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Minimum Weekly Temperature Forecasting using ANFIS

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Abstract
Temperature changes had a direct effect on crops. In the present study an adaptive neuro-fuzzy inference system (ANFIS) has been used to model the relationship between maximum and minimum temperature data. Time series data of weekly maximum temperature at a location is analyzed to predict the maximum temperature of the next week at that location based on the weekly maximum temperatures for a span of previous n week referred to as order of the input. Mean weekly maximum and mean weekly minimum temperature data of 10 years 1997 to 2006 (520 weeks) taken from regional center of Indian Meteorological Department at Dehradun, India. The objectives of this paper are to develop prediction model and validate its ability to provide weekly temperature data.
Keywords: Minimum weekly temperature, ANFIS, forecasting

Introduction
Weather prediction is a complex process and a challenging task for researchers. It includes expertise in multiple disciplines. The prediction of atmospheric parameters is essential for various applications. Some of them include climate monitoring, drought detection, severe weather prediction, agriculture and production, planning in energy industry, aviation industry, communication, pollution dispersal (Pal *et al.,* 2003). Accurate prediction of weather parameters is a difficult task due to the dynamic nature of atmosphere. Stochastic weather generators have been proposed as one technique for simulating time series consistent with the current climate as well as for producing scenarios of climate change. Various techniques like linear regression, auto regression, Multi-Layer Perceptron, Radial Basis Function networks are applied to predict atmospheric parameters like temperature, wind speed, rainfall, meteorological pollution etc.(Nayak *et al,*2004; and Nayak *et al,*200).It was found that the non-linear operator equations governing the atmospheric system are the ones who can better understand the dynamics of atmosphere.

Materials and Methods
Adaptive Neuro-Fuzzy Inference Systems (ANFIS)
Adaptive Neuro Fuzzy Inference System (ANFIS) is a fuzzy mapping algorithm that is based on Tagaki-Sugeno-Kang (TSK) fuzzy inference system (Jang *et al.,* 1997 and Loukas, 2001).ANFIS is integration of neural networks and fuzzy logic and have the potential to capture the benefits of both these fields in a single framework. ANFIS utilizes linguistic information from the fuzzy logic as well learning capability of an ANN for automatic fuzzy if-then rule generation and parameter optimization.

A conceptual ANFIS consists of five components: inputs and output database, a Fuzzy system generator, a Fuzzy Inference System (FIS), and an Adaptive Neural Network. The Sugeno- type Fuzzy Inference System, (Takagi and Sugeno, 1985) which is the combination of a FIS and an Adaptive Neural Network, was used in this study for rainfall-runoff modeling. The optimization method used is hybrid learning algorithms.
For a first-order Sugeno model, a common rule set with two fuzzy if-then rules is as follows:
Rule 1: If x_1 is A_1 and x_2 is B_1, then $f_1 = a_1 x_1 + b_1 x_2 + c_1$.
Rule 2: If x_1 is A_2 and x_2 is B_2, then $f_2 = a_2 x_1 + b_2 x_2 + c_2$.
where, x_1 and x_2 are the crisp inputs to the node and A_1, B_1, A_2, B_2 are fuzzy sets, a_i, b_i and c_i (i = 1, 2) are the coefficients of the first-order polynomial linear functions. Structure of a two-input first-order Sugeno fuzzy model with two rules is shown in Figure 1 It is possible to assign a different weight to each rule based on the structure of the system, where, weights w_1 and w_2 are assigned to rules 1 and 2 respectively.
and f = weighted average
The ANFIS consists of five layers (Jang, 1993), shown in Figure 1. The five layers of model are as follows:
Layer1: Each node output in this layer is fuzzified by membership grade of a fuzzy set corresponding to each input.

$$O_{1,i} = \mu_{Ai}(x_1) \qquad i = 1, 2$$
or
$$O_{1,i} = \mu_{Bi-2}(x_2) \qquad i = 3, 4 \qquad (1)$$

Where, x_1 and x_2 are the inputs to node i (i = 1, 2 for x_1 and i = 3, 4 for x_2) and x_1 (or x_2) is the input to the i^{th} node and A_i (or B_{i-2}) is a fuzzy label.

Layer 2: Each node output in this layer represents the firing strength of a rule, which performs fuzzy, AND operation. Each node in this layer, labeled Π, is a stable node which multiplies incoming signals and sends the product out.

$$O2,i = Wi = \mu Ai\ (x1)\ \mu Bi\ (x2) \qquad i = 1, 2 \qquad (2)$$

Layer 3: Each node output in this layer is the normalized value of layer 2, i.e., the normalized firing strengths.

$$O_{3i} = \overline{W}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1, 2 \qquad (3)$$

Layer 4: Each node output in this layer is the normalized value of each fuzzy rule. The nodes in this layer are adaptive. Here $\overline{W}_i$ is the output of layer 3, and $\{a_i, b_i, c_i\}$ are the parameter set. Parameters of this layer are referred to as consequence or output parameters.

$$O_{4i} = \overline{W}_i f_i = \overline{W}_i (a_i x_1 + b_i x_2 + c_i) \qquad i=1,2 \qquad (4)$$

Layer 5: The node output in this layer is the overall output of the system, which is the summation of all coming signals.

$$Y = \sum_1^2 \overline{W}_i f_i = \frac{\sum_1^2 W_i f_i}{\sum_1^2 W_i} \qquad (5)$$

In this way the input vector was fed through the network layer by layer. The two major phases for implementing the ANFIS for applications are the structure identification phase and the parameter identification phase. The structure identification phase involves finding a suitable number of fuzzy rules and fuzzy sets and a proper partition feature space. The parameter identification phase involves the adjustment of the premise and consequence parameters of the system.

Optimizing the values of the adaptive parameters is of vital importance for the performance of the adaptive system. Jang et al. (1997) developed a hybrid learning algorithm for ANFIS to approximate the precise value of the model parameters. The hybrid algorithm, which is a combination of gradient descent and the least-squares method, consists of two alternating phases: (1) in the backward pass, the error signals recursively propagated backwards and the premise parameters are updated by gradient descent, and (2) least squares method finds a proper set of consequent parameters (Jang *et al*., 1997). In premise parameters set for a given fixed values, the overall output can be expressed as a linear combination of the consequent parameters.

$$AX = B \qquad (6)$$

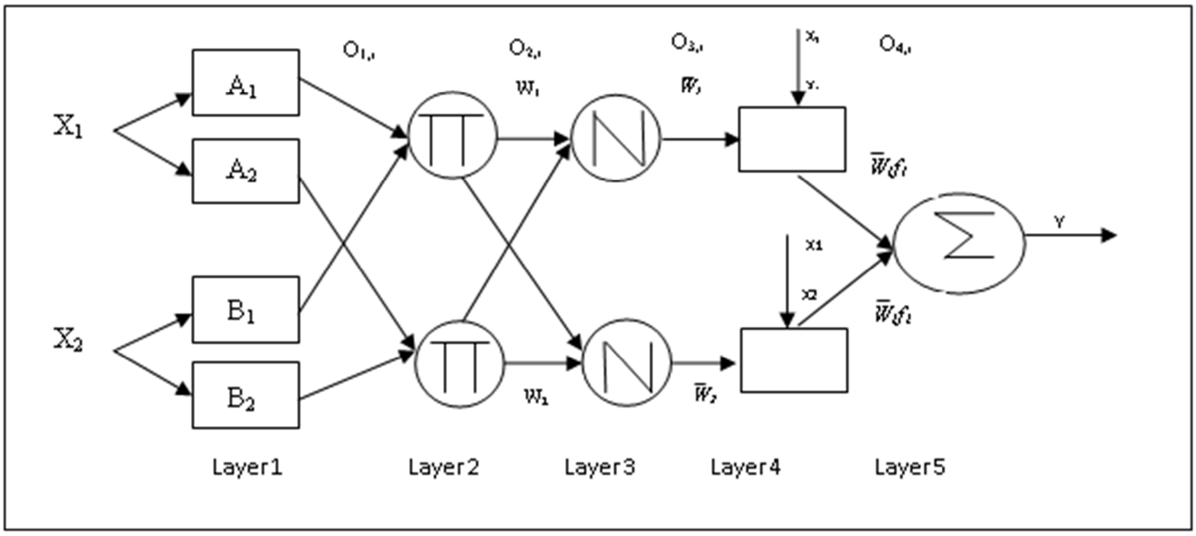

Figure 1.ANFIS architecture

Where, X is an unknown vector whose elements are the consequent parameters. A least squares estimator of X, namely X^*, is chosen to minimize the squared error $\|AX - B\|^2$. Sequential formulas are employed to compute the least squares estimator of X. For given fixed values of premise parameters, the estimated consequent parameters are known to be globally optimal.

Study Area and Model Application

Study area

Mean weekly maximum and mean weekly minimum temperature data of 10 years from 1997 to 2006 (520 weeks) taken from regional center of I.M.D. at Dehradun, India. Dehradun lies between 30° 19′ 48″ N latitude and 78° 3′ 36″ E longitudes and at an altitude of 733 meter having generally temperate climate. The area receives an average annual rainfall of 2073.3 mm and average annual minimum temperature is 13.3 °C and average annual maximum temperature is 27.8 °C respectively.

Model Application

After pre-processing of data set in desired time lag format, the selection of input and output variables for the models were done by taking different sets of training data for various input and time lag combinations. Combination for one week ahead predicting model with three input, one output was found best. For one week ahead prediction model, 400 weeks data were used in training and 117 weeks data in testing period respectively. The inputs for model were current week maximum mean weekly temperature $X_{max}(k)$, two week before maximum mean weekly temperature $X_{max}(k-2)$ and two week back mean minimum weekly temperature data $X_{min}(k-2)$ and result was current day mean weekly minimum temperature $X_{min}(k)$.

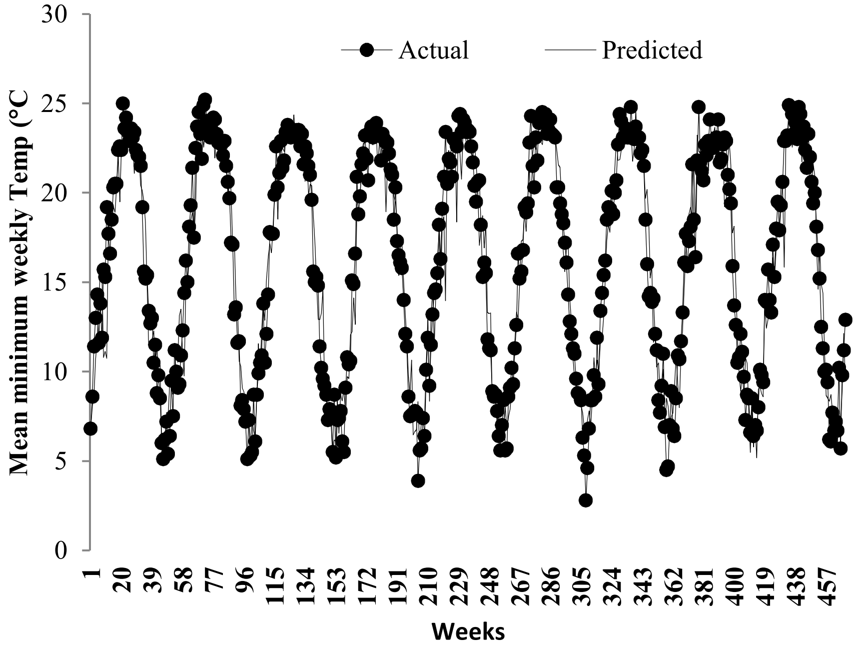

Figure 2.Observed and predicted weekly temperature during training period

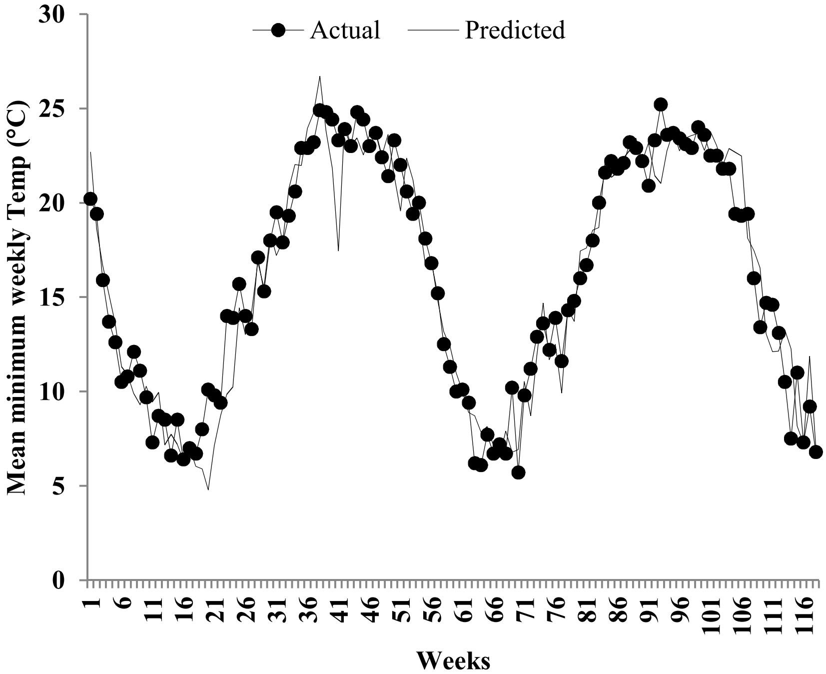

Figure 3.Observed and predicted weekly temperature during testing period

Result and Discussions

For this three inputs and one output model, four Bell-shaped Gauss types of membership functions were found suitable and hybrid learning algorithms method was used for the optimization. To judge the predictive capability of the developed methodology, based on ANFIS Model, the performance indicators show that root mean square error value is 1.25 for training and 1.76 for testing period, Coefficient of variation is 0.077 for training period and 0.109 for testing period and Coefficient of efficiency is 96.12 % for training and 91.63% for testing period.

Conclusions

The present study discusses the application and usefulness of adaptive neuro fuzzy inference system based forecasting approach for forecasting of minimum weekly temperature. The visual observation based on the graphical comparison between observed and predicted values and the qualitative performance assessment of the model indicates that ANFIS can be used effectively for minimum weekly temperature forecasting.

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