December, 2013

Temperature Forecasting Using Artificial Neural Networks (ANN)

Pankaj Kumar
Pradeep Singh Kashyap
Javed Ali, *G.B. Pant University of Agriculture & Technology, Pantnagar, India*

Journal of Hill Agriculture 4(2): 110-112, July – December, 2013

SHORT COMMUNICATION

Temperature forecasting using artificial neutral networks (ANN)

PANKAJ KUMAR • PS KASHYAP • JAVED

Received: Feb 5, 2013; Revised: June 22, 2013; Accepted: July 10, 2013

ABSTRACT The objective of this paper is to develop an artificial neural network (ANN) model which can be used to predict weekly mean temperatures in Pantnagar, Uttarakhand, India. In order to determine the optimal network architecture, various network architectures were designed; different training algorithms were used; the number of neuron and hidden layer and transfer functions in the hidden layer/output layer were changed. Training of the network was performed by using Levenberg–Marquardt feed-forward back-propagation algorithms. Root mean square error and correlation coefficient statistics was used to measure the performance of the models. The results show that the ANN approach is a steadfast model for weekly temperature prediction.

KEYWORDS Forecasting, temperature, artificial neural network

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, 2005). It was found that the non-linear operator equations governing the atmospheric system are the ones who can better understand the dynamics of atmosphere.

ANN was first introduced as a mathematical aid by (McCulloch et al. 1943). They were inspired by the neural structure of the brain. Fig. 1 is a general architecture of a Feed Forward ANN, with one hidden layer. Most ANNs have three layers or more: an input layer, which is used to present data to the network; an output layer, which is used to produce an appropriate response to the given input; and one or more intermediate layers, which are used to act as a collection of feature detectors. The ability of a neural network to process information is obtained through a learning process, which is the adaptation of link weights so that the network can produce an approximate output. In general, the learning process of an ANN will reward a correct response of the system to an input by increasing the strength of the current matrix of nodal weights.

There are several features in ANN that distinguish it from the empirical models. First, neural networks have flexible nonlinear function mapping capability which can approximate any continuous measurable function with arbitrarily desired accuracy, whereas most of the commonly used empirical models do not have this property. Second, being non-parametric and data-driven, neural networks impose few prior assumptions on the underlying process from which data are generated. Because of these properties, neural networks are less susceptible to model misspecification than most parametric nonlinear methods.

KUMAR PANKAJ • KASHYAP PS • JAVED

Department of Soil and Water Conservation Engineering, College of Technology, GB Pant University of Agriculture and Technology, Pantnagar, Uttarakhand - 263 145, India

PS Kashyap (✉)
E mail: pskashyap@yahoo.com

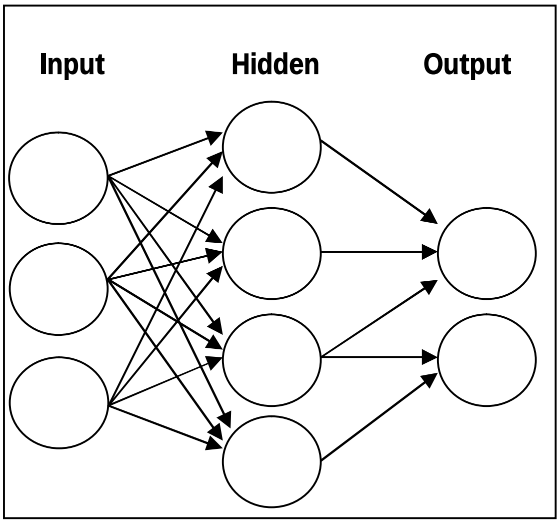

Fig 1 Architecture of multilayer feed forward neural network

There are a wide variety of algorithms available for training a network and adjusting its weights. In this study, an adaptive technique momentum Levenberg–Marquardt based on the generalized delta rule was adopted.

Let x_i (i = 1,2, ... n) are inputs and w_i (i = 1,2, ... n) are respective weights. The net input to the node can be expressed as

$$net = \sum_{i=1}^{n} x_i w_i \qquad (1)$$

The net input is then passed through an activation function f (.) and the output y of the node is computed as

$y = f(net)$

Sigmoid function is the most commonly used nonlinear activation function which is given by

$$y = f(net) = \frac{1}{1+e^{-net}} \qquad (2)$$

Throughout all ANN simulations, the adaptive learning rates were used for increasing the convergence velocity. For each epoch, if the performance decreases toward the goal, then the learning rate is increased by the factor of learning increment. If the performance increases, the learning rate is adjusted by the factor of learning decrement.

The weekly temperature data for the year 2002 to 2011 (520 weeks) were collected from Meteorological Observatory, GB Pant University of Agriculture and Technology, Pantnagar, District Udham Singh Nagar, India. Pantnagar falls in sub-humid and subtropical climatic zone and situated in *Tarai* belt of Shivalik range, of foot hills of Himalayas. Geographically it is located at 29°N latitude and 79.29°E longitude and an altitude of 243.84 m above mean sea level. Generally, monsoon starts in the last of June and continues up to September. The mean annual rainfall is 1364 mm of which 80-90 % occurs during June to September. May to June is the hottest months and December and January the coldest. The mean relative humidity remains almost 80-90 % from mid-June to February end.

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 six inputs, one output was found best. The inputs for model were one week back temperature X (k-1), two week before temperature X (k-2) , three week back weekly temperature data X (k-3), four week back weekly temperature data X (k-4), five week back weekly temperature data X (k-5) and six week back weekly temperature data X (k-6) and result was one week ahead temperature X (k).

Different Feed Forward ANN architectures were tried using these inputs and the appropriate model structures were determined for each input combination. Then, the ANN models were tested and the results were compared by means of correlation coefficient and root mean square error statistics. For one week ahead prediction model, 7 years data from 2002 to 2007 were used in training and last 3 years data of 2008 to 2011 were used in testing period respectively.

Various networks of single and two hidden layers were trained for a maximum iteration of 1500, with different combination of hidden neurons and the best suited network was selected based on the minimize values of mean square error (MSE), and maximum value of correlation coefficient (CC). For best fit ANN model in present study multilayer perceptron with two hidden layers and with sigmoid activation function was used as it works well for this data set. Levenberg-Marquardt back propagation algorithm was used to train the network for the temperature prediction model.

For this six inputs and one output model, 5 neurons in each hidden layer were found sufficient. The performance of the model was evaluated by comparing ordinates of observed and estimated evaporation graphs. The observed and estimated values of evaporation for training period (2002 to 2007) for selected network are depicted in Fig.2. The observed and the forecasted values of temperature during testing period (2008 to 2011) with selected network depicted in Fig. 3. It is observed from the figures that there is a close agreement between observed and forecasted values of weekly temperature. Thus, developed model may be regarded as satisfactory on the basis of the visual observations evaluation. To judge the forecasting capability of the developed methodology, based on ANN Model, the performance indicators show that mean square error value is 0.0028 for training and 0.0023 for testing period, Correlation coefficient is 0.967 for training period and 0.975 for testing period respectively.

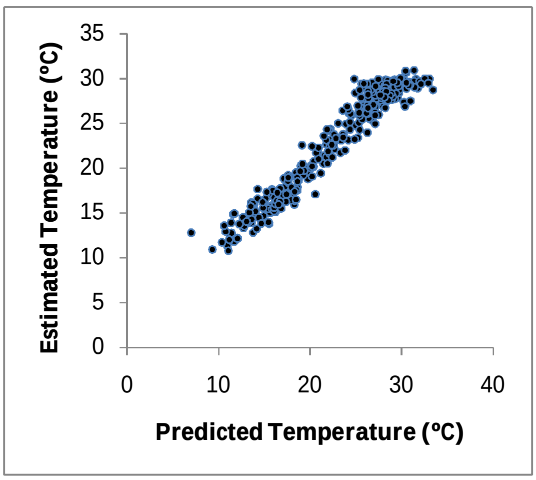

Fig 2 Observed and forecasted weekly temperature during training period

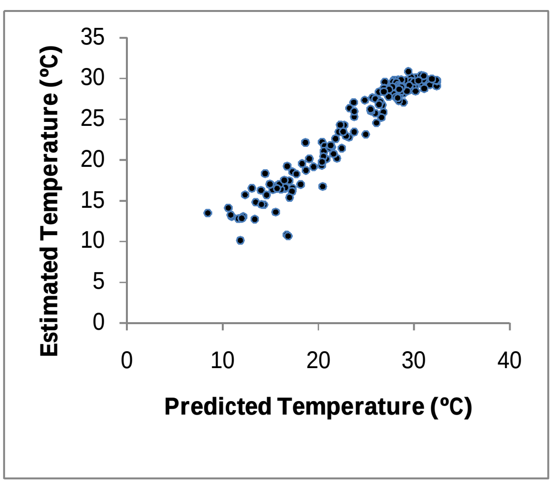

Fig 3 Observed and forecasted weekly temperature during testing period

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

REFERENCE

Nayak PC, Sudheer KP, Rangan DM, Ramasastri KS 2004. A neuro-fuzzy computing technique for modelling hydrological time series. J Hydrol 291: 52-66.

Nayak PC, Sudheer KP, Rangan DM, Ramasastri KS 2005. Short term flood forecasting with a neurofuzzy model. Water Resourc Res 41:2517–2530.

Pal NR, Pal S, Das J, Majumdar K 2003. SOFM-MLP - a hybrid neural network for atmospheric temperature prediction, IEEE Transac Geosci Remote Sensing 41:2783-2791.

McCulloch WS, Pitts W 1943. A logic calculus of the ideas immanent in nervous activity. Bull Mathematical Biophy 5: 115-133.