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WEATHER FORECASTING MODELS USING NEURAL NETWORKS AND ADAPTIVE NEURO FUZZY INFERENCE FOR TWO CASE STUDIES AT HUOSTON, TEXAS AND DALLAS STATES

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ABSTRACT

Forecasting of precipitation is one of the most challenging operational tasks done by hydrologists. This operation can be described as most complicated procedure that includes multiple specialized fields of expertise. In this research a comprehensive study was employed to forecast daily precipitation depending on different weather parameters. This was done by using two different methods which are back propagation neural networks BPNN and adaptive neuro inference system ANFIS. Two case studies were selected for this operation which are Huoston, Texas and Dallas, Texas. The high performance of the applied models in forecasting the daily precipitation was concluded especially by using auxiliary weather data with the lagged day precipitation values since the BPNN and ANFIS were able to learn from continuous input data

Contribution/ Originality: This study uses new estimation methodology in forecasting the daily precipitation by using different weather parameters for two regions at United states of America. The study can be considered as a comparison between the two well-known methods which are artificial networks and Adaptive Neuro-Fuzzy Inference System.

1. INTRODUCTION

Forecasting of precipitation is one of the most challenging operational tasks done by hydrologists. This operation can be described as most complicated procedure that includes multiple specialized fields of expertise. Weather forecasting methodologies could be divided into two main branches in terms of numerical modeling and scientific processing of meteorological data. The common methods which are used for precipitation forecasting are the numerical and statistical methods. The efficiency of the used models is dependent upon the initial conditions that are inherently incomplete. Different methods were used by many researches to deal with forecasting of different weather parameters. Luk [1] compared three different kinds of artificial neural networks ANNs by using Multi Layer Feed forward Neural Network (MLFN) for precipitation prediction in catchment's upper Parramatta River in Australia. The comparison showed that MLFN has more accuracy in precipitation modeling in comparison to Time Delay Neural Network (TDNN) and Recurrent Neural Network (RNN) Luk [1]. Brath, et al. [2]

produced time series analysis technique for improving the real time flood forecast by a deterministic lumped rainfall runoff model and they concluded that apart from ANNs with adaptive training , all the time series analysis techniques considered allow significant improvements if flood forecasting accuracy compared with the use of empirical rainfall predictors Brath, et al. [2]. Iseri, et al. [3] have developed medium term forecasting of August rainfall in Fukuoka city. In order to identify the sufficient predictors, the partial mutual information was used for the candidate predictors, which are Sea Surface Temperature anomalies (SSTa) in the Pacific Ocean and three climate indices. When data with lead times between one and twelve months were used to forecast August rainfall, it was found that a model with the North Pacific index and selected SSTa as inputs performed reasonably well. Iseri, et al. [3]. Nayaka, et al. [4] have applied an adaptive neuro-fuzzy inference system (ANFIS) to hydrologic time series modeling, and it was concluded that the ANFIS model preserves the potential of the ANN approach fully, and eases the model building process Nayaka, et al. [4]. KISI [5] used three different neural network (NN) architectures, i.e. ANN, Auto-Regressive Models and sum of square errors, for comparison of forecasting probabilities and it was found in this study that ANNs were able to produce better performance than AR models when given the same data inputs KISI [5]. Ramirez, et al. [6] also used a Multi Layer Feed-forward Perceptron (MLFP) neural network for daily precipitation prediction in the region of Sao Paolo State, Brazil. The potential temperature, vertical component of the wind, specific humidity, air temperature, perceptible water, relative vorticity and moisture divergence flux were used as input data for training of networks. The results s of ANN were superior when compared with the obtained results by using the linear regression model Ramirez, et al. [6]. Saplioglu, et al. [7] used a three layer feed-forward neural network for daily precipitation prediction in the meteorological stations of Burdur, Egirdir, and Isparta cities in Turkey. The researches found that the results showed that the ANN models are best than the other applied methods in the study Saplioglu, et al. [7]. Afshin, et al. [8] produced an integrated artificial neural network-fuzzy logic-wavelet model to predict Long term rainfall. The results of the integrated model showed superior results when compared to the two year forecasts to predict the six-month and annual periods. As a result of the root mean squared error, predicting the two-year and annual periods is 6.22 and 7.11, respectively Afshin, et al. [8]. El-Shafie, et al. [9] have compared and studied Dynamic Vs Static neural network models for rainfall forecasting, they have developed AI based forecasting architectures using Multi-Layer Perceptron Neural Networks (MLPNN), RBFNN and Adaptive Neuron-Fuzzy Inference Systems (ANFIS), finally they concluded that the dynamic neural network namely IDNN could be suitable for modeling the temporal dimension of the rainfall pattern, thus, provides better forecasting accuracy El-Shafie, et al. [9]. In this study the back propagation neural network BPNN and adaptive neuro inference system ANFIS were used with different structures to forecast daily precipitation values for two case studies at Houston and Dallas, Texas using different weather parameters.

2. RESEARCH METHODS

2.1. Artificial Neural Networks

The artificial neural network ANN can be described as a basic engineering concept of knowledge in the field of artificial intelligence. This network is designed by adopting the human nervous system. An artificial neural network (ANN) is an interconnected group of different nodes or neurons. These nodes can store experiential knowledge and can make it available for use. These nodes or nodes are the basic units of information processing. The process of training the ANN has many types and uses, including Perceptron, Back propagation, Self-Organizing Map (SOM), and Delta(. Therefore, this study proposes BPNN algorithm to predict precipitation data by studying and analyzing the patterns non-linear of the past data of the precipitation with different parameters of weather in order to obtain more accurate prediction results with minimum error. Furthermore, BPNN is briefly described Hung, et al. [10].

2.1.1. The Back propagation Neural Network

Paul Werbos in 1974 produced a supervised learning method for training ANN and called it a back propagation Neural Network BPNN. This method then was popularized by Rumelhart and McCelland in 1986 [11] . The BPNN is forwarding the output layer to the input layer in changing the weights. Basheer and Hajmeer [12]; Haviluddin and Alfred [13]. The BPNN consists of three layers , namely input layer, hidden layer and output layer as shown in Fig. 1.

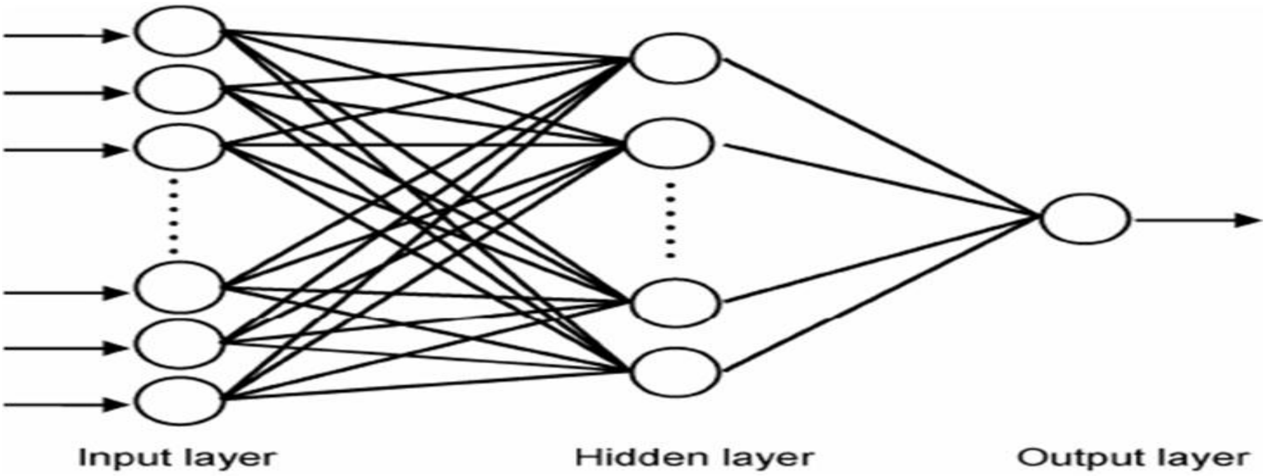

Figure-1. The structure of BPNN.

The best ANN architecture may be described as a network which producing the best performance in terms of error minimization, while retaining a simple and compact structure.

The most important issues which must be considered in the implementation of artificial neural networks, are the number of nodes and layers in the network and finding the optimal values for the connection weights , this can be determined by a good selection of a training algorithm. Through operation of ANN size determination, an insufficient number of hidden nodes causes difficulties in learning data whereas an excessive number of hidden nodes might lead to unnecessary training time with marginal improvement in training outcome as well as make the estimation for a suitable set of interconnection weights more difficult. Zealand, et al. [14] a higher number of nodes in hidden layer tend the network to memorize, instead of learning and generalization, and it might lead to the problem of local minima. On the other hand, increasing the hidden nodes will help to adjust to larger fluctuation of target function and allow the model to consider the presence of volatilities in the data. Such as trends and seasonal variation often appear a lot with rainfall. There is actually no specific rule to determine the suitable number of hidden nodes.The common method used is trial and error based on a total error criterion. This method starts with a small number of nodes, gradually increasing the network size until the desired accuracy is achieved. Fletcher and Goss [15] suggested the number of node in the hidden layer ranging from (2n+1) to ($(2\sqrt{n} + m)$ where n is the number of input node, and m is the number of output node. The number of input and output nodes is problem-dependent, and the number of input nodes depends on data availability [15].

2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive neuro fuzzy inference system ANFIS are a class of adaptive networks that are functionally equivalent to fuzzy inference systems. ANFIS models represent Sugeno Tsukamoto fuzzy models. which uses a hybrid learning algorithm. This model assume that the fuzzy inference system has two inputs x and y and one output z.
A first-order Sugeno fuzzy model has rules as followings :

- Rule1: If x is A1 and y is B1, then $f_1 = p_1x + q_1y + r_1$ ....(1).

• Rule2: If x is A2 and y is B2, then $f_2 = p_2x + q_2y + r_2$..................(2).

Adaptive neuro fuzzy inference network consisted from five layers .Each of these layers are contains several nodes, Jang JSR [16]. The structure of this system is shown in figure (2) .

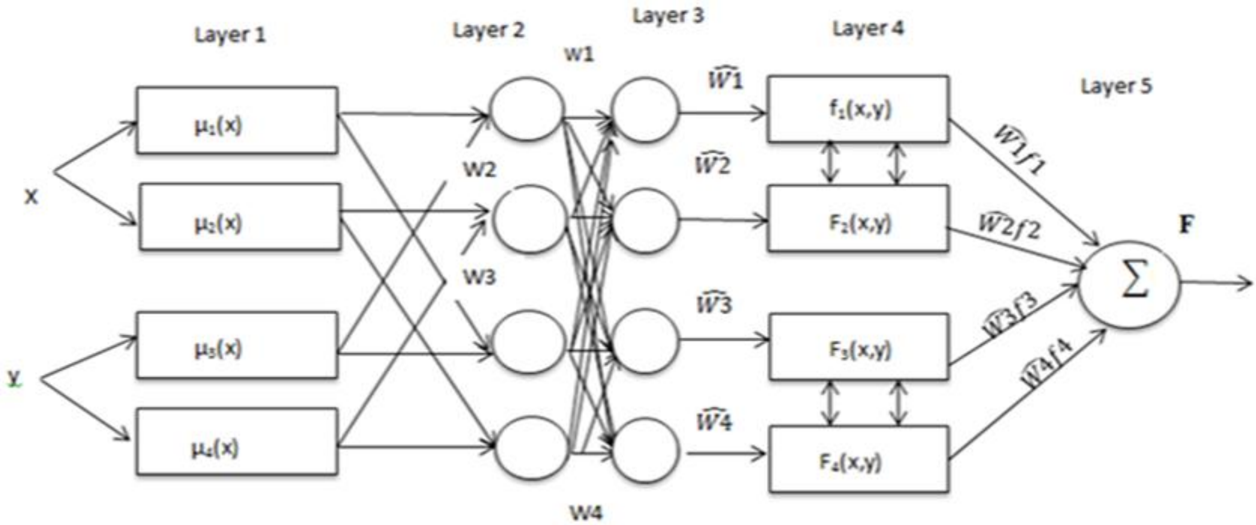

Figure-2. ANFIS Structure.

The first layer in this system executes a fuzzification process which denotes membership functions (MFs) to each input . Each node i in the first layer is an adaptive node. This node represents member ship functions which can be described by generalized bell functions :

$$Z_{1,i}=\mu_1(X) = \frac{1}{1+\left|{}^{(X-c_1)}/_{a_1}\right|^{2b_1}} \dots\dots\dots\dots (3).$$

where X=input to the node and a_1, b_1 and c_1=adaptable variables known as premise parameters. The outputs of this layer are the membership values of the premise part. This product represents the firing strength of a rule. The second layer consists of the nodes which multiply incoming signals and sending the product out.

$$Z_{2,1} = W_1 = \mu_1(x)\mu_4(y)\dots\dots\dots\dots\dots(4).$$

The nodes in the 3rd layer calculate the ratio of the ith rules firing strength to the sum of all rules' firing strengths.

$$z_{3,1} = \widehat{W_1} = \frac{W_1}{W_1+W_2+W_3+W_4}\dots\dots\dots\dots\dots(5).$$

The nodes in the fourth layer are adaptive with node functions

$$Z_{4,1} = \widehat{W_1}f_1 = \widehat{W_1}(p_1X + q_1y + r_1)\dots\dots\dots\dots(6).$$

where $\widehat{W_1}$ is the output of Layer 3 and { pi, qi, r1 } are the parameter set. Parameters of this layer are referred to as consequent parameters.

The single node in the fifth layer computes the final output as the summation of all incoming signals

$$f = \sum_{i=1}^{n} \widehat{W_i}\, f_i\dots\dots\dots\dots\dots(7).\ [16].$$

2.3. Model Verification

Three different forecast consistency measures are used in order to Model verification which are the determination coefficient (R^2), Nash-Sutcliffe efficiency (E_{Nash}) and percent bias (R_{Bias})were used to assess the models' performances. These parameters are defined as:

$$R^2 = \frac{(\sum_{t=1}^{n}(A_t - A_{mean})(S_t - S_{mean}))^2}{\sum_{t=1}^{n}(A_t - A_{mean})^2 \sum_{t=1}^{n}(S_t - S_{mean})^2} \ldots\ldots\ldots\ldots\ldots 8.$$

$$ENash = 1 - \frac{\sum_{t=1}^{n}(A_t - S_t)^2}{\sum_{t=1}^{n}(A_t - F_{mean})^2} \ldots\ldots 9.$$

$$R\ bias = 100 * \frac{\sum_{t=1}^{n}(S_t - A_t)}{\sum_{t=1}^{n} A_t} \ldots\ldots 10.$$

where A_t is the actual value and S_t is the Simulated value. S_{mean}, $A_{mean}$are the mean value of the series. Chokmani, et al. [17]; Teryaki, et al. [18] the best value of R^2 is 1.0 while . The optimum value of R_{Bias} is 0.0 and a better description of R_{Bias} and E_{Nash} was given also Moriasi, et al. [19]; Meral and Cheleng [20]. This description can be summarized as:

$$Very\ Good(VG) \qquad 0.75 < E_{nash} \leq 1 \qquad R_{bias} < \pm 10$$

$$Good(G) \qquad 0.65 < E_{nash} \leq 0.75 \qquad \pm 10 \leq R_{bias} \leq \pm 15$$

$$Satisfactory(S\ ) \qquad 0.5 < E_{nash} \leq 0.65 \qquad \pm 15 \leq R_{bias} \leq \pm 25$$

$$UN\,Satisfactory(US\ ) \qquad E_{nash} \leq 0.5 \qquad R_{bias} \geq \pm 25$$

3. CASE STUDIES AND NATURE OF DATA

In this study two case studies were selected to apply the methodology above in simulation and weather parameters forecasting . The different weather parameters of Dallas state at united states of America and Houston state were selected .The daily data of five different parameters for the two case studies were selected .These parameters are :

1.Max temperature , Minimum temperature, mean temperature

2. Max humidity ,Minimum humidity, mean humidity.

3. Max sea level pressure ,Minimum sea level pressure, mean sea level pressure.

4. Max wind speed ,Minimum wind speed, mean wind speed.

5. Summation of hourly precipitation . The available data for Houston, Texas are from 2008 till 2014 , the same daily parameters are available for the second state Dallas, Texas are from 1986 till 2016. Houston's climate can be classified as humid subtropical typical. During the summer, temperatures commonly reach over 90 °F (32 °C), with an average of 106.5 days per year, including a majority from June to September, with a high of 90 °F (32 °C) or above and 4.6 days at or over 100 °F (38 °C). According to NOAA [21] humidity usually yields a higher heat index. Summer mornings average over 90% relative humidity. In 1980, Houston was described as the "most air-conditioned place on earth". Officially, the hottest temperature ever recorded in Houston is 109 °F (43 °C), which was reached both on September 4, 2000, and August 28, 2011. Houston has mild winters. In January, the normal mean temperature is 53.1 °F (11.7 °C), while at the same station has an average of 13 days with a low at or below freezing.

Dallas city in the U.S. state of Texas has a humid subtropical climate that is characteristic of the Southern Plains of the United States. Dallas experiences distinct four seasons. January is typically the coldest month, with an average low of 37.3 °F (3 °C) and an average high of 56.8 °F (14 °C). Winter is mild but snowfall during winter is not uncommon. On average, there are 2 snowy days per year. Summers are very hot and humid. July and August are typically the hottest months, with an average low of 76.7 °F (25 °C) and an average high of 96.0 °F (36 °C). Located at the lower end of Tornado Alley, it is often prone to extreme weather, tornadoes and severe hailstorms. Winters in Dallas have a normal daily average temperature in January of 47.0 °F (8.3 °C) but sharp swings in temperature as strong cold fronts known as "Blue Northers" pass through the Dallas region, forcing daytime highs below the 50 °F (10 °C) mark for several days at a time and often between days with high temperatures above 80 °F (27 °C). Snow accumulation is seen in the city in about 70% of winter seasons, and snowfall generally occurs 1–2 days out of the year for a seasonal average of 1.5 inches (3.8 cm). Some areas in the region, however, receive more than that, while other areas receive negligible snowfall or none at all.The all-time record low temperature within the city itself is −3 °F (−19 °C), set on January 18, 1930, while the all-time record high is 113 °F (45 °C), set on June 26 and 27, 1980 during the Heat Wave of 1980 at nearby Dallas–Fort Worth Airport. The average daily low in Dallas is 57.4 °F (14.1 °C) and the average daily high is 76.9 °F (24.9 °C). Dallas receives approximately 37.6 inches (955 mm) of rain per year, Dallas [22]. All the mentioned data were pre- processed by standardization operation to ensure receiving equal attention during the training . In this research following equation was applied to all data set for two case studies and for both used methods .

$$Xi = 0.1 + 0.8\frac{(X-Xmin)}{(Xmax-Xmin)} \quad \text{.................................(11).}$$

Xmin, Xmax are the minimum and the maximum values of the observed data series.

4. RESULTS AND DISCUSSION

4.1. Forecasting of Daily Precipitation at Huoston, Texas

To get accurate forecasting results in the future using the BPNN and ANFIS models , all the data have been divided into two parts, namely the training and testing data. In this experiment, the data from 2008-2016 (3285 samples data series) for each variable or parameter have been taken from Weather under ground custom forecast and local radar web site (https://www.wunderground.com/weather/us/tx/houston) were used . After data normalization process, which had been carried out, then the data was divided into training data; 2464 (75%), and testing data; 821 (25%). The data had been governed by the rules of the neural network which consisted of different number of input neurons according to the built ANN and ANFIS models , and the output neuron was one, precipitation, The architecture of BPNN would comprise one-hidden-layer. The activation functions used from input to hidden layers were tansig and logsig, and purelin that were used for the hidden layers to the output, with Levenberg-Marquardt algorithm (trainlm). Table (1) shows the different architectures of the applied ANN and ANFIS models .

Table-1. Description of the applied ANN models.

Model Name	Inputs	Output
MI	Tem $_{max}$, Tem $_{min,}$ Tem $_{mean}$, hum $_{max}$, hum $_{min,}$ hum $_{mean,}$. SLP $_{max,}$ SLP $_{min,}$ SLP $_{mean,}$ wind speed$_{max}$, wind speed$_{min}$,wind speed$_{mean}$	summation of hourly precipitation for a day t .
MII	Tem $_{mean}$, hum $_{mean,}$ SLP $_{mean,}$ wind speed$_{mean}$	summation of hourly precipitation for a day t .
MIII	Tem $_{max}$, Tem $_{min,}$ Tem $_{mean}$, hum $_{max}$, hum $_{min,}$ hum $_{mean,}$. SLP $_{max,}$ SLP $_{min,}$ SLP $_{mean,}$ wind speed$_{max}$, wind speed$_{min}$,wind speed$_{mean}$,P $_{t-1}$,P $_{t-2}$,P $_{t-3}$	summation of hourly precipitation for a day t .
MIV	Tem $_{mean}$, hum $_{mean,}$ SLP $_{mean,}$ wind speed$_{mean,}$,P $_{t-1}$,P $_{t-2}$,P $_{t-3}$	summation of hourly precipitation for a day t .
MV	P $_{t-1}$, P $_{t-2}$, P $_{t-3}$, P $_{t-4}$, P $_{t-5}$,P $_{t-6}$	summation of hourly precipitation for a day t

Note: Tem $_{max}$, Tem $_{min,}$ Tem $_{mean}$: mean maximum ,minimum and mean temperature respectively.
hum $_{max}$, hum $_{min}$, hum $_{mean,}$: mean maximum ,minimum and mean relative humidity respectively.
SLP $_{max}$, SLP $_{min}$, SLP $_{mean}$: mean maximum ,minimum and mean sea level pressure respectively
wind speed $_{max}$, wind speed $_{min}$,wind speed $_{mean}$: mean maximum ,minimum and wind speed respectively. P $_{t-1}$, P $_{t-2}$, P $_{t-3}$, P $_{t-4}$, P $_{t-5}$,P $_{t-6}$: precipitation at lagged days .

4.1.1. Results of BPNN for Huoston, Texas

The one-day ahead forecast accuracy of the five BPNN models in preliminary testing stage (model MI-BPNN to MV-BPNN) were evaluated using determination coefficient (R^2), Nash-Sutcliffe efficiency (E_{Nash}), percent bias (R_{Bias}); the behavior of these parameters is presented in Table (2) for training and test period. The consistency in the results between training and test periods can be seen from the table . This was attributed to the fact that the cross validation approach was helpful in detecting the best generalization point. The applied BPNN models (MI-MV), which used the characteristics of different weather parameters values and lagged times precipitation values as input variables, provided very good accuracy of forecast. The lowest score was obtained by Model MI-BPNN . Changing the network inputs by adding the lagged time precipitation values improved the performance . This is very clear by comparing models MI-BPNN with MIII-BPNN and models MII-BPNN with MIV-BPNN. This suggests that the back propagation network using the precipitation values for the previous days performed better than ones depending on the weather parameters only. Figures (2) , shows the performance of the best models by comparing the forecasted values by these models against the observed values. No precipitation in forecasted results versus no rain in the observed record was considered as a very high forecasting result. It is also clear that using the mean values of weather parameters only is better than using maximum and minimum values of these parameters since this may confuse the training process.

Table-2. Performance results of ANN models for Training and test Period at Huoston,Texas.

Model Name	Inputs	Output	Best Architecture	period	E $_{nash}$	R²	R $_{bias}$
MI-BPNN	Tem $_{max}$, Tem $_{min,}$ Tem $_{mean}$, hum $_{max}$, hum $_{min,}$ hum $_{mean,}$. SLP $_{max,}$ SLP $_{min,}$ SLP $_{mean,}$ wind speed$_{max}$, wind speed$_{min}$,wind speed$_{mean}$	P $_t$	12-18-1	Training	0.74	0.74	-27.3
				Test	0.71	0.71	-29
MII-BPNN	Tem $_{mean}$, hum $_{mean,}$ SLP $_{mean,}$ wind speed$_{mean}$	P $_t$	4-7-1	Training	0.93	0.932	+11.1
				Test	0.912	0.912	+13.1
MIII-BPNN	Tem $_{max}$, Tem $_{min,}$ Tem $_{mean}$, hum $_{max}$, hum $_{min,}$ hum $_{mean,}$. SLP $_{max,}$ SLP $_{min,}$ SLP $_{mean,}$ wind speed$_{max}$, wind speed$_{min}$,wind speed$_{mean}$,P $_{t-1}$,P $_{t-2}$,P $_{t-3}$	P $_t$	15-26-1	Training	0.88	0.878	+16
				Test	0.88	0.88	+18
MIV-BPNN	Tem $_{mean}$, hum $_{mean,}$ SLP $_{mean,}$ wind speed$_{mean,}$,P $_{t-1}$,P $_{t-2}$,P $_{t-3}$	P $_t$	7-8-1	Training	0.975	0.975	-10
				Test	0.964	0.964	-10.2
MV-BPNN	P $_{t-1}$, P $_{t-2}$, P $_{t-3}$, P $_{t-4}$, P $_{t-5}$,P $_{t-6}$	P $_t$	6-9-1	Training	0.96	0.955	-12.8
				Test	0.956	0.957	-14

4.1.2. Results of ANFIS for Huoston, Texas

The precipitation forecasting is nonlinear system so ANFIS model has been developed with different input combinations based on previous mentioned data . Models of ANFIS have been designed, trained and tested with different membership functions and different number of members. After Defining ANFIS Models, it is run with various FIS Algorithm, error tolerance and number of epochs to analyses the effect of all these parameters on verification parameters. The parameter optimization is done in such a way during training session that the error between the target and the actual output is minimized. The data are divided into sets of 75-25 % ratio. For example 75 % data for training period and 25 % data for validation period to develop ANFIS model. ANFIS models are developed using different method, membership function and different alternative of inputs as was shown in Table(1). Table(3) shows the performance of different ANFIS models for training and test periods.

Table-3. Performance results of ANFIN models for Training Period at **Huoston,Texas.**

Model Name	Inputs	Output	period	[ethod	E_{nash}	R^2	R_{bias}
MI-ANFIS	Tem_{max} , $Tem_{min,}$ Tem_{mean} , hum_{max} , $hum_{min,}$ $hum_{mean,}$. SLP_{max}, $SLP_{min,}$ $SLP_{mean,}$ wind $speed_{max,}$ wind $speed_{min}$,wind $speed_{mean}$	P_t	Training	Hybrid	0.88	0.86	-19.11
			Test	Hybrid	0.89	0.89	-17.23
MII- ANFIS	Tem_{mean} , $hum_{mean,}$ $SLP_{mean,}$ wind $speed_{mean}$	P_t	Training	Hybrid	0.94	0.943	+11.1
			Test	Hybrid	0.94	0.94	+11
MIII- ANFIS	Tem_{max} , $Tem_{min,}$ Tem_{mean} , hum_{max} , $hum_{min,}$ $hum_{mean,}$. SLP_{max}, $SLP_{min,}$ $SLP_{mean,}$ wind $speed_{max,}$ wind $speed_{min}$,wind $speed_{mean}$,P_{t-1},P_{t-2},P_{t-3}	P_t	Training	Hybrid	0.94	0.948	+12.8
			Test	Hybrid	0.96	0.96	+11.7
MIV- ANFIS	Tem_{mean} , $hum_{mean,}$ $SLP_{mean,}$ wind $speed_{mean,}$,P_{t-1},P_{t-2},P_{t-3}	P_t	Training	Hybrid	0.99	0.997	+6.7
			Test		0.988	0.988	+6
MV- ANFIS	P_{t-1}, P_{t-2}, P_{t-3}, P_{t-4}, P_{t-5} ,P_{t-6}	P_t	Training	Hybrid	0.98	0.97	+7
			Test	Hybrid	0.98	0.981	+7

according to the above results it can be seen that all the used ANFIS models showed high performance especially the last two models MIV-ANFIS and MV-ANFIS with values of $\mathbf{R^2}$ 0.988 and 0.981 respectively for test period and 0.988 ,0.98 as E_{nash} values for the same two models respectively .The positive sign of R_{bais} for the two successive models reflexes an over estimation with high performance . By comparing the two different methods BPNN and ANFIS one can see an increasing of forecasting performance by ANFIS model. It is also clear that using the data of precipitation for previously days can improve the forecasting efficiency . Figure (3) show the comparison between the observed precipitation and the two best models among all the applied BPNN and ANFIS models .

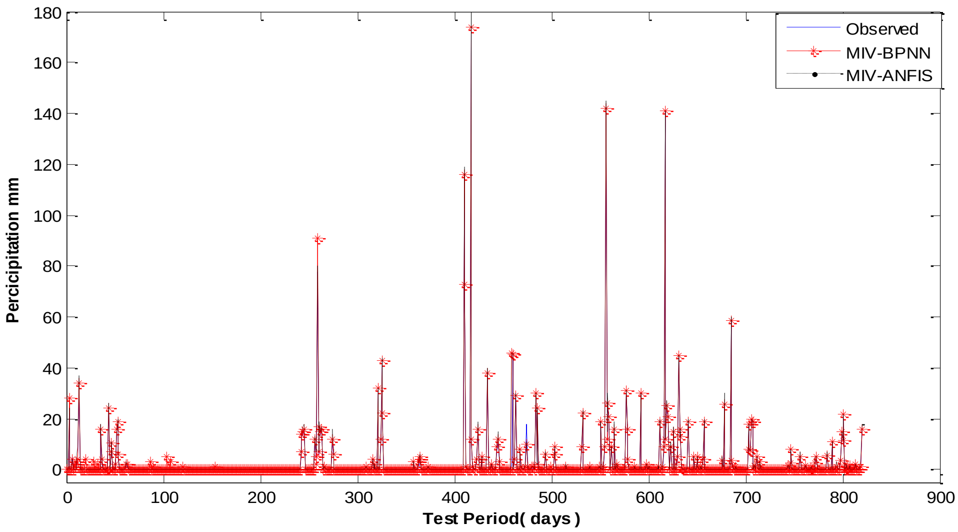

Figure-3. The comparison between the observed precipitation MIV-BPNN and MIV-ANFIS models for(Houston ,Texas).

4.2. Forecasting of Daily Precipitation at Dallas

The data of Dallas state parameters have been divided into two parts, namely the training and testing data as was done before with pervious case study. In this experiment, the available data was more lengthy and extended from 1986-2016 (11315 samples data series) for each variable or parameter . After data normalization process, which had been carried out, then the data was also divided into training data; 8486 (75%), and testing data; 2829(25%), https://www.wunderground.com/weather/us/tx/Dallas. The same input combinations with one hidden layer and same output were used for BPNN and ANFIS models

4.2.1. Results of BPNN for Dallas

After applying the same architectures of ANN on the Dallas data with the mentioned input combinations. The performance of the most BPNN models indicated to a very small forecast error and the high performance of the applied models was ensured. This can be seen from Table(4) which illustrates the applied models performance for both training and test periods . By comparing the different models it can be concluded that the best performance was for model MIV-BPNN which uses all the mean weather parameters in addition to the lagged values of precipitation with 0.989 E_{nash} value , R^2 =0.989 and R_{bias}= +8 with a little overestimation. Using the lagged values of precipitation for six days also gave a high performance, this is clear from the results of MV-BPNN model but with a low underestimation.

Table-4. performance results of ANN models for Training and test Period at **Dallas.**

Model Name	Inputs	Output	Best Architecture	period	E_{nash}	R^2	R_{bias}
MI-BPNN	Tem_{max} , Tem_{min}, Tem_{mean} , hum_{max} , hum_{min}, hum_{mean}, . SLP_{max}, SLP_{min}, SLP_{mean}, wind $speed_{max}$, wind $speed_{min}$,wind $speed_{mean}$	P_t	12-23-1	Training	0.91	0.91	+15.9
				Test	0.90	0.91	+13
MII-BPNN	Tem_{mean} , hum_{mean}, SLP_{mean}, wind $speed_{mean}$	P_t	4-9-1	Training	0.90	0.90	+11.2
				Test	0.89	0.89	+13.7
MIII-BPNN	Tem_{max} , Tem_{min}, Tem_{mean} , hum_{max} , hum_{min}, hum_{mean}, . SLP_{max}, SLP_{min}, SLP_{mean}, wind $speed_{max}$, wind $speed_{min}$,wind $speed_{mean}$,P_{t-1},P_{t-2},P_{t-3}	P_t	15-31-1	Training	0.93	0.96	+10
				Test	0.929	0.929	+11.1
MIV-BPNN	Tem_{mean} , hum_{mean}, SLP_{mean}, wind $speed_{mean}$, ,P_{t-1},P_{t-2},P_{t-3}	P_t	7-9-1	Training	0.99	0.96	+8.6
				Test	0.989	0.989	+8
MV-BPNN	P_{t-1}, P_{t-2}, P_{t-3}, P_{t-4}, P_{t-5} ,P_{t-6}	P_t	6-10-1	Training	0.98	0.98	-8.8
				Test	0.979	0.979	-8.7

4.2.2. Results of ANFIS for Dallas

The same ANFIS models were applied to the data of Dallas and the performance results were recorded in Table (5) as shown. It can be seen that the network inputs has a valuable effect on the network output . This provides feedback as to which input parameters are the most significant. Based on this feedback, it may be decided to prune the input space by removing the insignificant parameters. This also reduces the size of the network, which in turn reduces the network complexity and the training time. This is very clear when studying the ANFIS models since the MI-ANFIS model here is the lowest performed model if compared with others . The best model for this case study was by using the mean values of weather parameters with the lagged values of precipitation MIV-BPNN . Although this model was the best among all applied models , other models showed a very good forecast results . Figure(4) shows the comparison between the observed precipitation values and the best two applied BPNN and ANFIS models which are MIV-BPNN and MIV-ANFIS for just three years from the test period .

Table-5. Performance results of ANFIS models for Training Period at **Dallas.**

Model Name	Inputs	Output	period	lethod	E_{nash}	R^2	R_{bias}
MI-BPNN	Tem_{max} , $Tem_{min,}$ Tem_{mean} , hum_{max} , $hum_{min,}$ $hum_{mean,}$. SLP_{max}, SLP_{min}, SLP_{mean}, wind $speed_{max}$, wind $speed_{min}$,wind $speed_{mean}$	P_t	Training	Hybrid	0.81	0.81	+21
			Test	Hybrid	0.79	0.80	+25
MII-BPNN	Tem_{mean} , $hum_{mean,}$ SLP_{mean}, wind $speed_{mean}$	P_t	Training	Hybrid	0.95	0.95	+8.9
			Test	Hybrid	0.948	0.95	+8.9
MIII-BPNN	Tem_{max} , $Tem_{min,}$ Tem_{mean} , hum_{max} , $hum_{min,}$ $hum_{mean,}$. SLP_{max}, SLP_{min}, SLP_{mean}, wind $speed_{max}$, wind $speed_{min}$,wind $speed_{mean}$,P_{t-1},P_{t-2},P_{t-3}	P_t	Training	Hybrid	0.92	0.928	+11.8
			Test	Hybrid	0.918	0.913	+11.6
MIV-BPNN	Tem_{mean} , $hum_{mean,}$ SLP_{mean}, wind $speed_{mean,}$,P_{t-1},P_{t-2},P_{t-3}	P_t	Training	Hybrid	0.99	0.99	+5.88
			Test		0.989	0.989	+7
MV-BPNN	P_{t-1}, P_{t-2}, P_{t-3}, P_{t-4}, P_{t-5} ,P_{t-6}	P_t	Training	Hybrid	0.95	0.95	+8.1
			Test	Hybrid	0.95	0.956	+9

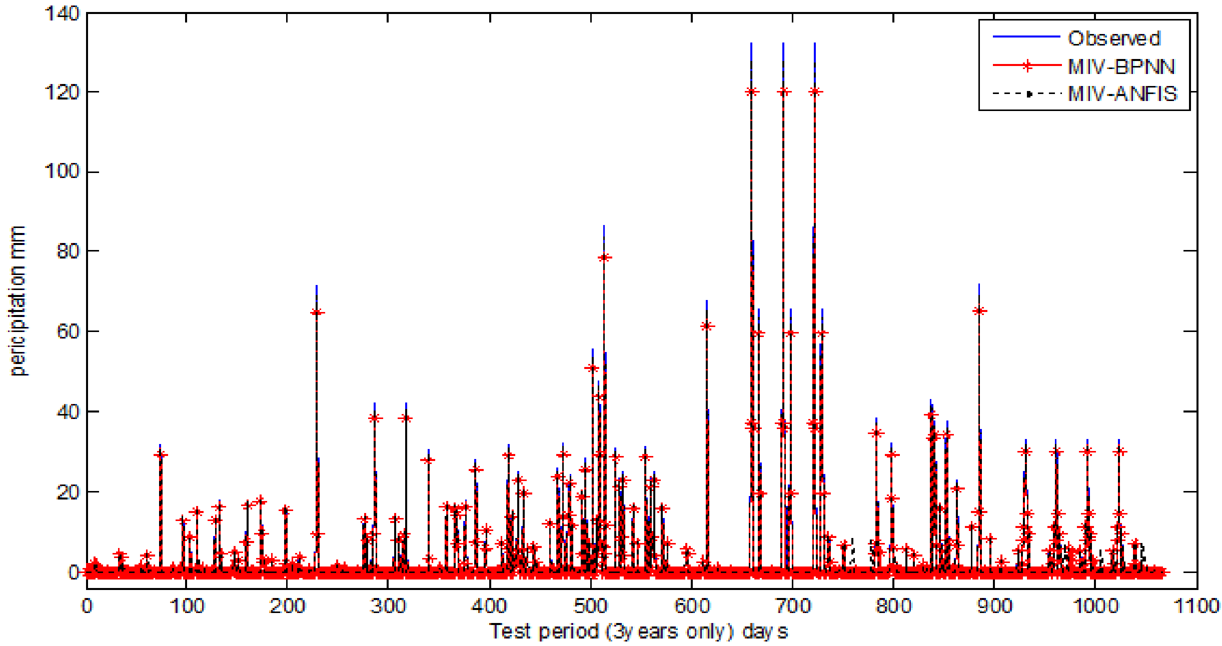

Figure-4. The comparison between the observed precipitation MIV-BPNN and MIV-ANFIS models for(Dallas).

5. CONCLUSIONS

In this study an application of BPNN back propagation neural network with different input combinations and different number of hidden layer neurons was used to forecast daily precipitation at two stations of Huston ,Texas and Dallas regions using different weather parameters Temperature , relative humidity, sea level pressure and wind speed. In addition to this application an adaptive neuro fuzzy inference system ANFIS for the same two case studies was done using same input combinations . Followings were found during the study:

1- Comparison of the precipitation forecasting by the applied different models considered in preliminary test showed that a combination of meteorological parameters such as temperature , relative humidity, sea level pressure and wind speed with lagged time precipitation data at the forecasting station, as an inputs for the model could significantly improve the forecast accuracy and efficiency for both methods.

2- The results also indicated that using the lagged time precipitation alone could give also a very good performance in error minimizing.

3- By using an appropriate network architecture and especially with the use of auxiliary data, the ANN and ANFIS models were able to learn from continuous input data .

4- It was concluded also that using more data variables such as maximum and minimum values of the different weather parameters can confuse the training process and the network performance.

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