wind speed	0.85233	0.000711	1.9 s, reached the epoch 312
FCM-5	Sun shine	0.99475	0.000928	2.0 s, reached the epoch 395

function equals to 58.3265; the total lapsed time is 0.459 s. The modeling errors are measured through RMSE where the outcome error is 0.000326 Table 4.

Results and Discussion

The introduced model in this study was effective platform for forecasting weather variables for the study area, which employs three different ANNs that are trained and gathered in one model works in four stages as predictor model. This model can be used for carrying out related scientific studies like drought assessment as an example. Fifteen ANNs were designed as five RBF, five NARX and five FCM sub-models. General test for the designed ANNs has been made using five weather variables. Those data records are used in training, testing and checking the performance of the established weather forecasting model. The best developed sub-models that give minimum statistical errors are RBF-1, NARX-1 and FCM-1 as illustrated in Tables 2–4. Figure 7 shows the performance accuracy of the best developed models.

In order to determine the best prediction performance accuracy of the designed ANNs sub-models, values of the statistical errors criteria R^2,

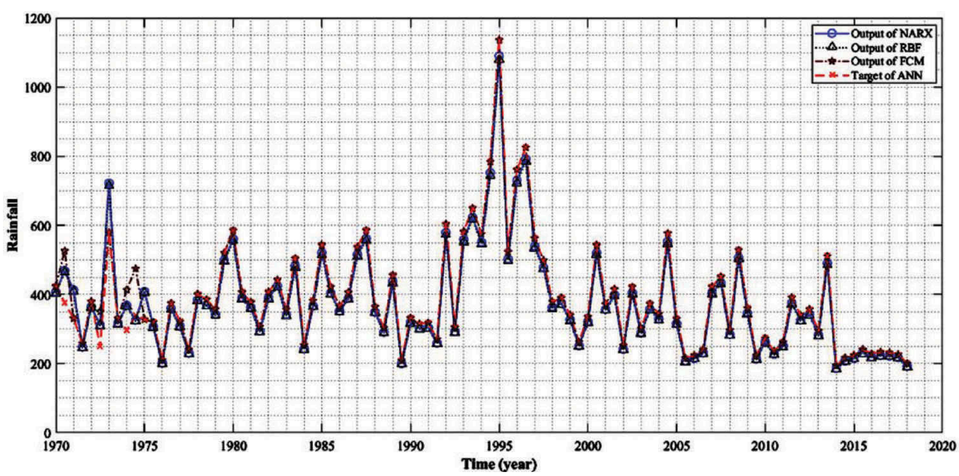


Figure 7. The performance accuracy of the sub-models RBF-1, NARX-1 and FCM-1.

Table 5. Best result of performance accuracy of the designed sub-models.

Statistical errors	RBF	NARX	FCM
		15% as testing dataset	
R^2	0.9389	0.9699	0.9131
RMSE	0.9672	0.8467	0.9526
MAPE	0.9284	0.8538	0.9126

RMSE and MAPE were calculated to prove the prediction accuracy Table 5.

After checking the operational effectiveness of the model by comparing the percentage of statistical errors criteria, the model has been run to predict the rainfall values for the existing years values for the period (2009–2017) to determine the statistical percentage error as illustrated in Table 6 that shows the statistical percentage error obtained from the comparison between the averages predicted results of the three ANNs and the actual data using the developed model. This result was compared with average weather data records from 1972 to 2017 that was obtained from Iraqi Meteorological Network Data (2017) where the average percentage of predicted errors was very small (6.08%). To minimize this percentage error, more types of ANNs should be selected and more other data should be added to the input dataset, especially before 1972 and updating the model data base with data variables for 2018 and above.

The model was run again to predict the rainfall values for the period from 2018 to 2050 were the three predicted time series of the rainfall variable shows marked homogeneity with each other Figure 8. It is noted that this model give reasonable prediction results till 2050 then it is results begins to collapse and its results are irrational. One of the reasons of this collapsing is the increasing of percentage predicted errors with time; in any case, this

Table 6. Comparing the actual and predicted results of rainfall using the developed model.

Rainfall prediction results					Statistical error	
Year	RBF	NARX	FCM	Predicted average	Actual data	% Error
2009	223.8	224.3	224.1	224.06	218.4	2.59
2010	240.6	223.5	223.9	229.33	222.1	3.25
2011	228.3	229.1	227.6	228.33	233.6	2.25
2012	232.9	233.1	232.6	232.33	251.5	7.62
2013	231.2	231.6	231.0	231.26	217.2	6.47
2014	226.2	225.6	225.7	225.83	234.2	3.57
2015	200.1	195.6	197.3	197.60	213.5	7.44
2016	424.5	426.9	424.5	425.3	469.4	8.96
2017	376.2	364.3	349.8	363.4	415.7	12.58
2018	331.1	351.8	331.1	338.0	–	–
2019	258.1	306.6	258.1	274.2	–	–
2020	379.5	441.3	352.9	391.2	–	–
2021	250.2	332.9	250.2	277.7	–	–
2022	579.2	536.7	538.6	551.5	–	Ave. 6.08

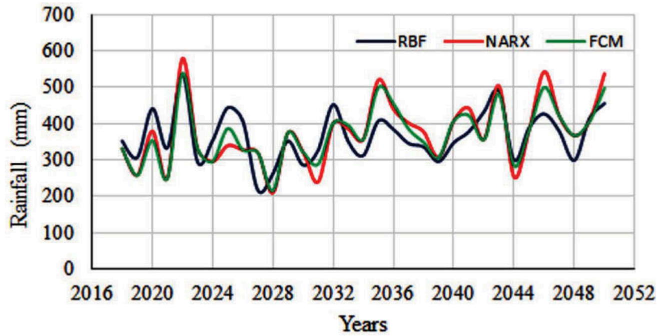


Figure 8. The predicted time series of rainfall from 2018 to 2050.

collapsing must be studied carefully taking into account several fundamental points like redesign the ANNs by increasing hidden layers and setting appropriate neurons number.

Due to the rapid pace of climate change in the study area, whose effects cannot be predicted using conventional methods, the results obtained from this model will continue to be an effective indicator for decision-makers to make future plans to prevent or minimize these impacts.

Conclusion

Nowadays, ANNs are used in various areas of real life according to their characteristic to solve many problems. Prediction or forecasting is a powerful ability that ANNs are characterized by. This ability is effective in serving humanity if it can meet the conditions of realism and accuracy through the obtained results. For the purpose of this study that highlighted the procedure of forecasting several weather variables throughout designing a model based on three deferent ANNs approaches, many factors must be taken into account to obtain best results and that can be listed as follows:

- The amount and the quality of all available weather data records.
- Extensive studies of the weather physical processes which change over time due to different human and environmental factors.
- Selecting the effective methods for analyzing the past weather data and finding the changes in their patterns over time, taking into account the modern methods for updating these data.
- Selected more ANNs approaches gathered them in one model after studying each of them closely to know their mathematical basis in the analysis and test their accuracy prediction results on real weather data.

The developed model works efficiently and is fast, simple and easy to use with clear interface window. Reasonable prediction results with small prediction errors which were obtained; these results are supported by output forms in figures and tables. The new version of this model can be developed for all Iraqi central government institutions that deal with solving environmental and agricultural problems where the interface window can be redesigned for more options like selecting any target provinces or stations.

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