On a Neurocomputing based predictive model forecasting the Winter Shower in India

S. S. De, B. Bandyopadhyay, Goutami Chattopadhyay, Suman Paul, and D. K. Sinha

Centre of Advanced Study in Radio Physics and Electronics, University of Calcutta
1, Girish Vidyaratna Lane, Kolkata- 700 009, India
e-mail: de_syam_sundar@yahoo.co.in

Abstract

The development of a neurocomputing technique to forecast the average winter shower in India has been modeled from 48 years of records (1950 to 1998). The complexities in the rainfall-sea surface temperature relationships have been statistically analyzed along with the collinearity diagnostics. Presence of multicollinearity has been revealed and a variable selection has been executed accordingly. Absence of persistence is also exhibited. For this reason, Artificial Neural Net Model as predictive tool for the said meteorological event in the form of Multiple Layer Perceptron has been generated with sea surface temperature anomaly and monthly average winter shower data over India during the above period. After proper training and testing, a Neural Net model with small prediction error is developed and supremacy of Artificial Neural Net over conventional statistical predictive procedure has been established statistically.

1. Introduction

It is widely accepted that the climate and its variability are the result of a complex system of air-sea interactions and atmosphere-ocean feedbacks [1]. Sea Surface Temperature (SST) anomalies influence the atmosphere by altering the flux of latent heat and sensible heat from the ocean. The changes in SST influence the large-scale atmospheric circulation, which in turn influences the rainfall [2]. El-Niño-Southern Oscillation (ENSO) is a coupled Ocean-atmosphere phenomenon that has worldwide impact on climate in general and Indian monsoons in particular [3].

The winter or northeast monsoon rainfall, which occurs mainly from October to December, is dominant over southern peninsular India. Several works have already been done on the prediction of summer monsoon over India using artificial neural network (ANN) and regression techniques. However, less number of works is available on the prediction of winter monsoon rainfall over India. Bhanu Kumar *et al.* [4] established a possible link between mean September upper-air temperatures at Indian stations and the following winter monsoon rainfall over southern India where the winter monsoon accounts for a large percentage of mean annual rainfall. The ANN, which is particularly useful when the underlying physical processes are not fully understood or display chaotic properties has not been attempted to forecast the winter-monsoon rainfall in India. In a study by Chattopadhyay *et al.* [5], neural network was attempted to forecast the winter monsoon with SST anomalies are predictors. The present paper differs from the said paper in the sense that, a stepwise variable selection procedure has been adopted and subsequently different ANN models have been generated with variable number of inputs. This method is expected to enhance the quality of prediction.

Here, the time series pertaining to the winter-shower over the study zone has been first viewed for its non-stationarity and associated non-persistence over time. ANN model has been generated as multi layer perceptron (MLP) in a multivariate environment. The outcome of this model work has been compared with conventional multiple linear regression (MLR). It has been observed that an ANN model in the form of MLP shows lower prediction error than the forecast produced by MLR.

2. Data

The monthly average winter (November-January) shower data from 1950 to 1998 have been collected from the Indian Institute of Tropical Meteorology (IITM) rainfall data series available at www.tropmet.res.in. In the study period, the time series for the predictors and the predictor would consist of 48 data points. For example, time series

978-1-4244-5118-0/11/$26.00 ©2011 IEEE

of SST anomaly for November would contain successive SSTs in November during the period from 1950 to 1997. To have a clear pattern of the data under consideration the auto correlation function (ACF) of the predictors and the predictand have been calculated from the following equation [6]

$$r_k = \frac{Co\,\mathrm{var}\,iance\left[\left(\bar{x}(n-k)\right),\left(\underset{-}{x}(n-k)\right)\right]}{\sqrt{Variance\left(\left(\bar{x}(n-k)\right)\right)}\sqrt{Variance\left(\left(\underset{-}{x}(n-k)\right)\right)}} \tag{1}$$

Although the autocorrelation coefficients for the rainfall time series indicate that there is no persistence over time, the past values of rainfall time series have been considered as predictors for the future values of rainfall. This has been done because of the capability of ANN in predicting a variable with low correlated predictors. To generate the ANN model, all the data are scaled to provide values between 0.1 and 0.9 as follows:

$$z_i = 0.1 + 0.8\times\left(\frac{x_i - x_{\min}}{x_{\max} - x_{\min}}\right) \tag{2}$$

After the modeling is completed, the scaled data are reverse scaled according to

$$P_i = x_{\min} + \left(\frac{1}{0.8}\right)\times\left[(y_i - 0.1)\times(x_{\max} - x_{\min})\right] \tag{3}$$

where, P_i denotes the prediction in original scale. This transformation is performed to get rid of the asymptotic effect arising from the sigmoid activation function to be used in the ANN model. The training of the data is done by Back propagation method:

$$y_d = f_d\left(x_1, x_2, x_3, x_4, x_5, x_6\right) \tag{4}$$

where, $x_1, x_2, ...x_6$ represent the six predictors and y_d is the predictand. Percent error of the prediction (PE) has been computed through,

$$PE = \frac{\left\langle\left|y_{predicted} - y_{actual}\right|\right\rangle}{\left\langle y_{actual}\right\rangle} \tag{5}$$

3. Methodology

An initial weight vector w_k of a feed forward neural network is iteratively adopted according to the recursion,

$$w_{k+1} = w_k + \eta d_k \tag{6}$$

where, w_j denotes the weight vector at the jth step. The quantity η is called the learning rate. Mathematically d_k is expressed as,

$$d_k = -\nabla E(w_k) \tag{7}$$

The weight vector w_k contains the weights computed during the kth iteration and the output error function *E* is the multivariate function of the weights of the network, i. e.,

$$E(w_k) = E_p(w_k) \tag{8}$$

where $E_p(w_k)$ represents the half-sum-of-squares error function of the network outputs for a certain input pattern p. The learning continues until *E* is less than a present value at the end of an epoch.

In equation (1), if the function f_d is nonlinear, then non-linear perceptron is achieved. For a good fitting of data a set of hidden nodes $z_{dk}\left(k = 1,2,.................., n\right)$ is introduced in such a way that,

$$z_{dk} = f(w_{dk_1}x_1 + ... + w_{dk_{24}}x_{24} + w_{dk_0})\text{ , and} \tag{9}$$

$$y_d = f\left(v_1 z_1 + ... + v_{d_n} z_d + v_{d0}\right) \tag{10}$$

The transfer function f is defined as, $$f(z)=\frac{1}{1+\exp(-z)} \tag{11}$$

To implement the ANN methodology in the present problem, the entire dataset under study is divided into two subsets, namely the training set and the test set. In the ANN literature, an exhaustive variable selection is recommended to get a better performance when the problem is a multivariate prediction. Sigmoid function given by equation (11) is used as activation function in both hidden and output layer. Minimization of mean squared error (MSE) has been chosen as the stopping criterion in all models.

4. Results and comparison

We have implemented ANN model learned through adaptive gradient. Three ANN models have been generated. The model performance is enhanced by variable selection from a given set of predictors. The prediction errors (PE) are presented in Figure 1. It is revealed in this figure that the ANN with selected variables and learned with first 70% of the data as the training data, performs the best among all the proposed models. As a further support to the results, a line diagram, showing the actual and predicted time series is presented in Figure 2. This figure shows that outputs from the model 2 (that produced lowest prediction error) are most closely associated with the observed values of the winter rainfall. In Figure 3, we have presented the line diagram showing the actual winter rainfall and those predicted by multiple linear regression. It should be noted that PE for the best ANN model, that is, the ANN with selected variables and learned with first 70% of the data as the training data, has significantly lower PE (0.1733). This indicates the variable selection has enhanced the quality of prediction.

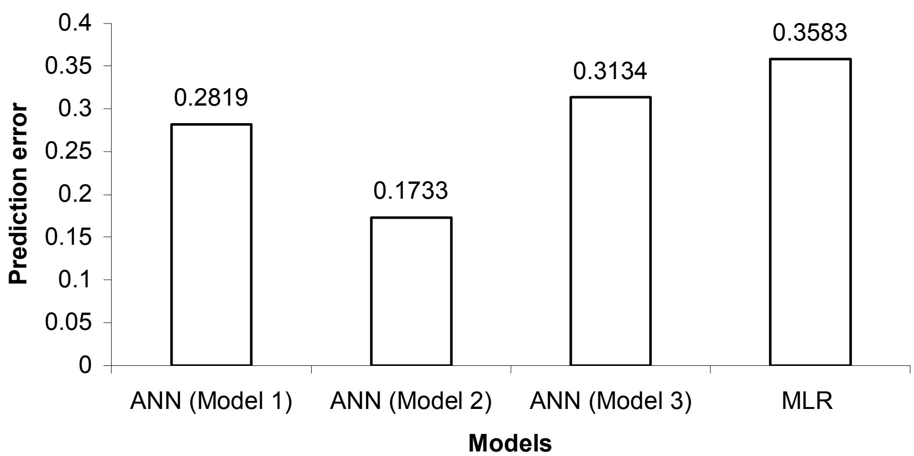

Figure 1. This figure compares the prediction errors (PE) produced by two competitive models in predicting average winter shower over India. The computation is made over the test cases.

5. Conclusion

It is found that the best model from the given study is the ANN model, where the first 70% of the data constitute the training set for adaptive gradient learning, and the final architecture contains 5 input nodes, 19 hidden nodes, and 1 output node. In the present paper, the basic purpose was to forecast the winter, i. e., the north-east-monsoon rainfall over India using low correlated and limited number of predictors instead of using a large set of meteorological parameters having strong physical relationship with the occurrence of rainfall.

6. Acknowledgments

This work is funded by Indian Space Research Organization (ISRO) through S K Mitra Centre for Research in Space Environment, University of Calcutta, Kolkata, India.

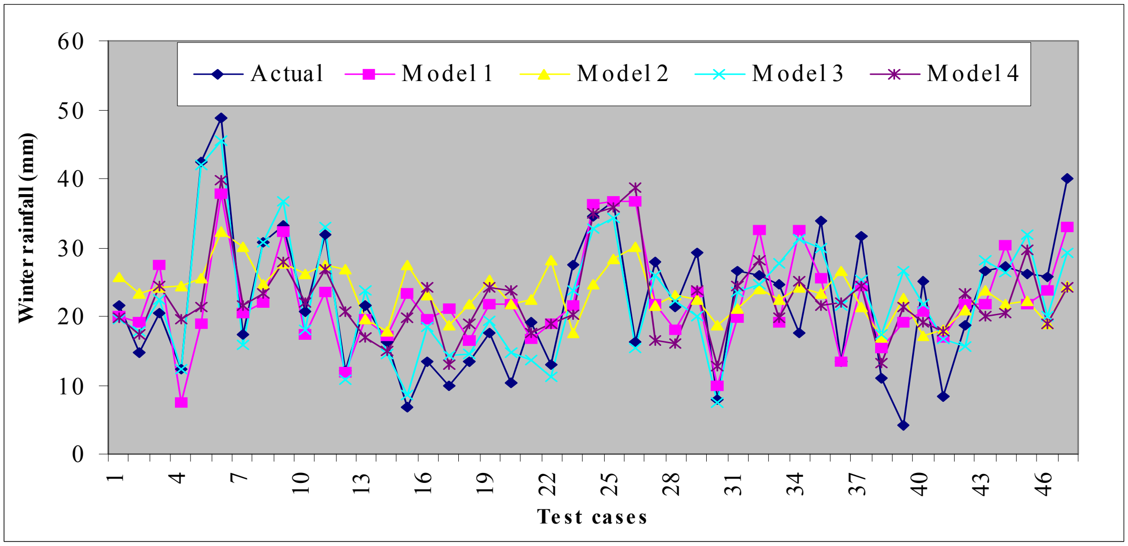

Figure 2. Actual winter rainfall time series and the predictions from different ANN models pertaining to the test cases under consideration

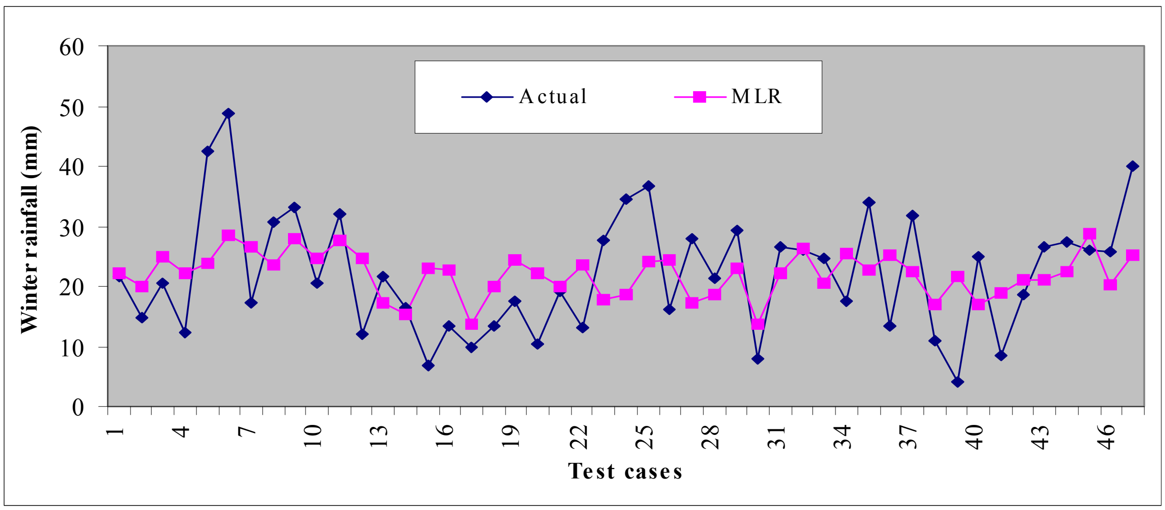

Figure 3. Actual winter rainfall time series and the predictions from multiple linear regression (MLR)

7. References

1. B. Wang, R. Wu, and T. Li, „Atmosphere–Warm Ocean Interaction and Its Impacts on Asian–Australian Monsoon Variation," *J. Clim.,* **16**, 2003, pp. 1195-1211.

2. R. Maity, and D. Nagesh Kumar, "Hydroclimatic teleconnection between global sea surface temperature and rainfall over India at sub divisional monthly scale," *Hydrological Processes,* **21**, 2007, pp. 1802-1813.

3. B. Kumar, "Impact of ENSO on Winter Monsoon Rainfall over South India," *Geophys. Res. Abstract,* **7,** 2005.

4. O. S. R. U. Bhanu Kumar, C. V. Naidu, S. R. L. Rao, and B. R. S. Rao, "Prediction of southern Indian winter monsoon rainfall from September local upper-air temperatures," *Met. Apps.,* **11**, 2004, pp. 189-199.

5. G. Chattopadhyay, S. Chattopadhyay, and R. Jain, "Multivariate forecast of winter monsoon rainfall in India using SST anomaly as a predictor: Neurocomputing and statistical approaches," *arXiv:0910.5296*, 2009.

6. D. S. Wilks, "Statistical Methods in Atmospheric Sciences," *Academic Press,* USA, 1995.