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# Climatic Prognosticate Identification using Soft Computing Techniques and Algorithmic Concepts

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## Abstract:-

Climatic prognosticates is the application of recent technology to forebode the state of the troposphere for a climate time at a given section. It is implementing by compile quantitative testimony about the current state of the atmosphere and past and/or present experiences. In this study flexible Adaptive Neuro-Fuzzy Inference System (ANFIS) and multiple linear regression models were used to inspect barometrical testimony sets access from the barometrical station. The Multiple linear regression models is elementary due to the actuality that it uses elementary algorithmic equation using Multiple Linear Regression (MLR) equations that can be simply understood by a medium educated farmer. 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. The testimony 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 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 multiple linear regression (MLR) model with a lower prediction error.

**KEYWORDS**: -barometrical, MSLP, RMSE, algorithmic equation

## **1. INTRODUCTION**

There is increasing recognition that climate has a central role in global economic and social sectors. Climate directly affects the prosperity within of many sectors, such as insurance, agriculture, energy and health. Similarly, unfavourable climatic conditions have negative and prolonged impacts, including decreased private sector investment and productivity associated with economic and environmental uncertainties. It is often used to warn about natural disasters are caused by abrupt change in climatic conditions. At immense level, Climatic prognosticate is mainly done using the testimony gathered by remote sensing satellites. Climatic prognosticate criterion like maximum temperature, minimum temperature, extent of rainfall, cloud, conditions, wind streams and their directions, are estimated using and testimony taken by images these meteorological satellites to access future trends. In this paper Multiple Linear Regression (MLR) and adaptive neuro fuzzy inference system (ANFIS) are used to develop models for Climatic prognosticate weather criterion.

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The prospective models are capable of Climatic prognosticate the weather conditions for a particular station using the testimony collected locally. In the testimony set, there are Maximum five criterion: Temperature, Minimum Temperature, Humidity and Wind speed, mean sea level pressure(MSLP) and this testimony are only on Delhi's weather condition. For analysis and forecast, we applied ANFIS and multiple linear regression techniques on this testimony and finally the performance of these two models is compared on the basis of root mean square error (RMSE). In this paper, ANFIS MATLAB Fuzzy Logic Toolbox is used to design ANFIS model. These tools apply fuzzy inference techniques to testimony modelling. The ANFIS toolbox function constructs a fuzzy inference system (FIS) whose Membership function criterion is tuned (adjusted) using back propagation algorithm. This allows our fuzzy systems to learn from the testimony.

# 2. MULTIPLE LINEAR REGRESSION (MLR) MODEL

Multiple regression models involve more than one repressor. Multiple linear regression models are often used as the empirical models or approximating functions. Any regression model that is linear in the parameters is a linear regression model, regardless of the shape of the surface that it generates. Variable Regression explains the nature of relationship, i.e., the average probable change in one variable given by certain Amount of change in the other variable. The general equation of regression of Y on X is

This equation is known as the algorithmic model for linear regression. As the special case the form  $Y = \alpha + X$  is called the deterministic model. Multiple Linear Regression equation, which describes the linear relationship with set of dependent variable Y, and k Sets of independent variables X<sub>1</sub>, X<sub>2</sub>, X<sub>3</sub>.....X<sub>k</sub> is,

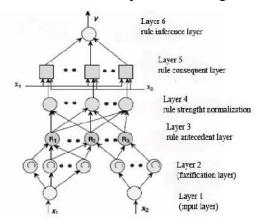
Where Y is predicting and X1, X2, X3....X<sub>k</sub> are the predictors. 'e' is the error which is distributed normally with zero mean and variance s 2, i.e.  $e \sim N(0, s2)$ . To develop the prospective model, the criterion  $\propto_{1, 2}, 3...$  K are estimated using the training sample sets. X1, X2, X3.....X<sub>k</sub> are among the extracted features mentioned earlier. The coefficient of determination, r<sup>2</sup>, explains the extent by which the variation of dependent variable Y is being Expressed by the independent variable X. It is obtained as

$$r^2 = (3)$$

A high  $r^2$  shows that there exists a linear relationship between the two variables. If  $r^2=1$ , it indicates the perfect relationship between the two variables.

# 3. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

An adaptive network is a network of nodes and directional links. Associated with the network is a learning rule: for example back propagation. It's called adaptive because some, or all, of the nodes have criterion which affect the output of the node. The networks learn the relationship between the inputs and outputs. The ANFIS approach learns the rules and membership functions from testimony. The ANFIS architecture is presented in figure 2.



### Figure.1. An ANFIS Architecture for a Two Rule Suge no System

If x is A<sub>1</sub> and y is B<sub>1</sub> THEN  $f_1 = p_1x + q_1y$ +r<sub>1</sub> (4) If x is A<sub>2</sub> and y is B<sub>2</sub> THEN  $f_2 = p_2x + q_2y$ +r<sub>2</sub>

<sup>=</sup>**x**+ +

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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.

In Layer 1, the output of each node is  $0_{1,i} = \mu_{Bi-2}$  (y) for i=3,4

And  $0_{1,i}$  (x) is membership functions grade for x and y. The membership functions could be any shape. Using the Gaussian membership function given by

 $\mu_{A}(x) = 1$ 

$$1+x^2$$

Every node in this layer is a fixed node labelled  $\Pi$ , representing the firing strength of each calculated by the fuzzy AND rule and is connective of product of the incoming signals by  $0_{2,I} = W_i = \mu_{A_i}(x) \mu_{B_i}(y)$  for i = 1, 2 Where,  $\mu_{A_i}(x)$  and  $\mu B_i(x)$  are membership grades of fuzzy sets A, B and also wi is firing strength of each rule. The ith node calculates the ratio of the ith rule's firing strength to the sum of two rule's firing strengths by using eq. i=1, 2 where, normalized firing strength that is the ratio of the ith rule's firing strength (wi) to the sum of the first and second rule's firing strengths (w1, w2). Every node in this layer is an adaptive node with a node function in eq.(10), indicating the contribution of ith rule toward the overall output. The single node in this layer is a fixed node labeled  $\Sigma$ , indicating the overall output as the summation of all incoming signals  $= \sum \Sigma$  Where, Z is the calculated by  $=\Sigma$ summation of all incoming signals.

#### **COMPONENTS** AND 4. **MECHANISM**

The case testimony for the study was obtained from the weather website and it covers a period of 5 years from January 2008 to December 2012. The preprocessing of the tetimony was first carried. Missing values were replaced with zeros. The Meteorological 1 tetimonyset, their type and description are presented in

		Pages: 14-18			
S.NO	INPUT	UNITS			
	VARIABLES				
1.	Max. Temperature	Deg.c			
2.	Min. Temperature	Deg.c			
3.	<b>Relative Humidity</b>	%			
4.	Wind speed	Kmph			
5.	MSLP	HPA			

Table 1.1. List of different input variables The Performance Criteria used Β. for Evaluating the Models Root Mean-Squared Error-- This is simply the square root of the mean squared error. The mean-squared error gives the error value the same dimensionality as the actual and predicted values.

## 5. RESULTS AND DISCUSSION

In this study, MLR and ANFIS models are designed to forecast various weather criterions. Weather criterion to be predicted is maximum temperature, minimum temperature, relative humidity, wind speed and MSLP. For both models

S.NO	SEASON	DURATION
1.	Winter	1 December – 28
		February
2.	Spring	1 March - 31 May
3.	Summer	1 June- 31 August
4.	Autumn	1 September – 30 November

#### Table 1.2 yearly testimonies is divided into four seasons

The best model suitable to forecast weather is evaluated by computing the root mean square error between the exact and predicted values. Theoretically, a prediction model is accepted as ideal when RMSE is small. Results for all weather criterions in terms of RMSE are shown in

### CONCLUSION

Based on the obtained results, it can be concluded that both of these models were able to capture the dynamic behaviour of the weather testimony, resulting in a more compact and natural internal representation of the Temperature, MSLP, Wind speed and

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Relative humidity information contained in the weather profile. However, regarding prediction accuracy, the ANFIS is highly appreciated for temperature Climatic prognosticate, relative humidity, wind speed. For MSLP only, Regression model performed better than ANFIS model.

DA TE	MAX.T EMP RMSE		MIN.TEP RSME		RELA TIVE HUMI DITY RMSE		WIN D SPEE D RMS E		MSLP RSME	
01- 01- 20 13	R E G	AN FIS	RE G	AN FIS	R E G	A N FI S	R E G	A N F I S	R E G	ANFI S
01- 02- 20 13	3. 1 6	3.1 1	12. 60	2.0	1 0. 2 5	1 0. 2 5	6. 1 4	5 2	4 7. 2 5	8.63
01- 03- 20 13	2. 7 2	2.6 0	14. 60	2.5 8	1 4. 2 5	1 1. 5	5. 0 5	4 2	2. 6 5	5.2
01- 04- 20 13	2. 0 7	1.5 2	13. 69	3.2 8	1 5. 5 6	1 2. 5	4. 1 5	5 6 8	4. 2 5	25.8
01- 05- 20 13	2. 5 4	2.2 0	14. 98	0.8	1 0. 5	1 0. 2 5	8. 2 5 8	6 2 4	8. 2 5	8.25
01- 06- 20 13	1. 7 0	1.7 2	10. 55	2.1 5	1 1. 5 8	1 1. 2 5	2. 7 7	4 2 4	7. 2 5	4.25
01- 07- 20 13	3. 1 5	2.8 1	12. 58	3.5 2	1 2. 5 6	1 1. 5 6	4. 2 6	7 2 5	4. 2 5	7.25
01- 08- 20 13	2. 4 8	2.2 6	14. 28	5.5 2	1 0. 8 5	1 2. 3 6	7 6. 2	4 2 5	5. 9 8	4.12
01- 09- 20 13	2. 0 9	1.9 3	12. 45	2.5 5	1 1. 2 5	1 0. 9 5	5 6. 5	4 0 5	6. 4 7	8.25
01- 10- 20 13	1. 7 3	1.5 5	14. 20	1.2 5	1 3. 8 5	1 1. 4 7	5 2. 2	1 2 2 5	1. 2 5	4.25
01- 11- 20 13	1. 1 5	1.3 0	14. 52	1.8	1 4. 2 1	1 2. 3 6	4 1. 5	6 2 4	1 4. 5 2	6.25
01- 12- 20 13	1. 3 0	2.2 0	12. 86	2.5 8	1 5. 7 3	1 1. 2 5	2 1. 3	7 2 5	4. 2 5	7.25

Table 1.3 performance comparison ofANFIS and regression model

#### REFERENCE

[1] A. Vinciarelli, "A survey on off-line cursive word recognition", Pattern Recognition, 35(7), pp. 1433–1446, 2002.

[2] S. N. Srihari, "Automatic handwriting recognition- Encyclopedia of Language & Linguistics", 2nd Edition, Elsevier, 2006.

[3] A. L. Koerich, R. Sabourin and C. Y. Suen, " Large vocabulary off-line handwriting recognition: A survey", Pattern Analysis and Applications, 6(2), 97–121, 2003.

[4] Velappa Ganapathy, and Kok Leong Liew, Handwritten Character Recognition Using Multiscale Neural Network Training Technique, Proceedings of World academy of Science, Engineering and Technology, vol. 29, ISSN 1307-6884, May 2008.

[5] Saurabh Shrivastava and Manu Pratap Singh, Performance evaluation of feedforward neural network with soft computing techniques for hand written English alphabets, Applied Soft Computing, vol. 11, pp. 1156–1182, 2011.

[6] Yoshimasa Kimura, "Feature Selection for Character Recognition Using Genetic Algorithm", Fourth International Conference on Innovative Computing, Information and Control 978-0-7695-3873-0/09© 2009 IEEE, 2009.