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An Efficient Weather Forecasting System using Adaptive Neuro-Fuzzy Inference System

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Abstract- Consistent weather prediction is very important for socio economic development and is necessary for food security of the human society. Because of time immemorial, human race has been absorbed by the increasingly changing and very much dynamic atmosphere around him and has provided significant efforts to recognize the controlling processes and attain better capabilities of weather forecasting. Temperature forecasts are performed by means of gathering quantitative data regarding the progress state of the atmosphere. The author in this paper utilized a neural network-based technique for determining the temperature in future. The Neural Networks package contains different training or learning methods. Fuzzy logic acts as a significant function in decision making procedure. Neuro-fuzzy systems are fuzzy systems which utilizes Artificial Neural Network for the purpose of identifying their properties (fuzzy sets and fuzzy rules) by processing the data. Neuro-fuzzy systems contain the influence of the two techniques: fuzzy logic and ANNs, by using the mathematical characteristics of ANNs in tuning rule-based fuzzy systems that approximate the way man processes the data. Because of these factors, this paper uses Adaptive Neuro-Fuzzy Inference System (ANFIS) for weather forecasting. The experimental result shows that the proposed technique results in better accuracy of prediction when compared to the conventional technique of weather prediction.

Keywords- Multi Layer Perception, Temperature Forecasting, Back propagation, Artificial Neural Network, Adaptive Neuro-Fuzzy Inference **System.**

I. INTRODUCTION

The enormous computational is necessary to resolve the equations that represents the atmosphere, error concerned in measuring the initial conditions, and an imperfect understanding of atmospheric procedures because of chaotic nature [8] of the atmosphere. This indicates that forecasts turn out to be less precise as the dissimilarity in current time and the time for which the forecast is performed (the range of the forecast) increases. The use of ensembles and model helps narrow the error and pick the most likely outcome.

Various proves involved in temperature prediction are

a. Data collection(atmospheric pressure, temperature, wind speed and direction, humidity, precipitation),
b. Data assimilation and analysis
c. Numerical weather prediction
d. Model output post processing

A neural network [1] is a dominant data modeling technique that has the capability to capture and symbolize complex input /output relationships. The inspiration for the growth of neural network is obtained from the aspiration to realize an artificial system that could carry out intelligent works related to those carry out by the human brain. Neural network [9] looks like the human brain in the following manners:

a. A neural network acquires knowledge through learning
b. A neural network's knowledge is stored within interneuron connection strengths known as synaptic weights.

The exact supremacy and merits of neural networks occurs in the capability to symbolize both linear and non linear relationships straightforwardly from the data being modeled. Conventional linear models are simply insufficient when it approaches for true modeling data that consists of non linear features.

A neural network model is a formation that can be altered to result in a mapping from a provided set of data to characteristics of or relationships between the data. The model is modified, or trained, with the help of collection of data from a provided source as input, usually referred to as the training set. When the training phase completed successful, the neural network will be capacity to carry out classification, estimation, prediction, or simulation on new data from the same or similar sources.

An Artificial Neural Network (ANN) [5] is a data processing model that is motivated by the manner biological nervous systems like the brain, process those data. The main constituent of this model is the new structure of the data processing system. It consists of a large number of extremely interrelated processing elements (neurons) functioning together in order resolve particular problems. ANNs, like people, be trained by illustrations. An ANN is constructed for some application like pattern recognition or data classification, by means of a learning process. Learning in biological systems provides alterations to the synaptic relation that occurs among the neurons.

This paper uses Adaptive Neuro-Fuzzy Inference System which has both the advantages of neural network and fuzzy logic. This will helps in better prediction when compared to usage of neural network alone for prediction. The projected Temperature Prediction System is evaluated with the help of the dataset from [17]. The results are contrasted with practical temperature prediction outcome [18, 19]. This system supports the meteorologist to forecast the expectation weather effortlessly and accurately.

The remainder section of this paper is organized as follows: Section 2 discusses various temperature predicting systems that were earlier proposed in literature. Section 3 explains the proposed work of developing An Efficient Temperature Prediction System using Adaptive Neuro-Fuzzy Inference System (ANFIS). Section 4 illustrates the results for experiments conducted on sample dataset in evaluating the performance of the proposed system. Section 5 concludes the paper with fewer discussions.

II. RELATED WORK

Several works were performed related to the temperature prediction system and BPN network conventionally. Some of the works summarized below.

Y.Radhika *et al.*, [3] presents an application of Support Vector Machines (SVMs) for weather prediction. Time series data of every day maximum temperature at place is considered to forecast the maximum temperature of the successive day at that place according to the every day maximum temperatures for a period of earlier n days referred to as organize of the input. Significance of the system is practical for different spans of 2 to 10 days with the help of optimal values of the SVM kernel.

Mohsen Hayati *et.al*, [5] studied about Artificial Neural Network based on MLP was trained and tested using ten years (1996-2006) meteorological data. The outcome suggests that MLP network has the lesser prediction error and can be recognized as a better technique to model the short-term temperature forecasting [STTF] systems. Brian A. Smith *et.al*,[6] aims at creating a ANN models with lesser average prediction error by means of enhancing the number of distinct observations utilized in training, adding together extra input expressions that explain the date of an observation, raising the duration of prior weather data considered in all observation, and reexamining the number of hidden nodes utilized in the network. Models were generated to predict air temperature at hourly intervals from one to 12 hours before it happens. The entire ANN model, containing a network architecture and set of associated parameters, was calculated by instantiating and training 30 networks and computing the mean absolute error (MAE) of the resulting networks for few set of input patterns.

Arvind Sharma *et.al*, [7] briefly provided the way of the various connectionist models could be created with the help of various learning techniques and then examines whether they can afford the necessary level of performance, that are adequately good and robust so as to afford a reliable prediction model for stock market indices.

Mike O'Neill [11] considers two major practical concerns: the relationship among the amounts of training data and error rate (equivalent to the attempt to collect training data to create a model with provided maximum error rate) and the transferability of models' expertise among various datasets (equivalent to the helpfulness for common handwritten digit recognition).Henry A. Rowley reduces the complicated work of manually choosing nonface training illustrations, that must be preferred to period the entire space of nonface images. Simple heuristics, like utilizing the detail that faces infrequently overlie in images, can additional enhance the accuracy. Contrasting with more than a few other state-of-the-art face detection techniques are presented; representing that the proposed system has better performance by means of detection and false-positive rates.

III. METHODOLOGY

A. Adaptive Neuro-Fuzzy Inference System (ANFIS) Architecture of ANFIS

The ANFIS is a framework of adaptive technique to assist learning and adaptation. This kind of framework formulates the ANFIS modeling highly organized and not as much of dependent on specialist involvement. To illustrate the ANFIS architecture, two fuzzy if-then rules according to first order Sugeno model are considered:

$$Rule\ 1: If\ (x\ is\ A_1)\ and\ (y\ is\ B_1)\ then\ (f_1 = p_1 x + q_1 y + r_1)$$

$$Rule\ 2: If\ (x\ is\ A_2)\ and\ (y\ is\ B_2)\ then\ (f_2 = p_2 x + q_2 y + r_2)$$

where x and y are nothing but the inputs, A_i and B_i represents the fuzzy sets, f_i represents the outputs inside the fuzzy region represented by the fuzzy rule, p_i, q_i and r_i indicates the design parameters that are identified while performing training process. The ANFIS architecture to execute these two rules is represented in figure 1, in which a circle represents a fixed node and a square represents an adaptive node.

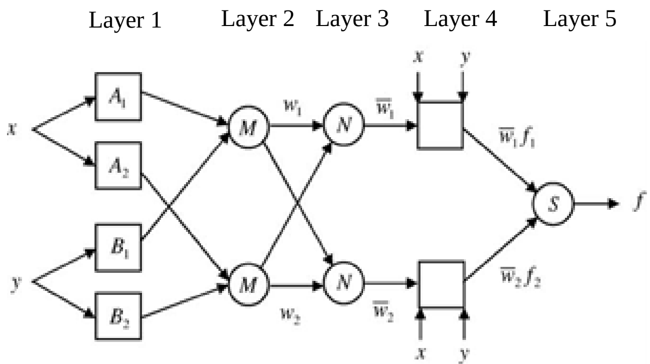

Figure 1: ANFIS Architecture

In the first layer, every node are adaptive nodes. The outputs of first layer are the fuzzy membership grade of the inputs that are represented by:

$$O_i^1 = \mu_{A_i}(x) \quad i = 1,2 \qquad (1)$$

$$O_i^1 = \mu_{B_{i-2}}(y) \quad i = 3,4 \tag{2}$$

where $\mu_{A_i}(x), \beta_{B_{i-2}}(y),$ can accept any fuzzy membership function. For example, if the bell shaped membership function is employed, $\mu_{A_i}(x)$ is represented by:

$$\mu_{A_i}(x) = \frac{1}{1 + \left\{\left(\frac{x - c_i}{a_i}\right)\right\}^{b_i}} \tag{3}$$

where a_i, b_i and c_i represents the parameters of the membership function, controlling the bell shaped functions consequently.

In layer 2, the nodes are fixed nodes. These nodes are labeled with M, representing that they carry out as a simple multiplier. The outputs of this layer can be indicated by:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad i = 1,2 \tag{4}$$

which are the called as firing strengths of the rules.

The nodes are fixed in layer 3 as well. They are labeled with N, representing that they are engaged in a normalization function to the firing strengths from the earlier layer.

The outputs of this layer can be indicated as:

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{5}$$

which are the called as normalized firing strengths.

In layer 4, all the nodes are adaptive nodes. The output of the every node in this layer is merely the product of the normalized firing strength and a first order polynomial. Therefore, the outputs of this layer are provided by:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \quad i = 1,2 \tag{6}$$

In layer 5, there exists only one single fixed node labeled with S. This node carries out the operation like summation of every incoming signal. Therefore, the overall output of the model is provided by:

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \tag{7}$$

It can be noted that layer 1 and the layer 4 are adaptive layers. Layer 1contains three modifiable parameters such as a_i, b_i, c_i that is associated with the input membership functions.

These parameters are called as premise parameters. In layer 4, there exists three modifiable parameters as well such as $\{p_i, q_i, r_i\}$, related to the first order polynomial. These parameters are called consequent parameters.

B. Learning Algorithm of ANFIS

The intention of the learning algorithm is to adjust all the modifiable parameters such as $\{a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$, for the purpose of matching the ANFIS output with the training data.

If the parameters such as a_i, b_i and c_i of the membership function are unchanging, the outcome of the ANFIS model can be given by:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{8}$$

Substituting Eq. (5) into Eq. (8) yields:

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \tag{9}$$

Substituting the fuzzy if-then rules into Eq. (15), it becomes:

$$f = \bar{w}_1(p_1 x + q_1 y + r_1) + \bar{w}_2(p_2 x + q_2 y + r_2) \tag{10}$$

After rearrangement, the output can be expressed as:

$$f = (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 + (\bar{w}_2 y)q_2 + (\bar{w}_2 \tag{11}$$

which is a linear arrangement of the adjustable resulting parameters such as p_1, q_1, r_1, p_2, q_2 and r_2. The least squares technique can be utilized to detect the optimal values of these parameters without difficulty. If the basis parameters are not adjustable, the search space becomes larger and leads to considering more time for convergence. A hybrid algorithm merging the least squares technique and the gradient descent technique is utilized in order to solve this difficulty. The hybrid algorithm consists of a forward pass and a backward pass. The least squares technique which acts as a forward pass is utilized in order to determine the resulting parameters with the premise parameters not changed. Once the optimal consequent parameters are determined, the backward pass begins straight away. The gradient descent technique which acts as a backward pass is utilized to fine-tune the premise parameters equivalent to the fuzzy sets in the input domain. The outcome of the ANFIS is determined by using the resulting parameters identified in the forward pass. The output error is utilized to alter the premise parameters with the help of standard back propagation method. It has been confirmed that this hybrid technique is very proficient in training the ANFIS.

IV. EXPERIMENTAL RESULT

To experiment the proposed system a sample dataset is taken from Madras Minambak, India (VOMM) [17]. This dataset contains the real time observation of the weather for a particular period of time. For this experiment, an observation of the complete previous year from January 2009 to December 2009 is taken. The dataset contains many attributes such as Altimeter, Temperature, Dew, RH, DIR, SPD and VIS. From conducted experiments it is found that following key changes in the atmospheric pressure signature that can be related to dynamic states of atmospheric conditions and for meaningful short duration weather prediction. From the observation, it can examine that the temperature peeks during the month of May; its range is 41 degree centigrade. The temperature falls to the dead end during the month of January. The minimum temperature is 6 °C. The wet days occur during the month of November. The speed of the wind remains constant with slight changes throughout the annum. The relative humidity is exceeding 43°C during the month of August. The humidity remains constant in the month of March and April at the same time it's the least scale of humidity.

The least average temperature occurs during the month of December and its peek occurs in the month of June and July. The average sunlight lies in the range of 5-10 °C throughout the entire year. The precipitation is maximum (20 cm) during the month of mid August. These observations are very much helpful to train the Neural Network.

From figure 2, can be observed that the error is high when the iteration is less and vice versa. In the above graph it explains that when the iteration count is below 1000 the sum squared error is maximum (i.e. 0.26) and when the count reaches 5000 the error value is merely 0. By using the proposed technique, the maximum sum squared error is only 0.13 and is even less than the usage of BPN for all cases.

This results that for more accurate results, the iteration count should be high which is shown in figure 2.

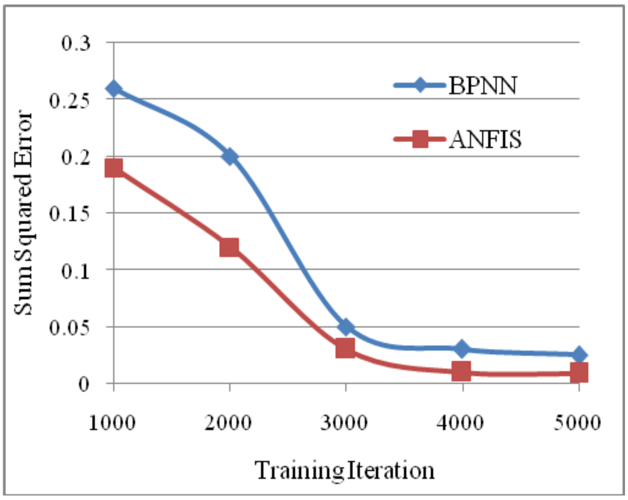

Figure.2: Sum Square Error Comparison

The present considerations on the meteorological time series leads to two possible interpretations of the global climate: one is that a low-dimensional climate attractor may exist and that the climate dynamics may have altered. The other temperature variations may be colored noise with many degrees of freedom. The latter interpretation would lead to the following forecast of the future trend in the climate: the global temperature would begin to decrease at some point in the future, since colored noise has a zero mean in a long time period. Within the framework of the present study neither of the interpretations is dismissed. The present work is still in a preliminary stage.

The distribution of prediction errors crossways all horizons is centered near zero, while the variance of these error distributions increases relative to horizon length. The increased divergence between observed and predicted temperatures at longer horizons is apparent in the plots. As prediction horizon increases, so does deviation from the line of perfect fit. The trend holds, specifically, in cases where a model fails to predict freezing temperatures. At the other extreme, the use of a logistic activation function in the output node, and the inverse of the scaling function to convert the output to a temperature, placed an upper bound on the model predictions. Because the scaling range was smaller than the output range of a logistic node, this bound was several degrees higher than the 20°C threshold used to select observations for the development and evaluation sets. As a result, models were constrained from predicting temperatures above 25°C. At temperatures near 25°C, models are more likely to under predict. The number of observed temperatures above this threshold increases, as the prediction horizon increases.

Another experiment was done to see performance of overall system. Artificial neural network was trained by using 200 training data. Training process results the weight and bias of the network. This indicates inverse kinematic model of robot manipulator. For testing, the network was tested by using data that are not used for training process. And experimental result shows that artificial neural network can model the inverse kinematic of robot manipulator with average error of 2.01%.

The performance of proposed system is indicated by the RMSE value. Experiment was done in various training parameter value of artificial neural network, i.e., various numbers of hidden layers, various number of neuron per layer, and various value of learning rate. There were 200 training data used in this research for training the artificial neural network. The training data were created by running the robot manually and measuring the position of each link directly. After training the system with the above mentioned observations it is tested by predicting some unseen day's temperature. The obtained results with error and exact values are tabulated and the graph is plotted as follows.

Table 1: Exact and Predicted Values for Unseen Days

Unseen days	Minimum error		Maximum error	
	BPN	ANFIS	BPN	ANFIS
02-Jan-2009	0.0079	0.0065	0.6905	0.0511
27-Aug-2009	0.1257	0.0910	0.8005	0.0612
09-Jun-2009	0.0809	0.0248	0.9921	0.8184
29-Nov-2009	0.0336	0.0102	0.9874	0.8952

Table 1 shows the shows the minimum and maximum error between exact values and predicted values of unseen days so that the generalization capacity of network can be checked after training and testing phase.

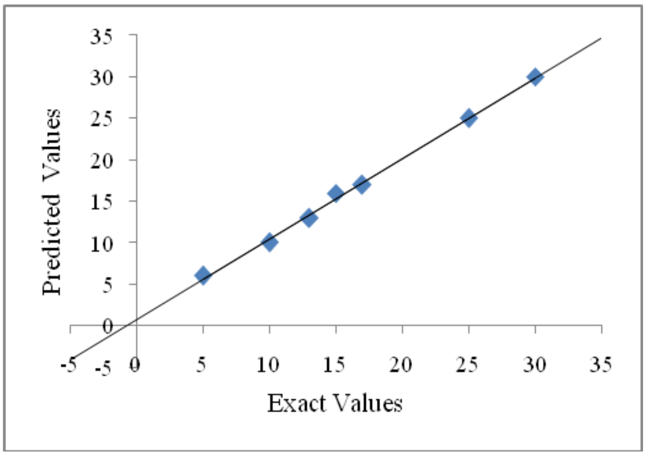

Figure 3: Comparison between Exact and Predicted Values for Unseen Day

The exact and predicted values for each unseen days by the proposed technique is shown in Fig. 3. From the result shown in Fig. 2, Fig. 3 and Table 1, it is observed that the predicted values are in good agreement with exact values and the predicted error is very less. Therefore the proposed prediction system using ANFIS can perform good prediction with least error.

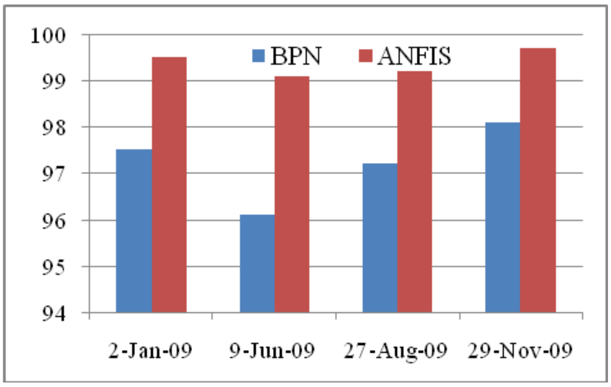

Figure 4: Accuracy of Prediction

The resulted accuracy for BPN and proposed technique for prediction is provided in figure 4. It can be observed that the proposed technique results in better accuracy of prediction.

V. CONCLUSION

In this paper, back propagation neural network is used for predicting the temperature based on the training set provided to the neural network. Through the implementation of this system, it is illustrated, how an intelligent system can be efficiently integrated with a neural network prediction model to predict the temperature. This algorithm improves convergence and damps the oscillations. This method proves to be a simplified conjugate gradient method. When incorporated into the software tool the performance of the back propagation neural network was satisfactory as there were not substantial number of errors in categorizing. Back propagation neural network approach for temperature forecasting is capable of yielding good results and can be considered as an alternative to traditional meteorological approaches. This paper uses Adaptive Neuro-Fuzzy Inference System (ANFIS) for weather forecasting which has the advantages of both neural network and fuzzy logic. Experimental results show that the proposed technique results in better accuracy of prediction when compared to the conventional techniques.

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