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Enhance the performance of weather parameters in Short-Term Weather forecasting using ANFIS

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Abstract- **Weather prediction is an ever challenging area of investigation for scientists. The Adaptive Neuro-Fuzzy Inference System (ANFIS) has been widely used for modeling different kinds of nonlinear systems including rainfall forecasting. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) combines the capabilities of Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS) to solve different kinds of problems, especially efficient in rainfall prediction. In this paper the application of artificial neural networks to predict the Weather of Delhi city has been proposed using knowledge base in the Neuro-Fuzzy Inference system. The weather parameters like minimum temperature, maximum temperature, relative humidity, sea level pressure, rain fall, wind speed, wind direction and sun shine etc. has been used for prediction. When performing weather predictive model the key criteria is always accuracy. We are trying to predict future weather condition based upon above parameters by Artificial Neural Network. The model performance is contrasted with multi layered perceptron network. The proposed network train with actual data of the five years (2008 to 2012) of Safdarjung station, New Delhi and tested which comes from meteorological department. MLP used with Fuzzy logic.**

Keywords- *Adaptive Neuro-Fuzzy Inference systems (ANFIS), Weather prediction, RMSE, MSE, RMASE, Coefficient Correlation, SNR.*

I. INTRODUCTION

Weather simply refer to the condition of air on earth at a given place and time .The application of science and technology are to predict the state of the atmosphere in future time for a given location is so important due to its effectiveness in human life. Today, weather forecasts are made by collecting quantitative data about the current state of the atmosphere and using scientific understanding of atmospheric processes to project how the atmosphere will evolve. The chaotic nature of the atmosphere implies the need of massive computational power required to solve the equations that describe the atmospheric conditions. This is resulted from incomplete understanding of atmospheric processes which mean that forecasts become less accurate as the difference in time between the present moment and the time for which the forecast is being made increases. Weather is a continuous, data-intensive, multidimensional, dynamic and chaotic process and these properties make weather prediction a big challenge. Generally, two methods are used for weather forecasting

(a) The empirical approach and

(b) The dynamical approach.

The first approach is based on the occurrence of analogs and is often referred by meteorologists as analog forecasting. This approach is useful for predicting local-scale weather if recorded data's are plentiful. The second approach is based on equations and forward simulations of the atmosphere and is often referred to as computer modeling. The dynamical approach is only useful for modeling large-scale weather phenomena and may not forecast short-term weather efficiently. Most weather prediction systems use a combination of empirical and dynamical techniques Artificial Neural Network (ANN) provides a methodology for solving many types of nonlinear problems that are difficult to be solved by traditional techniques .Most meteorological processes often exhibit temporal and spatial variability. They are suffered by issues of nonlinearity of physical processes, conflicting spatial and temporal scale and uncertainty in parameter estimates [7].

II. LITERATURE SURVEY

Pankaj Kumar was proposed ANFIS with 4- Bell-shaped Gauss types of membership functions and hybrid learning algorithms method was used for the optimization of Minimum Weekly Temperature Forecasting using [1]. In this paper three inputs are used for minimum temperature forecast and mean weekly value used as input data set. Kumar Abhishek applied multilayered artificial neural network with learning by back-propagation algorithm configuration. There are two tools for implementing the algorithms in Matlab [2]. They are-

a. Nntool – open network/data manager. The single layer and the multi layer algorithms are implemented in the nntool- open network/ data manager.

b. Nftool – Neural network fitting tool. Only back propagation algorithm is implemented in this Matlab tool.

Back Propagation Algorithm (BPA) was implemented in the Nftool. A minimum MSE was obtained and a graph was plotted between the predicted values and the target values. The following are the values recorded using the Nftool MSE=3.6456. The implementation of multi-layer architecture was done using NNTOOL in MTALAB.

Three algorithms were tested in multi-layer architecture:

a. Back Propagation Algorithm (BPA)

b. Layer Recurrent Network (LRN)

c. Cascaded Back-Propagation (CBP)

A.C. Subhajini at all made comparisons among Radial Basis Function, Back Propagation Neural, Network, Regression Neural Networks, Fuzzy ARTMAP (Neuro-fuzzy Hybrid with Recurrent Network as the host architecture). Find ARTMAP is best among all these method of forecasting [3]. B. Putra, at all applied Fusion of Fuzzy- Artificial Neural Network for Short Term Weather Forecasting. In those work have used Fuzzy C- Mean clustering. In this research another different system was proposed to improve the performance and accuracy of weather prediction built from the fusion of Neural Network and Fuzzy Inference and C-Means system [4]. Arti R. at all was proposed Back Propagation Feed Forward Neural Network for Weather Forecasting using Weather parameters temperature, pressure, humidity, wind direction [5]. Muhammad Buhari, Member, IAENG and Sanusi Sani Adamu, applied Levenberg-Marquardt back propagation n algorithm for Short term load forecasting. The input consists of daily 24 hour load data for 12 months of the year 2005 and daily average maximum temperature altogether making 25 inputs rows by 365 days. The output layer will be a day's 24 hours load forecast for the utility company. The Target data is the same as the input's daily 24 hours load data [6]. Ch. Jyosthna Devi, B. Syam Prasad Reddy, K. Vagdhan Kumar, B. Musala Reddy and N. Raja Naya, applied Back Propagation for weather forecast. The aim is to gather dataset consisting weather parameters like temperature, humidity, dew point, visibility ,atmospheric pressure ,sea level, wind speed, wind direction etc. The Work Done, How neural networks are useful in forecasting the weather and the working of most powerful prediction algorithm called back propagation algorithm was explained. A 3-layered neural network is designed and trained with the existing dataset and obtained a relationship between the existing non-linear parameters of weather. So many parameters are taken and their relationships are taken into consideration those factors for the temperature forecasting. Like temperature, humidity, dew point, visibility, atmospheric pressure, sea level, wind speed, wind direction etc. The data is normalized using min-max normalization to scale the dataset into the range of 0 to 1. Basically the work is done to check two different ANN architecture which is better. These are Back Propagation (BPN) feed forward network and Radial basis function network (RBN). BPN is found the best and taken for further development for prediction of temperature but there is an drawback that time consuming process. The research was focused on proper initialization of weights and bias of weather forecasting system [7].

After going through the above detailed study we find the following key results that play a major role in any forecasting model building first is the methodology ANFIS which is used for accuracy and convergence and second is combination of parameters is an important fact of weather forecasting because the parameters of weather are correlated each other. This reason selection of parameters is also an important work in forecasting.

III. Adaptive Neuro-Fuzzy Inference System (ANFIS)

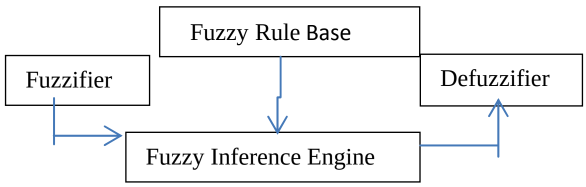
An Adaptive neuro-fuzzy inference system (ANFIS) is a combination of ANN and Fuzzy Inference System (FIS) in such a way that neural network learning algorithms are used to determine the parameters of FIS. An even more important aspect is that the system should always be interpretable in terms of fuzzy if-then rules, because it is based on the fuzzy system reflecting vague knowledge. We have used first–order Sugeno fuzzy model among many FIS models. The Sugeno fuzzy model is most widely applied one for its high interpretability and computational efficiency and built-in optimal and adaptive techniques. The Sugeno fuzzy model provides a systematic approach to generate fuzzy rules from a set of input–output data pairs. Further the optimal values of the consequent parameters (parameters in adaptive neuro-fuzzy inference system) can be found by using the least square method (LSM). When the premise parameters are not fixed, the search space becomes larger and the convergence of training becomes slower. The hybrid learning (HL) algorithm combining LSM and BP algorithms can be used to solve this problem. It was shown in that the HL algorithm is highly efficient in training the ANFIS. This algorithm converges much faster since it reduces the dimension of the search space of the BP algorithm. During the learning process, the premise parameters and the consequent parameters are tuned until the desired response of the FIS is achieved.

The HL algorithm has a two-step process. First, the consequent parameters are identified using LSM when the values of the premise parameters are fixed. Then, the consequent parameters are held fixed while the error is propagated from the output end to the input end, and the premise parameters are updated by the BP algorithm [18].

A. Neuro-Fuzzy Approach

The neural-fuzzy model is an effective method for modeling nonlinear systems such as weather data due to the combination of advantages of neural systems and fuzzy logic systems. The neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to gain information about a dataset, in order to compute the membership function parameters which allow the associated fuzzy inference system to track the given input/output data (Jang 1993).

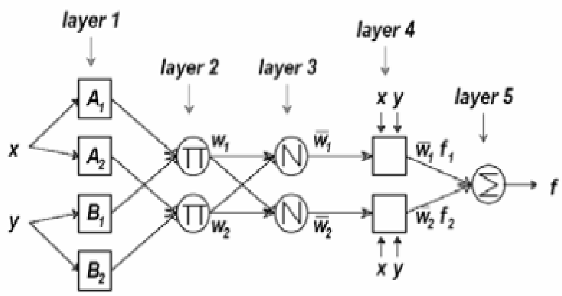
Each fuzzy system contains three main parts: fuzzification, inference and defuzzification (Fig.1).



Fig, 1 Fuzzy interface system

B. Architecture of ANFIS

The ANFIS approach learns the rules and membership functions from data. The ANFIS architecture is presented in figure 2. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt.



Fig, 2 An ANFIS architecture for a two rule Sugeno system

A two Rule Sugeno ANFIS has rules of the form:

If x is A_1 *and y is* B_1 *THEN* $f_1 = p_1 x + q_1 y + r_1$……………………1

If x is A_2 *and y is* B_2 *THEN* $f_2 = p_2 x + q_2 y + r_2$ … … … … … … … 2

When Training the Network there is a forward pass and a backward pass. The forward pass propagates the input vector through the network layer by layer. In the backward pass, the error is sent back through the network in a way similar to back propagation [1].

In Layer 1, the output of each node is:

$$O_{1,i} = \mu_{B_{i-2}}(y) \quad for\ i = 3,4 \quad \ldots\ldots\ldots 3$$

And $O_{1,i}(x)$ is membership functions grade for *x* and *y*.

The membership functions could be any shape. Using the Gaussian membership function given by:

$$\mu_{\bar{A}}(x) = \frac{1}{(1+x)^2} \ldots\ldots\ldots 4$$

In layer 2, every node in this layer is fixed. Here used ‘AND’, ‘OR’ membership grades for example the product:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \qquad i = 1,2 \ldots\ldots 5$$

Layer3 contains the fixed node which calculates the ratio of the firing strengths of the rules:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad \ldots\ldots\ldots 6$$

The nodes in layer 4 are adaptive and perform the consequent of the rules:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \ldots\ldots\ldots 7$$

The parameters in this layer $(p_i x,\ q_i y, r_i)$ are to be determined and are referred to as the consequent parameters.

In layer 5 there is a single node that computes the overall output:

$$O_{5,i} = \sum \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \ldots\ldots\ldots 8$$

IV. Proposed Work

STEP 1: Evaluate the Performance of the different combinations of weather parameters in Relative Humidity forecasting using ANFIS.

Here used many different combinations of parameters and find which parameters are necessary for prediction of Relative Humidity. Table 1 shows the combinations of parameters for relative humidity. Here Min T, Max T, Slp, Ssh, Rain, WS, WD, RH are used for respectively minimum temperature, maximum temperature, pressure, sun shine, rain fall, wind speed, wind direction and relative humidity.

TABLE1
DIFFERENT COMBINATIONS OF PARAMETERS FOR RELATIVE HUMIDITY

Model no.	Input Parameters	output
A	Min T, Max T, Slp	RH
B	Min T, Max T, Slp, Ssh	RH
C	Min T, Max T, Slp, Ssh, Rain	RH
D	Min T, Max T, Slp, Ssh, Rain, WS	RH
E	Min T, Max T, Slp, Ssh, Rain, WS,WD	RH
F	Min T, Max T, Ssh, Rain	RH

STEP 2: Here we will use the combination of ANN and Fuzzy Logic with Gaussian membership function for convergence and accuracy. Set different–different no of membership function per input and epochs for reducing error.

STEP 3: Five different criteria are used in order to evaluate the effectiveness of each network and its ability to make precise predictions. The Five statistical analysis parameters are Mean Bias Error (MBE) (Eq.1) is an indication of the average deviation of the predicted values from the corresponding measured data and can provide information on long term performance of the models. A positive value indicates the amount of overestimation in the predicated rain fall and vice versa, Root Mean Square Error (RMSE) (Eq.2) provides information on the short term performance which is a measure of the variation of predicted values around the measured data. The lower the RMSE, the more accurate is the estimation, Correlation Coefficient (R^2) (Eq.3), Root Mean Absolute Error (RMAE) (Eq.4) and Signal to Noise Ratio (SNR) (Eq.5). The higher SNR and R^2, the smaller the RMSE and RMAE show the better prediction effect.

That performance expressed below mathematically:

Mean Bias Error:

$$(MBE) = \frac{1}{n}\sum_{i=1}^{n}(X_t - X_o) \qquad (1)$$

Root Mean Square Error:

$$(RMSE) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_t - X_t)^2} \qquad (2)$$

Root Mean Absolute Error:

$$(RMAE) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|X_t - X_o|} \qquad (3)$$

Correlation Coefficient (R^2):

$$R^2 = \frac{\sum_{i=1}^{n}(X_t - \overline{X_t})(X_o - \overline{X_o})}{\sqrt{\sum_{i=1}^{n}(X_t - \overline{X_t})^2 (X_o - \overline{X_o})^2}} \qquad (4)$$

Signal to Noise Ratio (SNR):

$$SNR = 10\log\left[\frac{\sum X_t^2}{\sum (X_t - X_o)^2}\right] \qquad (5)$$

Where X_t is the observation data and X_o computed data and n is the number of data. $\overline{X_t}$ is the mean of actual data and $\overline{X_o}$ are the mean of the computed data.

In this study, two scenarios were introduced; in the first scenario, monthly rainfall and Relative humidity was used as an input, second scenario used the modified ANFIS to improve the forecasting efficiency. The result showed that the model based Modified ANFIS performed higher rainfall forecasting accuracy; low errors and lower computational complexity.

V. METHODOLOGY

Designing ANFIS models follows a number of systemic procedures. In general, there are five basics steps: (a) Collecting Data, (b) Preprocessing data, (c) building the network, (d) train, and (e) test performance of model as shown in fig.

A. Collecting Data

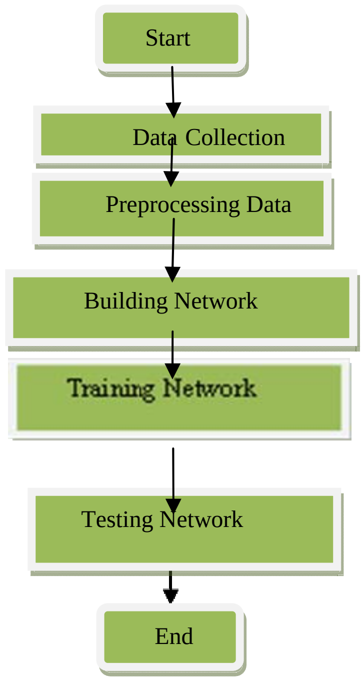
The data related to prediction is provided to the network input layer. The data can we gathered using weather software also meteorological department. Weather data is observation of 8:30 A.M. daily.

B. Preprocessing Data

The noise in the data is removed in this step so as to get better prediction results.

C. Building Network

The network is multilayered feed forward neural network and train with ANFIS.



Fig, 3 Flow chart for weather forecasting

D. Training Network

Training the network using Hybrid (combination of least square method (LSM) and Back propagation (BP)) ANFIS with Gaussian membership function. I was used four year data for training. In training I gave input and output both type of data and then train or adjust the network. Graph was plotted between output and actual data.

E. Testing Network

I was used in testing one year data and calculate the error.

Validation used the training network means that after the training of network save this network and then testing done. In testing I only gave input and check the error between output and actual data. Saved result in numerical form and plotted the graph between actual data and output. Flow chart of this work shows in figure 3.

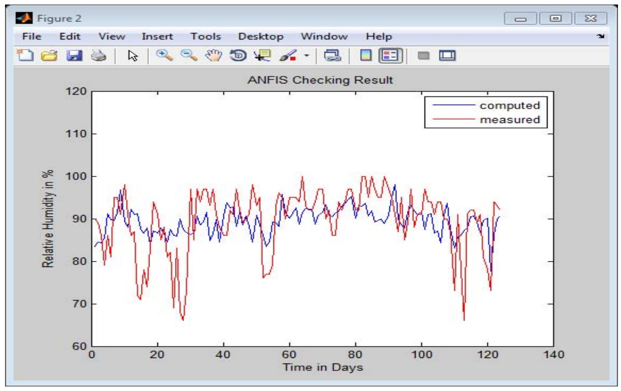
VI. RESULTS AND DISCUSSION

Training and validation result for the Relative Humidity.

The training and validation results of the Relative Humidity and Rain Fall models using the combination of Back propagation and least square error in ANFIS are presented.

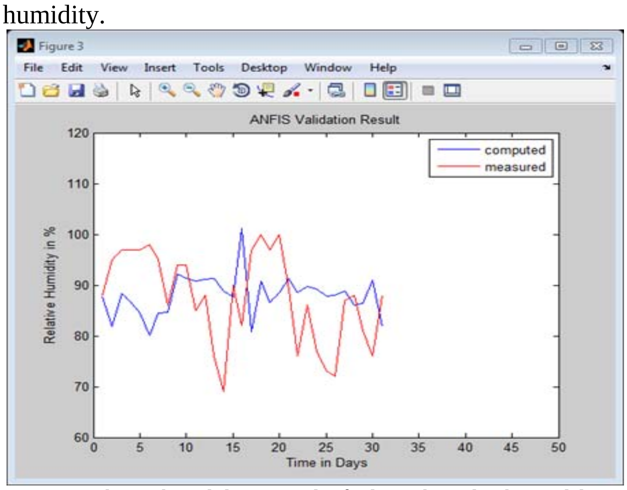
Figure 3 shows the result of relative humidity training by model A, figure 4 shows the result of relative humidity validation by model A, figure 5 shows the result of relative humidity training by model B, figure 5 shows the result of relative humidity validation by model B, figure 6 shows the result of relative humidity training by model C, figure 7 shows the result of relative humidity validation by model E, figure 8 shows the result of relative humidity training by model E. Here shows some model figures for explanations.

Table 2 shows the number of epochs, which membership function and how many numbers is used, number of input parameters for forecasting for relative humidity and computing time, table 3 shows the checking result of relative humidity for all models and table 4 shows the validation results of relative humidity for all models. In this observation model E has maximum errors and B has minimum errors in result.

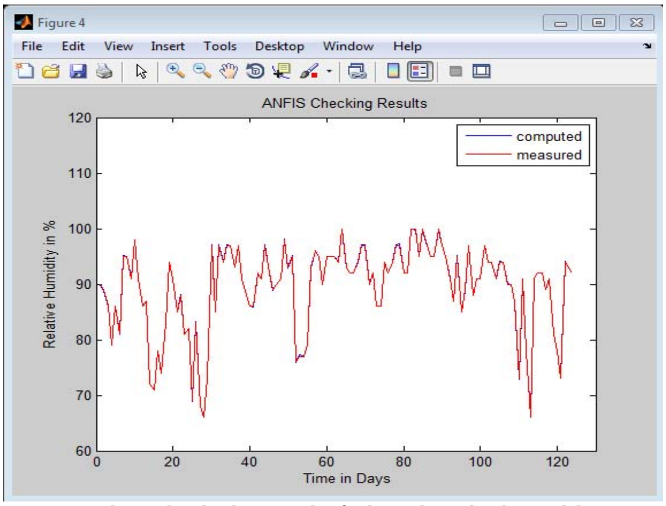


Fig, 3 shows the checking result of relative humidity by model A

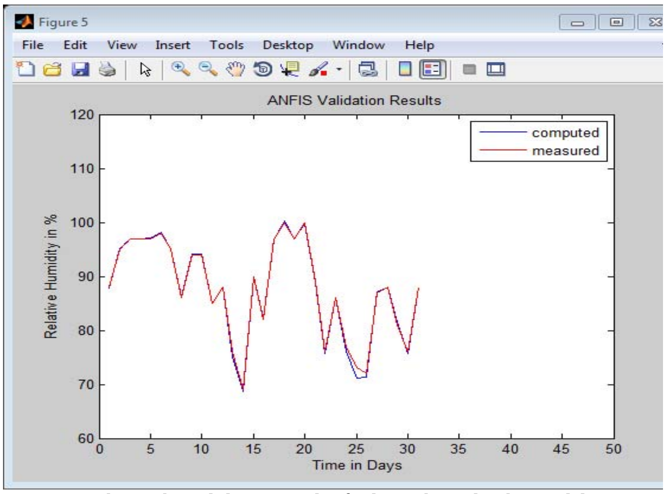
This is a short-term forecasting. Four year data were used for training and one year data were used for validation. Figure 9 shows the result of training for relative humidity and figure 10 shows the result of validation for relative humidity.



Fig, 4 shows the validation result of relative humidity by model A



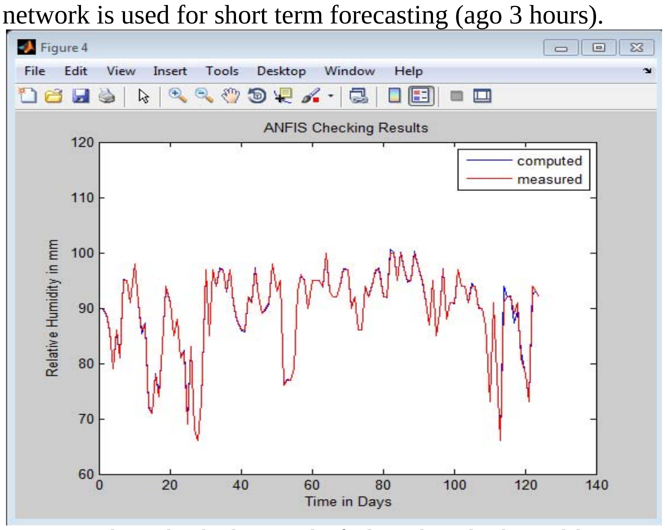
Fig, 5 shows the checking result of relative humidity by model B



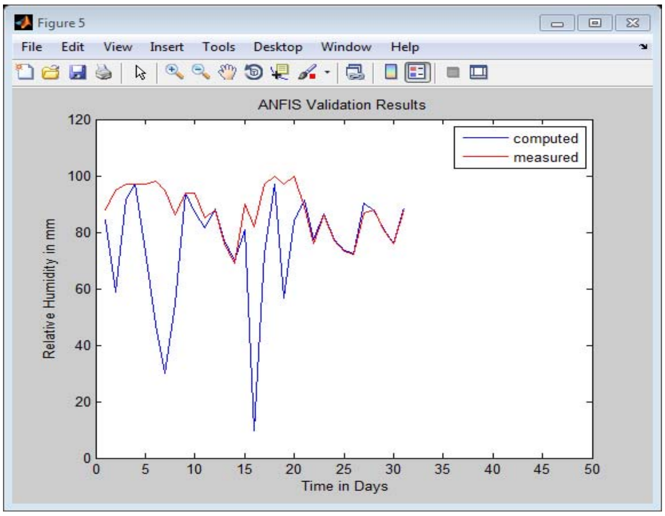
Fig, 6 shows the validation result of relative humidity by model B

Four input minimum temperature, maximum temperature, sea level pressure, sun shine are used for forecasting relative humidity. These are best parameters for relative humidity forecast. On the basis of this observation I can say that weather parameter combination also effects the forecasting.

On the basis of these observations, model B is the best in among models. So implement all data with model B. Train network is used for short term forecasting (ago 3 hours).



Fig, 7 shows the checking result of relative humidity by model E



Fig, 8 shows the validation result of relative humidity by model E

Actual data and computed data in crisp form shown in table 5. Here showed only some data for example November of 2012. This data show difference between computed and actual data.

TABLE2
SHOWS THE NO OF EPOCHS, MEMBERSHIP FUNCTION AND COMPUTING TIME

Model no.	Computing time	Membership function	No of MF	No of epoch	No of input
A	1.153s	Gaussian	3	3	3
B	1.273s	Gaussian	3	500	4
C	1.480s	Gaussian	3	50	5
D	2.224s	Gaussian	3	3	6
E	5.055s	Gaussian	3	3	7
F	1.318s	Gaussian	3	100	4

TABLE3
SHOWS THE CHECKING RESULT OF RELATIVE HUMIDITY FOR ALL MODELS

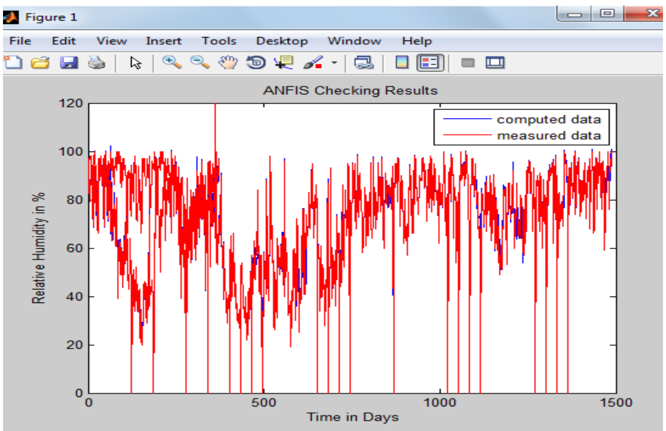
Model no	Checking results				
	MBE	RMSE	RAE	CC	SNR
A	-4.6013e-005	7.1453	0.0719	3.9937	104.8637
B	-4.38632e-005	0.0856	0.0079	5.7241	105.2795
C	-1.5761e-004	2.3452	0.0412	5.8046	94.1696
D	-2.4361e-004	0.4755	0.0186	5.7357	90.3874
E	-3.5902e-004	0.4265	0.0176	5.7278	87.0191
F	-8.2359e-005	2.9088	0.0459	5.8168	99.8072

TABLE4
SHOWS THE VALIDATION RESULTS OF RELATIVE HUMIDITY FOR ALL MODELS

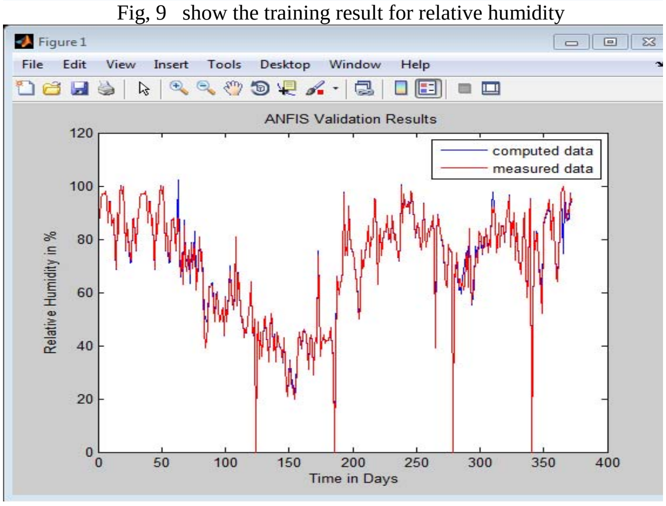
Model no	Validation results				
	MBE	RMSE	RAE	CC	SNR
A	0.3177	10.8973	0.0719	3.9937	104.8637
B	-0.1523	0.4779	0.0526	3.8536	40.3341
C	-0.8379	5.2113	0.1738	4.0701	25.5244
D	-7.7232	20.0856	0.3411	1.9068	6.2328
E	-12.2662	23.8176	0.3715	0.5732	2.2146
F	-1.3374	4.9906	0.1700	3.9959	21.4639

TABLE5
SHOWS CRISP DATA FOR NOVEMBER

Day	Actual data	Computed data
1	92.0000	92. 1917
2	88.0000	87 .8466
3	75.0000	74 .8126
4	78.0000	77 .6775
5	86.0000	85 .7332
6	77.0000	76 .8592
7	85.0000	84 .7484
8	85.0000	84 .6972
9	79.0000	78 .7148
10	86.0000	85 .8451
11	90.0000	90 .0271
12	92.0000	92 .2305
13	96.0000	96 .7475
14	77.0000	76 .8575
15	86.0000	85 .8819
16	84.0000	83 .9877
17	90.0000	90 .1012
18	72.0000	72 .0025
19	86.0000	85 .8561
20	72.0000	72 .3205
21	70.0000	70 .1852
22	67.0000	67 .2872
23	76.0000	75 .4426
24	86.0000	85 .4352
25	90.0000	89 .8519
26	70.0000	70 .1206
27	58.0000	58 .9619
28	66.0000	66 .1994
29	88.0000	87 .3915
30	95.0000	95 .2430
31	0.0000	0.0000



Fig, 9 show the training result for relative humidity



Fig, 10 shows the validation result of relative humidity

VII. CONCLUSION

A neural fuzzy network model was proposed for relative humidity prediction on the basis of best combination of parameters. Short term prediction is an important part of the latest control technology for operation of building systems. This work discusses the possibility of using meteorological data with local observation data for short-term prediction. Neural Network has gained great popularity in weather prediction because of their simplicity and robustness. In this study the performance of different parameters of weather is compared by using ANFIS (adaptive neuro-fuzzy inference system) for relative humidity forecasting. The study also says that Neural Network with Fuzzy Logic is the best combination for weather forecasting. The dataset selection, input variable selection, the relationship and inter-dependencies among the data, the proper training set and the proper architecture are most vital for best prediction results. After going through all the above study and result discussion we see that minimum temperature, maximum temperature, sea level pressure, sun shine are most effective parameters in prediction of relative humidity. ANFIS is the best computing technique on the basis of running time and accuracy of results.

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