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Using Adaptive Neuro-Fuzzy Inference System (ANFIS) to Improve the Long-term Rainfall Forecasting

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***Abstract*: A hybrid intelligent system is one that combines at least two intelligent technologies, for example, combining a neural network with a fuzzy system results in a hybrid neuro-fuzzy system. In This study we propose an Adaptive Neuro-Fuzzy Inference System (ANFIS) to develop long-term weather forecasting model for rainfall prediction. Monthly meteorological data that obtained from Central Bureau of Statistics Sudan from 2000 to 2012, for 24 meteorological stations distributed among the country has been used. In the experiments we built several ANFIS models using different types of membership functions, different optimization methods and different dataset ratios for training and testing. The proposed models have been evaluated and compared by using correlation coefficient, mean absolute error and root mean-squared error as performance metrics. The results show that ANFIS neuro-fuzzy model is able to capture the dynamic behavior of the rainfall data and it produced satisfactory results, so it may be useful in long term rainfall prediction.**

Keywords: long-term weather forecasting, Rainfall prediction, hybrid intelligent system, neuro-fuzzy system, ANFIS.

I. Introduction

Weather forecasting is the application of science and technology to predict the state of the atmosphere for a future time and a given location [1]. One of the main fields of weather forecasting is rainfall prediction, which is important for food production plan, water resource management and all activity plans in the nature. The occurrence of prolonged dry period or heavy rain at the critical stages of the crop growth and development may lead to significant reduce crop yield. Undoubtedly, the accurate forecasting in rainfall signals could present useful information for water resource management, flood control and disaster relief.

Weather forecasting (particularly rainfall prediction) is one of the most imperatives, important and demanding operational tasks and challenge made by meteorological services around the world. It is a complicated procedure that includes numerous specialized fields of knowledge. The task is complicated because in the field of meteorology all decisions are to be taken with a degree of uncertainty, because the chaotic nature of the atmosphere limits the validity of deterministic forecasts [2]. There are several types of weather forecasts made in relation to time:

- A short-range forecast is a weather forecast made for a time period up to 48 hours.
- Medium range forecasts are for a period extending from about three days to seven days in advance.
- Long-range forecasts are for a period greater than seven days in advance but there are no absolute limits to the period.

The success of the seasonal forecasts depends on a detailed knowledge of how the atmosphere and ocean interact. Short-range forecast predictions, where the forecast is made for a time period for today or tomorrow (up to 48 hours), are generally more accurate than the other types of forecasts. Weather forecasts still have their limitations despite the use of modern technology and improved techniques to predict the weather. For example, weather forecasts for today or tomorrow are likely to be more dependable than predictions about the weather about two weeks from now. Some sources state that weather forecast accuracy falls significantly beyond 10 days [3]. Weather forecasting is complex and not always accurate, especially for days further in the future, because the weather can be chaotic and unpredictable. For example, rain or snow cannot always be predicted with a simple yes or no. Moreover, the Earth's atmosphere is a complicated system that is affected by many factors and can react in different ways.

Long-range weather forecasts are widely used in the energy industry, despite their limited skill; long-range forecasts can still be a valuable tool for managing weather risk. Long term

Prediction of rainfall has several benefits for efficient resource planning and management including agriculture, famine and disease control, rainwater catchment and ground water management.

A hybrid intelligent system is one that combines at least two intelligent technologies [4], For example, combining a neural network with a fuzzy system results in a hybrid neuro-fuzzy system.

Neuro-fuzzy or fuzzy-neural structures [5], has largely extended the capabilities of both technologies in hybrid intelligent systems. The advantages of neural networks in learning and adaptation and those of fuzzy logic systems in dealing with the issues of human-like reasoning on a linguistic level, transparency and interpretability of the generated model, and handling of uncertain or imprecise data, enable building of higher level intelligent systems. The synergism of integrating neural networks with fuzzy logic technology into a hybrid functional system with low-level learning and high-level reasoning transforms the burden of the tedious design problems of the fuzzy logic decision systems to the learning of connectionist neural networks. In this way the approximation capability and the overall performance of the resulting system are enhanced.

A neuro-fuzzy system is, in fact, a neural network that is functionally equivalent to a fuzzy inference model. It can be trained to develop IF-THEN fuzzy rules and determine membership functions for input and output variables of the system. Expert knowledge can be easily incorporated into the structure of the neuro-fuzzy system. At the same time, the connectionist structure avoids fuzzy inference, which entails a substantial computational burden.

A number of different schemes and architectures of this hybrid system have been proposed, such as fuzzy-logic-based neurons [6], fuzzy neurons [7], neural networks with fuzzy weights [8], neuro-fuzzy adaptive models [9], etc. The proposed architectures have been successful in solving various engineering and real-world problems, such as in applications like system identification and modeling, process control, systems diagnosis, cognitive simulation, classification, pattern recognition, image processing, engineering design, financial trading, signal processing, time series prediction and forecasting, etc.

The adaptive neuro-fuzzy inference system is a common approach in which the two techniques such as a neural network and a fuzzy logic get combined [10] to create a complete shell. Basically the system of ANFIS applies the technique of the artificial neural network learning rules to determine and tune the fizzy inference systems' structure and parameters. A number of important features of ANFIS can help the system accomplish a task brilliantly; these features are characterized as easy to implement, fast and accurate learning, strong generalization abilities, excellent explanation facilities through fuzzy rules, and easy to incorporate both linguistic and numeric knowledge for problem solving [11-15].

In Neuro-Fuzzy technique a neural network is introduced to devise the fuzzy system so that the structure and parameters which identify the fuzzy rules are accomplished by adopting and optimizing the topology and the parameters of corresponding neuro fuzzy network based on data sets. The system is considered to be an adaptive fuzzy inference system with the capability of learning fuzzy rules from data and as a connectionist architecture provided with linguistic meaning. Jang had developed one type of hybrid neuro-fuzzy inference expert system that works in Takagi-Sugeno type fuzzy inference system [16-18]. This is called ANFIS that is one of the most successful schemes which combine the benefits of these two powerful paradigms into a single capsule.

There are several features of the ANFIS which enable it to achieve great success in a wide range of scientific applications. The attractive features of an ANFIS include: easy to implement, fast and accurate learning, strong generalization abilities, excellent explanation facilities through fuzzy rules, and easy to incorporate both linguistic and numeric knowledge for problem solving [13].

II. Related Research Works

The Adaptive Neuro-Fuzzy Inference System (ANFIS), first introduced by Jang [11], is a universal approximator and, as such, is capable of approximating any real continuous function on a compact set to any degree of accuracy [13]. Thus, in parameter estimation, where the given data are such that the system associates measurable system variables with an internal system parameter, a functional mapping may be constructed by ANFIS that approximates the process of estimation of the internal system parameter. Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. Jang [11] introduced architecture and a learning procedure for the fuzzy inference systems (FIS) that uses a neural network learning algorithm for constructing a set of fuzzy if-then rules with appropriate membership functions (MFs) from the specified input-output pairs. There are two approaches for FIS, namely Mamdani [19] and Sugeno [20]. The differences between these two approaches arise from the consequent part. Mamdani's approach uses fuzzy MFs, whereas Sugeno's approach uses linear or constant functions.

Many researchers employed ANFIS approach in whether forecasting, F. Castellanos and N. James [21] explored Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to forecast the average hourly wind speed. To determine the characteristics of ANFIS that best suited the target wind speed forecasting system, several ANFIS models were trained, tested and compared. Different types and number of inputs, training and checking sizes, type and number of membership functions were analyzed. Comparisons of the different models were performed and the results showed that the 4 inputs models generated by grid partitioning and the 6 inputs models generated by subtractive clustering provided the smallest errors with the models using wind speed and air pressure as inputs having the best forecasting accuracy. M. Sharma et al.

[22] used ANFIS and Multiple linear regression model to analyze metrological data sets The data covers a five year period (2008-2012) were for the monthly means of minimum and maximum temperature, wind speed, and relative humidity and mean sea level pressure (MSLP). The performance evaluation of the two models that was carried out on the basis of root mean square error (RMSE) showed that the ANFIS model yielded better results than the multiple linear regression (MLR) model with a lower prediction error. N. Babu et al. [23] built Auto-Regressive Integrated Moving and Average (ARIMA) and Adaptive Network Based Fuzzy Inference System (ANFIS) models for weather forecasting. The climate determining is taken from University of Waterloo. The information was taken as Relative Humidity, Ambient Air Temperature, Barometric Pressure and Wind Direction. The results showed that ARIMA is most effective methods for weather forecasting when compared with ANFIS but, it took more time. M. Sharma et al. [24] tried to analyze metrological data sets by using Adaptive Neuro-Fuzzy Inference System (ANFIS) and Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN) models. The data covers a five year period (2008-2012) were for the monthly means of minimum and maximum temperature, rainfall, wind run, and relative humidity and mean sea level pressure (MSLP). The results showed that both models could be applied to weather prediction problems. The performance evaluation of the two models that was carried out on the basis of root mean square error (RMSE) showed that the ANFIS model yielded better results than the MLP ANN model with a lower prediction error.

In [25] K. Ramesh et al., used an adaptive neuro-fuzzy inference system (ANFIS) to retrieve profiles of temperature and humidity up to 10 km over the tropical station Gadanki (13.5_ N, 79.2_ E), India. ANFIS is trained by using observations of temperature and humidity measurements by co-located Meisei GPS radiosonde (henceforth referred to as radiosonde) and microwave brightness temperatures observed by radiometrics multichannel microwave radiometer MP3000 (MWR). ANFIS is trained by considering these observations during rainy and non-rainy days (ANFIS (RDCNRD)) and during non-rainy days only (ANFIS (NRD)). The comparison of ANFIS(RDCNRD) and ANFIS(NRD) profiles with independent radiosonde observations and profiles retrieved using multivariate linear regression (MVLR: RDCNRD and NRD) and artificial neural network (ANN) indicated that the errors in the ANFIS(RDCNRD) are less compared to other retrieval methods.

In the field of rainfall prediction and prediction of groundwater level, M. Mayilvaganan and K. Naidu [26] built ANFIS models for predicting groundwater level in Thurinjapuram watershed, Tamilnadu, India. The results were compared with different type of membership functions. The model with Gaussian membership functions gave the best performance among all given models. Bisht and Jangid [27] investigated the best model to forecast river discharge. They developed ANFIS and Linear Multiple Regression (MLR). The developed models were trained, tested & validated on the data of Godavari river at Rajahmundry, Dhawalaishwaram Barrage site in Andhra Pradesh. The results proved that the developed ANFIS models predicted better results the traditional models, like MLR. Z. Alipour et al. [28] used artificial neural networks, Adaptive Neuro-Fuzzy Inference System and Time Series to find the best way to predict ground water levels in North Mahyar plain, Isfahan. The rainfall, temperature, relative humidity, the operation wells and aquifer fed by the near aquifer are considered as input data, and groundwater levels of 14 observed wells were considered as output. The results showed that the Adaptive Neuro- Fuzzy Inference System can give more accuracy for predicting groundwater level than Time Series analysis and artificial neural network.

The adaptive neuro-fuzzy inference system (ANFIS) has been widely used for modeling different kinds of nonlinear systems including rainfall forecasting. In [29] S. Akrami et al. have developed modified ANFlS (MANFlS) to making ANFIS technique more efficient regarding to Root Mean Square Error, Correlation Coefficient, Root Mean Absolute Error, Signal to Noise Ratio and computing epoch. In their study, two scenarios were introduced; in the first scenario, monthly rainfall was used solely as an input in different time delays from the time (t) to the time (t-4) to conventional ANFIS, second scenario used the modified ANFIS to improve the rainfall forecasting efficiency. The result showed that the model based Modified ANFIS performed higher rainfall forecasting accuracy; low errors and lower computational complexity (total number of fitting parameters and convergence epochs) compared with the conventional ANFIS model. Y. Ytoui [30] studied the rainfall-runoff relationship modeling at monthly and daily time by comparing the performance of neuro-fuzzy inference system with Conceptual models GR2M and GR4J. The results showed the neuro-fuzzy inference system was more accurate than the Conceptual models.

E. Aldrian and Y. Djamil [31] investigated the use of multi variable Adaptive Neuro Fuzzy Inference System (ANFIS) in predicting daily rainfall using several surface weather parameters as predictors. The data used in that study came from automatic weather station data collected in Timika airport from January until July 2005 with 15-minute time interval. They found out that relative humidity is the best predictor with a stable performance regardless of training data size and low RMSE amount especially in comparison to those from other predictors. Other predictors showed no consistent performances with different training data size. Performances of ANFIS reached a slightly above 0.6 in correlation values for daily rainfall data without any filtering for up to 100 data in a time series. Gowda and Mayya [32] developed ANFIS models for rainfall runoff modeling. The ANFIS models used different membership functions Triangular, Trapezoidal, Bell-shaped, Sigmoid and Gaussian method. West flowing river Nethravathi located in Karnataka, India has been selected as study area. It was observed that adaptive neuro fuzzy inference system using Triangular membership function show a good performance compared to other models developed. M. Vafakhah et al. [33] used artificial neural networks (ANNs) and adaptive neuro-fuzzy interface system (ANFIS) for rainfall-runoff modeling. Rainfall, temperature and snow water Equivalent (SWE) were used as inputs for ANN and ANFIS. Root mean square error (RMSE), Nash–Sutcliffe efficiency coefficient (NS) and determination coefficient (R2) statistics are employed to evaluate the performance of the ANN and ANFIS models for forecasting runoff. Based on the results of test stage ANN was very good and superior to rainfall-runoff modeling than the ANFIS. A. Solgi et al. [34] used wavelet analysis combined with artificial neural network and then compared with adaptive neuro-fuzzy system to predict the precipitation in Verayneh station, Nahavand, Hamedan, Iran. For this purpose, the original time series using wavelet theory decomposed to multiple sub time series. Then, these subseries were applied as input data for artificial neural network, to predict daily precipitation, and compared with results of adaptive neuro-fuzzy system. The results showed that the combination of wavelet models and neural networks has a better performance than adaptive neuro fuzzy system, and can be applied to predict both short- and long-term precipitations. M. Dastorani et al. [35] evaluated the applicability of artificial neural networks (ANN) and adaptive neoro-fuzzy systems (ANFIS) in prediction of precipitation yazd meteorological station in central Iran. Different architectures of ANN and ANFIS models have been done. Precipitation moving average, maximum temperature, relative humidity, mean wind speed, maximum wind direction and evaporation have been used as inputs of the models. Final results showed that the efficiency of time lagged recurrent network (TLRN) and ANFIS were almost the same.

N. Charaniya and S. Dudul [36] designed adaptive neuro fuzzy inference system (ANFIS), linear and nonlinear regressive models to predict the rainfall in future for the next year based on the rainfall pattern for past four years. the experimental results showed that ANFIS model has better prediction capability due to combined power of fuzzy logic and neural network. But the execution time taken is more. In [37] rainfall has been predicted using Adaptive Neural Fuzzy Inference System (ANFIS) and the best input combination has been identified using Gamma Test (GT) for the rainfall prediction. Then, runoff was simulated by a conceptual hydrological MIKE11/NAM model and the results were compared together. The study area is Qaleh Shahrokh basin located in Iran. The ability of ANFIS and MIKE11/NAM models were evaluated based on Root Mean Square Error (RMSE), correlation coefficient (R2) and Efficiency Index (EI). The results showed that both models (NAM and ANFIS) had good capabilities in simulating discharge during calibration and verification periods. Using the predicted rainfall instead of the observed rainfall caused lower efficiency in the NAM model and runoff simulation. R. Panchal et al. [38] have used Adaptive Neuro-Fuzzy Inference System (ANFIS) for rainfall-runoff modeling for the Dharoi sub-basin, India. Different combinations of rainfall were considered as the inputs to the model, and runoff was considered as the output. Input space partitioning for model structure identification was done by grid partitioning. A hybrid learning algorithm consisting of back-propagation and least-squares estimation was used to train the model for runoff estimation. The optimal learning parameters were determined by trial and error using Triangular membership function. Root mean square error (RMSE) and correlation coefficient (r) were used for selecting the best performing model. The results showed the best Rainfall-Runoff model for the Hadad, Khedbrhama and Dharoi rain gauge stations had 7 triangular type membership functions with the input and output training and testing ratio of 80-20%. In [39], an adaptive neuro-fuzzy inference system (ANFIS) model has been proposed to forecast the rainfall for Klang River in Malaysia on monthly basis. To be able to train and test the ANFIS and ANN models, the statistical data from 1997 to 2008, was obtained from Klang gates dam data. The optimum structure and optimum input pattern of model was determined through trial and error. Different combinations of rainfall were produced as inputs and five different criteria were used in order to evaluate the effectiveness of each network and its ability to make precise prediction. The performance of the ANFIS model is compared to artificial neural network (ANN) model. The five criteria are root mean square error, Correlation Coefficient, Nash Sutcliffe coefficient, gamma coefficient and Spearman correlation coefficient. The result indicate that the ANFIS model showed higher rainfall forecasting accuracy and low error compared to the ANN model. Furthermore, the rainfall estimated by this technique was closer to actual data than the other one.

M. Vafakhah et al. [40] proposed adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN) and wavelet-artificial neural network (Wavelet-ANN) models for modeling rainfall-runoff (RR) relationship. daily stream flow time series of hydrometric station of Hajighoshan on Gorgan River and the daily rainfall time series belonging to five meteorological stations (Houtan, Maravehtapeh, Tamar, Cheshmehkhan and Tangrah climatologic stations) were used for period of 1983-2007. Root mean square error and correlation coefficient statistics were employed to evaluate the performance of the ANN, ANFIS, ARX and ARMAX models for rainfall-runoff modeling. The results showed that ANFIS models outperformed the system identification, ANN and Wavelet-ANN models.

G. Fallah-Ghalhary et al. [41] tried to analyze 33 years of rainfall data in khorasan state, the northeastern part of Iran by using 3 soft computing based prediction models with 33 years of rainfall data. For performance evaluation, network predicted outputs were compared with the actual rainfall data. Simulation results reveal that soft computing techniques are promising and efficient. the test results using by ANN, FIS and ANFIS learning algorithms showed that the lowest RMSE was obtained using ANN, ANFIS and FIS, it was 41, 52 and 58 millimeter respectively. For modeling suspended sediment load (SSL), researchers [42] compared three different soft computing methods, namely, artificial neural networks (ANNs), adaptive neuro-fuzzy inference system

(ANFIS), coupled wavelet and neural network (WANN), and conventional sediment rating curve (SRC) approaches for estimating the daily SSL in two gauging stations in the USA. The performances of these models were measured by the coefficient of correlation, Nash-Sutcliffe efficiency coefficient, root mean-square error, and mean absolute percentage error (MAPE) to choose the best fit model. Obtained results demonstrated that applied soft computing models were in good agreement with the observed SSL values, while they depicted better results than the conventional SRC method. The comparison of estimation accuracies of various models illustrated that the WANN was the most accurate model in SSL estimation in comparison to other models.

B. Bekuretsion and T. Beshah [43] employed neural network, mamdani and sugeno adaptive neuro fuzzy models to predict rainfall of Ethiopian Upper Blue Nile Basin with different time lag. The result shows the soft computing models perform the prediction with relatively small error. The developed soft computing models show better skill than techniques used by Ethiopian National Meteorological Service Agency (ENMSA) and other previous studies which used statistical techniques. In [44] Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been investigated for estimation of effective rainfall. Tabriz synoptic station located in the northwest of Iran was considered as studying area and USDA-SCS method as the most widely used method for calculation of effective rainfall was applied to determine the monthly effective rainfalls, for the period of 1982 to 2010. The results showed the accuracies of both models are satisfied, and ANNs showed relatively more accurate results.

Abraham et al. [45] compared the performance of several Soft Computing (SC) models: Evolving Fuzzy Neural Network (EFuNN), Artificial Neural Network using Scaled Conjugate Gradient Algorithm (ANNSCGA), Adaptive Basis Function Neural, Network (ABFNN) and General Regression Neural Network (GRNN) with Multivariate Adaptive Regression Splines (MARS) which is a regression technique that uses a specific class of basis functions as predictors in place of the original data. 87 years of rainfall data in Kerala state have been used; SC and MARS models were trained with 40 years of rainfall data and tested with 47 years of rainfall data. Simulation results revealed that MARS is a good forecasting tool and performed better than the considered SC models. Patel and Parekh [46] investigated the development of an efficient model to forecast monthly monsoon rainfall for Gandhinagar station using Adaptive Neuro Fuzzy Inference System (ANFIS). Eight models were developed using various membership functions and climatic parameters as inputs. In their study, the generalized bell-shaped built-in membership function (gbell) has been used as a membership function in both Hybrid and Back propagation method for ANFIS. The four evaluation parameters Root mean square error, Correlation Coefficient, Coefficient of Determination and Discrepancy ratio are used to evaluate the developed model. The study showed that hybrid Model with seven membership functions and using three inputs, temperature, relative humidity and wind speed gives best result to forecast rainfall for study area. Niksaz and Latif [47] applied ANFIS for rainfall events evaluation. Four parameters: Temperature, relative humidity, total cloud cover and due point were the input variables for ANFIS model, each has 121 membership functions. The data is six years METAR data for Mashhad city [2007-2012]. Different models for Mashhad city stations were constructed depending on the available data sets. Among the overall 25 possibilities one model with one hundred twenty one fuzzy IF-THEN rules has chosen. The output variable is 0 (no rainfall event) or 1 (rainfall event). Results showed a high agreement with the actual data.

Faulina and Suhartono [48] proposed hybrid and ensemble model of forecasting method for ten-daily rainfall prediction based on ARIMA (Autoregressive Integrated Moving Average) and ANFIS (Adaptive Neuro Fuzzy Inference System) at six certain areas in Indonesia. To find an ensemble forecast from ARIMA and ANFIS models, the averaging and stacking method was implemented. In this study, Triangular, Gaussian, and Gbell function are used as membership function in ANFIS. The best model is measured by the smallest root of mean square errors (RMSE) at testing datasets. The results show that an individual ARIMA method yields more accurate forecast in five rainfall data, whereas ensemble averaging multi model yields better forecast in one rainfall data. In general, these results indicated that more complicated model not always yield better forecast than simpler one.

The main objective of this study is to investigate the ability of ANFIS for capturing the dynamic behavior of the rainfall data and produce satisfactory results, by using different types of membership functions, different optimization methods and different dataset ratios for training and testing.

III. Data and Method

A. Data

The meteorological data that used in this paper has been brought from Central Bureau of Statistics, Sudan for 13 years from 2000 to 2012 for 24 meteorological stations over the country with 3732 total number of examples. These stations are shown in Table 1.

The dataset had eight (8) attributes containing monthly averages data shown in table 2. In this study only the most influencing variables (Date, Minimum Temperature, Humidity and Wind Direction) that affect on the long term rainfall prediction out of 7 variables [49] have been used.

B. Data Normalization

One of the steps of data pre-processing is data normalization. Normalization may be applied. For example, normalization may improve the accuracy and efficiency of mining algorithms involving distance measurements [50].The need to make harmony and balance between data, data must be normalized between 0 and 1. (Eq. 1) has been used to normalize our dataset.

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where X is actual data and X_{min} is minimum value of original attribute's values and X_{max} is maximum value of original attribute's values

Code	Station
1	Khartoum
2	Dongola
3	Atbara
4	Abu Hamad
5	Karima
6	Wadi Halfa
7	Wad Medani
8	El Deweim
9	Kassala
10	Port Sudan
11	El Gadarif
12	Elobied
13	El Nihood
14	Kadugli
15	Nyala
16	Elgeneina
17	El Fashir
18	Kosti
19	El Damazen
20	New Halfa
21	Babanusa
22	Rashad
23	Abu Naama
24	Sinnar

Table 1. The names of meteorological stations.

No	Attribute
1	Station
2	Date
3	Maximum Temperature
4	Minimum Temperature
5	Relative Humidity
6	Wind Direction
7	Wind Speed
8	Rainfall

Table 2. The attribute names of meteorological dataset.

C. General Framework of Proposed Study

In order to perform rainfall forecasting using ANFIS and compare the performance criteria with different models, the following steps that shown in figure1 have been followed.

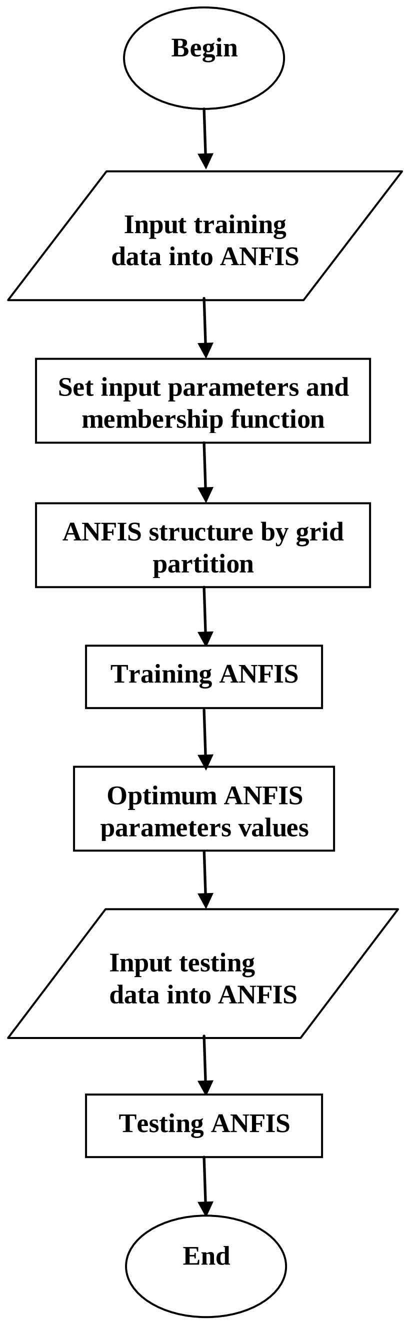

Figure 1. Flowchart for predicting rainfall using ANFIS

D.ANFIS structure

The architecture of Neuro Fuzzy used in this study is ANFIS. Six layered ANFIS Model has been developed with the learning algorithms for training the network are hybridization of forward pass and backward pass using least squares estimate and gradient descent. The total number of nodes for every layer is different for different experiment depending upon the number of membership function of an input variable. In the Figure 2, Input 1 (Date) with 3 membership functions (low, medium, high), Input 2(Average minimum temperature) with 3 membership functions (low, medium, high), Input 3 (Relative Humidity) with 3 membership functions (low, medium, high), Input 4 (wind direction) with 3 membership functions (low, medium, high), and a single output as average monthly Precipitation whose degree of membership is Linear.

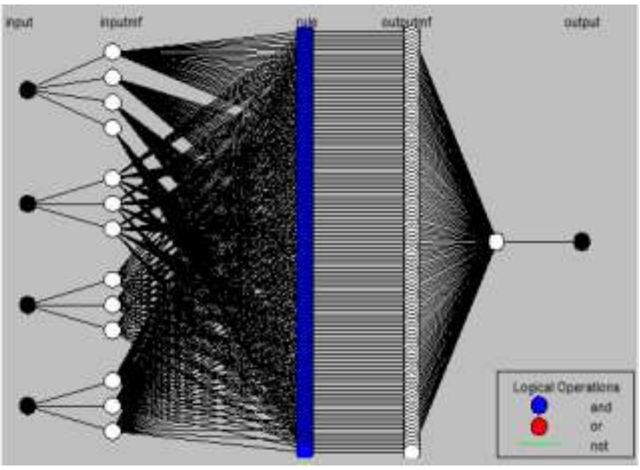

Figure 2. Structure of ANFIS used in this Research

Layer-1(input layer): No computation is done in this layer. Each node, which corresponds to one input variable, only transmits input values to the next layer directly. The link weight in Layer 1 is unity.

Layer-2 (fuzzification layer): Each node corresponds to one linguistic label (such as excellent, good) to one of the input variables in Layer 1. In other words, the output link represents the membership value, which specifies the degree to which an input value belongs to a fuzzy set, is calculated in layer 2. The final shapes of the MFs are fine tuned during network learning. Parameters in this layer are referred to as premise parameters. The outputs of this layer are membership values of the premise part. In this study different types of membership functions have been used, these membership functions were:

1) Generalized bell membership function

For three different sets of parameters {a, b, c}. This function is defined by (Eq. 2)

$$f(x;a,b,c)=\frac{1}{1+\left[\frac{x-c}{a}\right]^{2b}} \quad (2)$$

Where {ai,bi,ci} is the parameter set. The parameters a and c represent the width and the center of the bell function, and b represents the slopes at the crossover points. As the values of these parameters change, the bell-shaped function varies accordingly, thus exhibiting various forms of membership functions on linguistic label Ai.

2) Triangular shaped membership function

Is defined by (Eq. 3).

$$f(x;a,b,c)=\max\left[\min\left[\frac{x-a}{b-a},\frac{c-x}{c-b},0\right]\right] \quad (3)$$

Where a, b and c are parameters of the membership function, a and c set the left and right "feet," or base points, of the triangle. The parameter b sets the location of the triangle peak.

3) Trapezoidal membership function

Is defined by (Eq. 4)

$$f(x;a,b,c,d)=\max\left[\min\left[\frac{x-a}{b-a},1,\frac{d-x}{d-c},0\right]\right] \quad (4)$$

Where a, b, c and d are parameters of the membership function, the parameters a and d locate the "feet" of the trapezoid and the parameters b and c locate the shoulders.

4) Gaussian membership function

Is defined by (Eq. 5)

$$f(x)=\exp^{\frac{-(x-c)^2}{2\sigma^2}} \quad (5)$$

Where σ and c are parameters of the membership function, c is the mean and σ is the variance.

5) Gaussian2 membership function

Block implements a membership function based on a combination of two Gaussian functions. The two Gaussian functions are given by (Eq. 6).

$$f_k(x)=\exp^{\frac{-(x-c_k)^2}{2\sigma_k^2}} \quad (6)$$

Where k=1, 2. The parameters c_1 and σ_1 are the mean and variance defining the left-most curve. The parameters c_2 and σ_2 are the mean and variance defining the right-most curve.

6) Pi membership function

This spline-based curve is so named because of its Π shape. The membership function is evaluated at the points determined by the vector x. The parameters a and d locate the "feet" of the curve, while b and c locate its "shoulders." The membership function is a product of smf and zmf membership functions, and is given by (Eq. 7).

$$f\ (x;a,b,c,d)=\begin{cases} 0, x\le a \\ 2\left[\frac{x-a}{b-a}\right]^2, a\le x\le \frac{a+b}{2} \\ 1-2\left[\frac{x-b}{b-a}\right]^2, \frac{a+b}{2}\le x\le b \\ 1, b\le x\le c \\ 1-2\left[\frac{x-c}{d-c}\right]^2, c\le x\le \frac{c+d}{2} \\ 2\left[\frac{x-d}{d-c}\right]^2, \frac{c+d}{2}\le x\le d \\ 0, x\ge d \end{cases} \quad (7)$$

7) Dsig membership function

Is composed of difference between two sigmoidal membership functions. The sigmoidal membership function used depends on the two parameters a and c and is given by (Eq. 8).

$$f(x;a,c)=\frac{1}{1+e^{-a(x-c)}} \quad (8)$$

The membership function dsigmf depends on four parameters, a_1, c_1, a_2, and c_2, and is the difference between two of these sigmoidal functions.

$f_1(x; a_1, c_1) - f_2(x; a_2, c_2)$ (9)

The parameters are listed in the order: $[a_1\ c_1\ a_2\ c_2]$.

8) Psig membership function

Is composed of product of two sigmoidally shaped membership functions. The sigmoid curve plotted for the vector x depends on two parameters a and c as given by (Eq. 8). Psigmf is simply the product of two such curves plotted for the values of the vector x.

$f_1(x; a_1, c_1) \times f_2(x; a_2, c_2)$ (10)

The parameters are listed in the order $[a_1\ c_1\ a_2\ c_2]$.

Layer-3 (rule antecedent layer): A node represents the antecedent part of a rule. Usually a T-norm operator is used. The output of a Layer 3 node represents the firing strength of the corresponding fuzzy rule.

The fuzzy rule base of the ANFIS model is set up by combining all categories of variables. For example, if there are n inputs and if each input is divided into c categories then there will be c^n rules [51]. For 4 rainfall predictors represented by the inputs date, minimum temperature, humidity and wind direction, having 3 categories namely low, medium, and high each, there would be 81 rules in the rule base; the output for each rule is written as a linear combination of input variables. Part of the rule sets can be illustrated as in figure 3.

If (Date is low) and (Temperature is high) and (Humidity is high) and (Wind Direction is medium) then (Rainfall is very low)
If (Date is low) and (Temperature is low) and (Humidity is low) and (Wind Direction is low) then (Rainfall is very low)
If (Date is low) and (Temperature is low) and (Humidity is high) and (Wind Direction is medium) then (Rainfall is very low)
If (Date is low) and (Temperature is medium) and (Humidity is low) and (Wind Direction is low) then (Rainfall is low)
If (Date is low) and (Temperature is low) and (Humidity is medium) and (Wind Direction is high) then (Rainfall is low)
If (Date is medium) and (Temperature is low) and (Humidity is medium) and (Wind Direction is high) then (Rainfall is very low)
If (Date is medium) and (Temperature is low) and (Humidity is medium) and (Wind Direction is medium) then (Rainfall is low)
If (Date is medium) and (Temperature is low) and (Humidity is high) and (Wind Direction is low) then (Rainfall is very low)
If (Date is medium) and (Temperature is low) and (Humidity is high) and (Wind Direction is medium) then (Rainfall is very low)
If (Date is medium) and (Temperature is medium) and (Humidity is medium) and (Wind Direction is medium) then (Rainfall is low)
If (Date is medium) and (Temperature is medium) and (Humidity is medium) and (Wind Direction is high) then (Rainfall is low)
If (Date is medium) and (Temperature is medium) and (Humidity is high) and (Wind Direction is low) then (Rainfall is very low)
If (Date is medium) and (Temperature is medium) and (Humidity is high) and (Wind Direction is medium) then (Rainfall is low)
If (Date is medium) and (Temperature is high) and (Humidity is medium) and (Wind Direction is medium) then (Rainfall is medium)
If (Date is medium) and (Temperature is high) and (Humidity is medium) and (Wind Direction is high) then (Rainfall is low)
If (Date is medium) and (Temperature is high) and (Humidity is high) and (Wind Direction is low) then (Rainfall is very low)
If (Date is medium) and (Temperature is high) and (Humidity is high) and (Wind Direction is medium) then (Rainfall is medium)
If (Date is medium) and (Temperature is high) and (Humidity is high) and (Wind Direction is high) then (Rainfall is low)
If (Date is high) and (Temperature is low) and (Humidity is low) and (Wind Direction is medium) then (Rainfall is low)
If (Date is high) and (Temperature is low) and (Humidity is medium) and (Wind Direction is medium) then (Rainfall is high)
If (Date is high) and (Temperature is low) and (Humidity is high) and (Wind Direction is low) then (Rainfall is very low)

Figure 3. Part of ANFIS rules

Each neuron in this layer corresponds to a single Sugeno-type fuzzy rule. A rule neuron receives inputs from the respective fuzzification neurons and calculates the firing strength of the rule it represents. In an ANFIS, the conjunction of the rule antecedents is evaluated by the operator product. Thus, the output of neuron i in Layer 3 is obtained as:

$$y_i^{(3)} = \prod_{j=1}^{k} x_{ji}^{(3)} \quad (11)$$

Where $x_{ji}^{(3)}$ are the inputs and $y_i^{(3)}$ is the output of rule neuron i in Layer 3.

Layer-4 (rule strength normalization): Every node in this layer calculates the ratio of the i-th rule's firing strength to the sum of all rules' firing strength. In other word each neuron in this layer receives inputs from all neurons in the rule layer, and calculates the normalized firing strength of a given rule. The normalized firing strength is the ratio of the firing strength of a given rule to the sum of firing strengths of all rules. It represents the contribution of a given rule to the final result.

$$\overline{w_i} = \frac{w_i}{w_1 + w_2}, i = 1, 2, \ldots \quad (12)$$

Layer-5 (rule consequent layer): Every node i in this layer has a node function.

$$\overline{w_i} f_i = \overline{w_i}(p_i x_1 + q_i x_2 + r_i) \quad (13)$$

Where $\overline{w_i}$ is the output of layer 4, and $\{p_i, q_i, r_i\}$ is the parameter set.

Each neuron in this layer is connected to the respective normalization neuron, and also receives initial inputs, x_1 and x_2. A defuzzification neuron calculates the weighted consequent value of a given rule.

Layer-6 (rule inference layer) the single node in this layer computes the overall output as the summation of all incoming signals:

$$Overalloutput = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (14)$$

E. Grid Partitioning

For generating the initial fuzzy inference system (FIS), Grid Partitioning has been used. Once the grid partitioning technique is applied at the beginning of training, a uniformly partitioned grid, which is defined by membership functions (MFs) with a random set of parameters is taken as the initial state of ANFIS. During training, this grid evolves as the parameters in the MFs change. With the grid partitioning technique, the number of MFs in the premise part of the rules must be determined.

F. Grid Partitioning

Training of ANFIS models has been done using both hybrid optimization method and back propagation algorithm with error tolerance level 0.00001 for 100 epochs.

1) Hybrid learning algorithm

Is combines the least-squares estimator with the gradient descent method.

(a) In the forward pass

A training set of input patterns is presented, neuron outputs are calculated on a layer-by layer basis, and rule consequent parameters are identified by the least-squares estimator.

(b) In the backward pass

The error signals are propagated back and the rule antecedent parameters are updated according to the chain rule.

2) The back propagation algorithm

It looks for the minimum of the error function in weight space using the method of gradient descent. The combination of weights which minimizes the error function is considered to be a solution of the learning problem [52].

In this study different choices for dividing the dataset for training and testing have been tried, we used 60% for training and 40% for testing, 70% for training and 30% for testing, 80% for training and 20% for testing and 90% for training and 10% for testing respectively. Once the training is done, ANFIS model is always ready for the prediction. During this training, ANFIS will learn the whole pattern among different input in various years and within each year itself.

G. Performance Criteria

Three different criteria are used in order to evaluate the effectiveness of ANFIS and its ability to make precise predictions. The three criteria are Correlation Coefficient (CC) (Eq. 15), Root Mean Square Error (RMSE) (Eq. 16), and Mean Absolute Error (MAE) (Eq. 17) .The higher CC, the smaller the MAE and RMAE show the better prediction effect [53]. That performance expressed below mathematically:

$$CC = \frac{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2\left(Y_i - \overline{Y}\right)^2}} \quad (15)$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(X_i - Y_i)^2}{n}} \quad (16)$$

$$\mathrm{MAE} = \sum_{i=1}^{n}\frac{\left|X_i - Y_i\right|}{n} \quad (17)$$

Where X_i is the observation data and Y_i computed data and n is the number of data. $\overline{X}$ is the mean of actual data and $\overline{Y}$ is the mean of the computed data.

IV. Experimental Results and Discussions

ANFIS system is sensitive to number of membership function (MF). Giving additional number of membership function to the system did not always improve the result. Negnevitsky et al. [54] stated that a larger number of MFs better represents a complex system and therefore should produce better results. However, a large number of inputs or MFs in the premise part of the rules can produce a large number of fuzzy rules which can cause the learning complexity of ANFIS to suffer an exponential explosion. This is called the curse of dimensionality which can adversely affect the performance of ANFIS [13, 56, 57]. Not many literature papers have alluded to what is considered to be a large number of fuzzy rules. However, drawing on the experience of [13, 58] as a guide to choosing the number of MFs per input and since the largest number of inputs to be used was 7 then the smallest number of MFs that could produce overlapping while not invoking the curse of dimensionality is 2. The number of MFs was increased with one of the ANFIS models to get a greater understanding of the impact on the performance of ANFIS with this change.

In this study, by increasing number of membership function from 2 to 3 the results are better. But by increasing number of membership function from 3 to 4, in most cases the performances are decreasing. Applying 3 number of membership function gave the best results. Different types of membership functions have been used, Table3 compared between the results of ANFIS models with different membership functions using the measure performance.

Membership function	**CC**	**MAE**	**RMSE**
trapmf	0.85	0.0297	0.1724
trimf	0.47	3.6442	1.9090
gaussmf	0.83	0.0228	0.1512
gauss2mf	0.75	0.0378	0.1946
gbellmf	**0.90**	**0.0074**	**0.0861**
dsigmf	0.59	3.5171	1.8754
psigmf	0.59	3.5167	1.8753
pimf	0.61	3.2483	1.8023

Table 3. ANFIS results with different membership function.

As shown in Table 3 the model which used the bell-shaped membership function outperform the others, since it has the lowest both mean absolute error and root mean squared error and the highest correlation coefficient, close to unity. Other functions such as Gaussian and Trapezoidal were used as well to evaluate the performance with different types of MFs, and they come in second order after the bell-shaped. The results of the both ANFIS models that used Gaussian and Trapezoidal were close to each other and they performed better than the rest models. The ANFIS model which used triangular gave the worst performance.

The bell-shaped MF was favored over the other types since it offered more parameters which provided a greater number of degrees of freedom. The generalized bell-shaped MF is standard for ANFIS because of its smoothness and concise notation [13, 54, 56]. Figures 4 and 5 show the changes in generalized bell shaped membership functions before and after training stage.

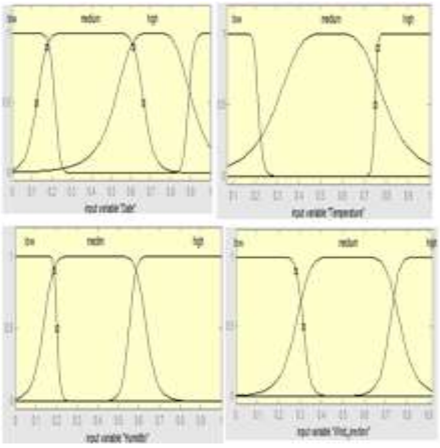

Figure 4. Initial membership functions for inputs date, minimum temperature, humidity and wind direction.

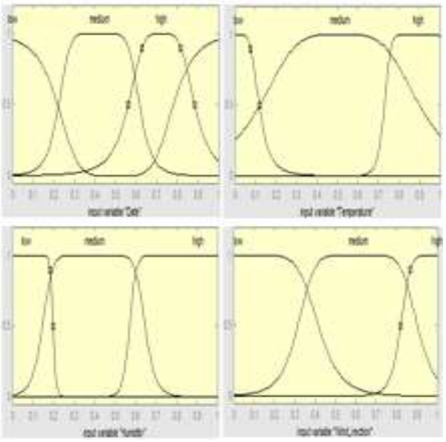

Figure 5. Final membership functions for inputs date, minimum temperature, humidity and wind direction.

The models were developed using 12 numbers of membership functions of type generalized bell with 81 If-then rules for all different sets of training and testing dataset for rainfall prediction in ANFIS. After obtaining the results the best model for the long term rainfall prediction was selected and highlighted by means of the evaluation parameters that are mean absolute error (MAE) root mean squared error (RMSE) and correlation coefficient (CC) values given in table 4.

Ratio%	**Training**		
	CC	**RMSE**	**MAE**
90	0.91	0.082	0.0069
80	0.93	0.0080	0.0064
70	**0.96**	**0.0056**	**0.0031**
60	0.81	1.3951	1.9460

Table 4. ANFIS results with different sets of training dataset.

Ratio%	**Testing**		
	CC	**RMSE**	**MAE**
10	0.81	0.1847	0.0341
20	0.84	0.1293	0.0167
30	**0.90**	**0.0861**	**0.0074**
40	0.79	1.7470	2.0520

Table 5. ANFIS results with different sets of testing dataset.

From the comparison of the four options of dataset ratio which have been used in this study and appear in tables 4 and 5, the best results have been obtained when we applied our ANFIS neuro-fuzzy model with ratio 70-30 of dataset for training and testing, thus it achieves the highest correlation coefficient and the lowest of both mean absolute error and root mean squared error in training and testing phases. When applying the ANFIS model with dataset ratios 80-20 and 90-10 results are close and still acceptable, but when the dataset ratio 60-40 has been used for training and testing we obtained the worst results.

There are two optimization methods: hybrid and back propagation. To develop the ANFIS rainfall prediction models, both of them were used. The hybrid technique is more popularly used with ANFIS than the back propagation [11, 59]. In addition, it is regarded as the faster of the two techniques [11].

Average errors of monthly rainfall as predicted by using the back-propagation method and by using the hybrid learning algorithm are shown in Table 6.

Method	**Training Error**	**Testing Error**
Hybrid	**0.005697**	**0.086139**
Back propagation	0.012586	0.114682

Table 6. Average Errors by the Back-propagation Method and the Hybrid Learning Algorithm.

From this table, the capability of the ANFIS model in predicting the rainfall using the hybrid learning algorithm is much better than when using the back propagation method. This is because the hybrid method comprises of back propagation and Least-Square methods.
Figures 6and 7 show training and testing errors for ANFIS model with bell membership function and hybrid learning algorithm.

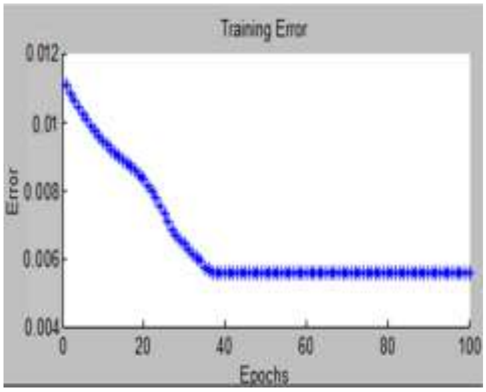

Figure 6. Training error for 70% of dataset at 100 epochs.

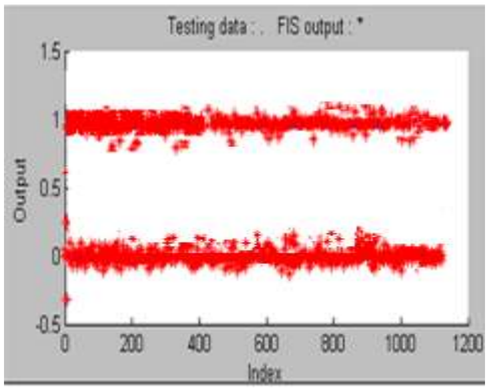

Figure 7. Training error for 70% of dataset at 100 epochs.

Figures 8-13 display Surface viewer for (a) Date with temperature and output rainfall, (b) Temperature with wind direction and output rainfall, (c) Date with humidity and output rainfall, (d) Date with wind direction and rainfall, (e) Humidity with wind direction and output rainfall and (f) Humidity with temperature and output rainfall respectively.

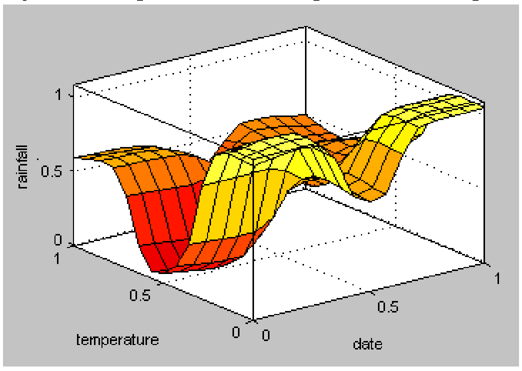

Figure 8. Surface viewer for date with temperature and output rainfall.

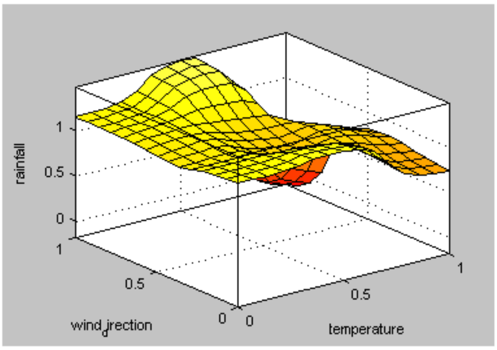

Figure 9. Surface viewer for temperature with wind direction and output rainfall.

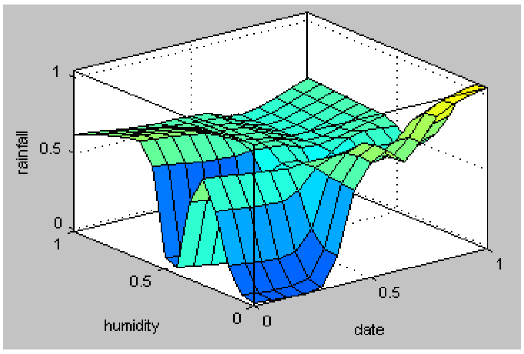

Figure 10. Surface viewer for date with humidity and output rainfall.

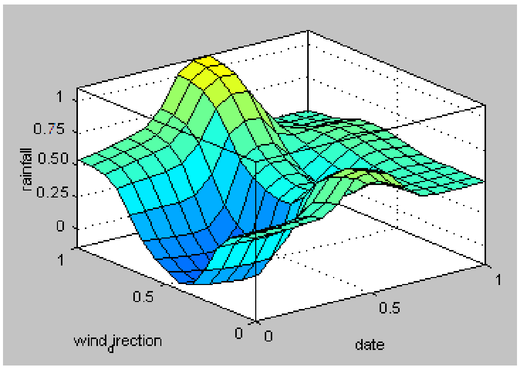

Figure 11. Surface viewer for date with wind direction and rainfall.

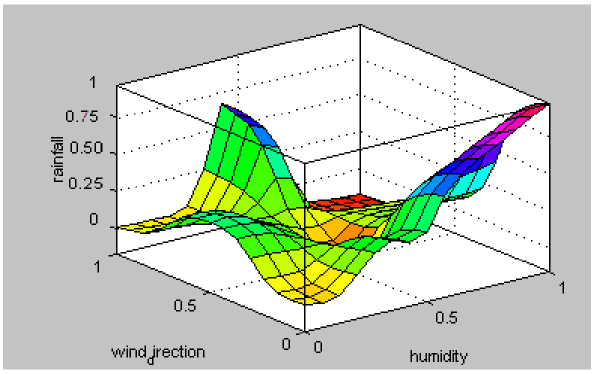

Figure 12. Surface viewer for humidity with wind direction and output rainfall.

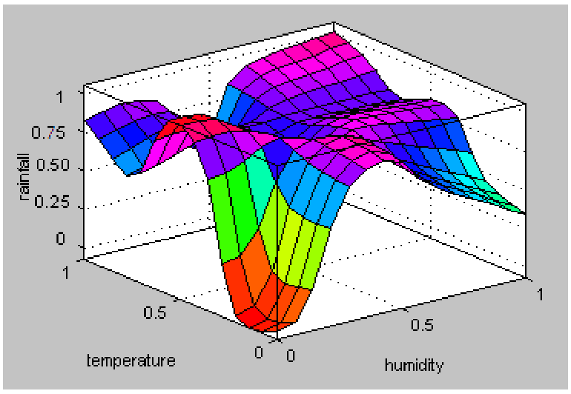

Figure 13. Surface viewer for humidity with temperature and output rainfall.

V. Conclusions

It is important to have reliable and accurate techniques to forecast the rainfall in the long term. One such technique is the use of ANFIS to develop rainfall prediction models. The approach that was taken in this study was one closer to a trial and error process that involved training different models with using different types of membership functions, various learning algorithms and different ratio of training and testing datasets, finally comparing them until a model that produced satisfactory results was obtained.

In this work, we have presented a formulation of the adaptive neuro-fuzzy inference system (ANFIS) model for long term rainfall prediction using date, minimum temperatures, humidity and wind direction as predictors. The empirical results indicate that ANFIS neuro-fuzzy model is able to capture the dynamic behavior of the rainfall data and it may be useful in long term rainfall prediction.

Different types of membership functions have been used to decide which one is the most appropriate for the target, the results showed that the model which used generalized bell shaped membership outperforms the others and achieve the highest performance accuracy.

Dividing dataset into 70-30 for training and testing respectively considered the best choice for dividing our dataset, since it provided the best results comparing with the other choices for both training and testing phases.

Also our experiments ensured that the hybrid learning method is much better than back propagation method as learning algorithm for ANFIS model and it give better and more accurate results.

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