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A Supervised Neural Network Model for Predicting Average Summer Monsoon Rainfall in India

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SUMMARY

Present study aims to develop a predictive model based on artificial neural network (ANN) for the average summer monsoon rainfall amount over India. The dataset made available by the Indian Institute of Tropical Meteorology, Pune, was explored. To develop the predictive model, Backpropagation method with scaled conjugate gradient descent algorithm has been implemented. The ANN model with the said algorithm has been trained thrice to reach a good result. After three runs of the model, it is found that a high prediction yield is available. Finally after rigorous assessment by Willmott's index, ANN with scaled conjugate gradient descent based Backpropagation algorithm was found to be skillful in predicting average summer monsoon rainfall amount over India. It has been found to be more skillful than non-linear regression in the said prediction task.

Keywords: Summer monsoon rainfall, Scaled conjugate descent, Artificial neural network, Prediction, Non-linear regression.

1. INTRODUCTION

Artificial neural networks (ANN) are parallel computational models; comprising closely interconnected adaptive processing units. The important characteristic of neural networks is their adaptive nature, where 'learning by example replaces programming'. This feature makes the ANN techniques very appealing in application domains for solving highly non-linear phenomena. During last four decades, various complex problems like weather prediction, stock market prediction etc. has been proved to be areas with ample scope of application of this sophisticated mathematical tool. A multilayer neural network can approximate any smooth, measurable function between input and output vectors by selecting a suitable set of connecting weights and transfer functions. Silverman and Dracup (2000) identified the advantages of ANN over conventional statistical methods as:

- A priori knowledge of the underlying process is not required.
- Existing complex relationships among the various aspects of the process under investigation need not be recognized.
- Constraints and a priori solution structures are neither assumed nor enforced.

Weather forecasting is one of the most urgent and challenging operational responsibilities carried out by meteorological services all over the world. It is a complicated procedure that includes numerous specialized fields of know-how (Gregory *et al*. 1993). Several authors (*e.g*. Brown and Murphy 1998; Wilks

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1991, 1998) have discussed the uncertainty associated with the weather systems. Chaotic features associated with the atmospheric phenomena also have attracted the attention of the modern scientists (Men *et al*. 2004; Sivakumar *et al*. 1999; Sivakumar 2001, 2004). Different scientists over the globe have developed stochastic weather models which are basically statistical models that can be used as random number generators whose output resembles the weather data to which they have been fit (Wong *et al*. 2003).

Amongst all weather happenings, rainfall plays the most crucial role in human life. Human civilization to a great degree depends upon its frequency and amount to various scales (Gadgil *et al*. 2005; Guhathakurata 2006). Several stochastic models have been attempted to forecast the occurrence of rainfall, to investigate its seasonal variability, to forecast monthly/yearly rainfall over some given geographical area. Daily precipitation occurrence has been viewed through Markov chain by Chin (1977). Gregory *et al*. (1993) applied a chain-dependent stochastic model, named as Markov chain model to investigate inter annual variability of area average total precipitation. Wilks (1998) applied mixed exponential distribution to simulate precipitation amount at multiple sites exhibiting realistic spatial correlation. Hu (1964) initiated the implementation of ANN in weather forecasting. Since the last few decades, voluminous development in the application field of ANN has opened up new avenues to the forecasting task involving atmosphere related phenomena (Gardner and Dorling 1998; Hsieh and Tang 1998; Wong *et al*. 1999). Michaelides *et al*. (1995) compared the performance of ANN with multiple linear regressions in estimating missing rainfall data over Cyprus. Kalogirou *et al*. (1997) implemented ANN to reconstruct the rainfall time series over Cyprus. Lee *et al*. (1998) applied Artificial Neural Network in rainfall prediction by splitting the available data into homogeneous subpopulations.

Despite so much of emphasis given to the application of ANN in prediction of different weather events all over the globe, Indian meteorological forecasters did not put much precedence on the application this potent mathematical tool in atmospheric prediction. Authors of the present papers think that summer monsoon rainfall, a highly influential weather phenomenon in Indian agro economy, may be an area that can be immensely developed with application of ANN.

Perusal of literatures reveals a report on the prediction of Indian summer monsoon rainfall using ANN. Navone and Ceccatto (1994) implemented ANN method to Indian monsoon rainfall time series using preseason predictors and derived better forecast than conventional approach. Sahai *et al.* (2000) applied backpropagation ANN to predict the average summer monsoon rainfall amount in India with previous five years data as predictors. Philip and Joseph (2003) filtered out the chaotic part of the rainfall pattern over Kerala, a region in the southern peninsula of India, using a new kind of neural network known as the adaptive basis function network, and revealed that performance of that ANN was better than existing methods to understand the long-term behavior of rainfall phenomena. Chattopadhyay (2007) implemented a feed forward ANN with one hidden layer to forecast average summer monsoon over India and established that it was giving a better forecast than multiple linear regression and persistence forecast. Chattopadhyay and Chattopadhyay (2008) compared various hidden layer sizes for an MLP with classical backpropagation learning and established suitability of MLP over regression approach in predicting monsoon rainfall time series over India.

2. MOTIVATION

Agriculture is the backbone of India's economy. Its contribution to the GDP has declined from 57% in 1950-51 to around 28% (1998-99) due primarily to growth in other sectors of the economy (Krishna Kumar *et al.* 2004). The declining share of agricultural sector, however, did not affect the importance of the sector in Indian economy. The growth of GDP has largely been determined by the trend in agricultural production. Its impact on the welfare of the country is much greater than the macroeconomic indicators suggest, as nearly 70% of the working population depends on agricultural activities for their livelihood. More than 60% of the cropped area in India still depends solely on monsoon rainfall (Krishna Kumar *et al.* 2004). Studies by several authors have shown that during last century there is observed increasing trend in surface temperature, no significant trend in rainfall on all India basis, and decreasing/increasing trends in rainfall in regional basis (Mall *et al.* 2006).

Mall *et al.* (2006) presented an overview of the state of the knowledge of possible effect of the climate variability and change on food grain production in India. The onset of the southwest monsoon in India is expected in June or July, depending on location. The highest concentration of rain fed agriculture occurs in western and southern oilseed, grain, and cotton areas and in the East, where much of the rice is rain fed. An extensive review of the impact of climate on the Indian agriculture has been made by Krishna Kumar (2004). There is increasing recognition amongst many in the scientific community that the components of the Earth System are intimately connected, and that interactions extend from local to global scales (Douglas *et al.* 2006). Traditionally, the effects of changes in atmospheric composition (*i.e.*, increased CO_2 concentrations) on land processes has been investigated with regional to global general circulation models, a so-called "top down" approach that does not always sufficiently simulate the linkages and non-linear responses of land-atmosphere interactions (Douglas *et al.* 2006). Parthasarathy *et al.* (1988) presented a regression model for estimation of Indian foodgrain production from summer monsoon rainfall. Considering the literature surveyed above the authors felt the necessity of developing an ANN based model for Indian summer monsoon rainfall in the yearly scale.

3. METHODOLOGY

3.1 Prediction by ANN

This paper develops ANN model step-by-step to predict the average rainfall over India during summer-monsoon by exploring the data available at the website http://www.tropmet.res.in published by Indian Institute of Tropical Meteorology, Pune. The problem discussed in this paper is basically a predictive problem. Here, four predictors have been used with one predictand. The four predictors are

- Homogenized Indian rainfall in June
- Homogenized Indian rainfall in July
- Homogenized Indian rainfall in August
- Homogenized average summer-monsoon rainfall in India

All these four predictors are considered for the year Y to predict the average summer-monsoon rainfall in India in the year $(Y + 1)$. The whole data set comprises the rainfall data of the years 1871-1999. The autocorrelation function for the time series pertaining to this data is presented in Fig. 1 and it is observed that

- The autocorrelation function has no sinusoidal pattern
- The autocorrelation function does to tend to 0
- The autocorrelation coefficients lie between –0.2 and 0.2

Thus the time series has no persistence or stationarity. Thus, ANN may be proposed for its prediction because of its ability to deal with complex and non-linear situations. Other statistical parameters are also calculated and the detailed statistics of the data are given in Table 1.

Table 1. Detailed statistical properties of the time series pertaining to average rainfall over India in the summer monsoon months

Statistics	June	July	August
Mean	127.57	259.47	223.45
Median	128.50	256.10	221.00
Mode	177.10	251.60	168.60
Standard Deviation	43.74	56.81	59.52
Sample Variance	1912.81	3227.55	3542.77
Kurtosis	–0.58	0.37	–0.76
Skewness	0.04	–0.32	0.16
Range	196.80	294.20	256.70
Minimum	30.00	94.50	88.80
Maximum	226.80	388.70	345.50
Sum	16456.60	33471.20	28824.70
Count	129.00	129.00	129.00
Largest(1)	226.80	388.70	345.50
Smallest(1)	30.00	94.50	88.80

Currently, the MLPs are most commonly seen in speech recognition, image recognition, and machine translation software, but they have also seen applications in other fields such as cyber security. In general, their most important use has been in the growing field of artificial intelligence, although the multilayer perceptron does not have connections with biological neural networks as initial neural based networks have. Several conjugate gradient algorithms are there in the literature of ANN learning.

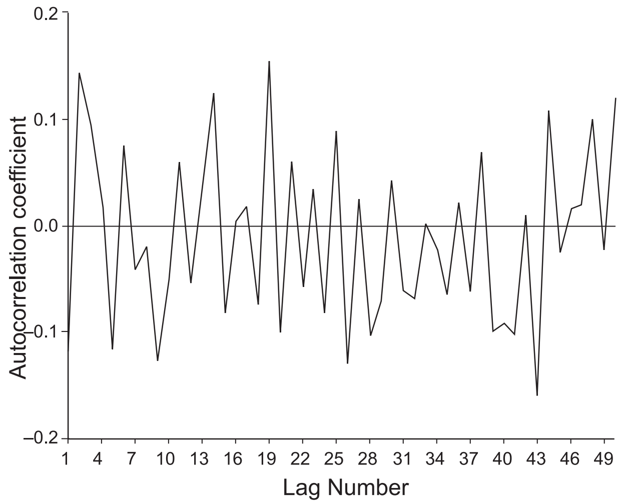

Fig. 1. Auto correlation function for the average summer monsoon rainfall time series.

In the present paper, an ANN based predictive model is developed for the homogenized average monsoon rainfall using the Backpropagation learning through the method of scaled conjugate gradient descent (CGD). Johansson *et al*. (1990) describes in detail the theory of general conjugate gradient methods and how to apply the methods in feed-forward ANNs. Møller (1993) introduced a variation of a conjugate gradient method (Scaled Conjugate Gradient, SCG), which avoids the line-search per learning iteration by using a Levenberg-Marquardt approach in order to scale the step size. The Conjugate Gradient (CG) methods choose the search direction and the step size more carefully by using information from the second order approximation (Møller 1993)

$$E(w+y) \approx E(w) + E'(w)^T y + \frac{1}{2} y^T E''(w) y \quad (1)$$

where, w is the weight vector, which is a vector in the real Euclidean space R^N, where N is the number of weights and biases in the network. A basis of R^N is chosen as the conjugate system $\{p_1, p_2, ..., p_N\}$. In SCG, a Lagrangian multiplier λ_k was introduced by Møller (1993) to regulate the indefiniteness of the Hessian matrix $E^n(w)$ and the second order information was set as

$$s_k = \frac{E'(w_k + \sigma_k p_k) - E'(w_k)}{\sigma_k} + \lambda_k p_k,$$

$$\text{where, } 0 < \sigma_k << 1 \quad (2)$$

Since its introduction, the SCG has been used in several ANN applications to geophysical problems (Abraham and Nath 2001; Khan and Coulibaly 2006). It should be further mentioned that the application of CG learning based backpropagation method is not new in hydrological time series forecasting. Chiang *et al*. (2004) implemented CG and demonstrated its superiority over classical backpropagation approach in rainfall-runoff modeling. Cigizoglu and Kisi (2005) implemented CG algorithm in river flow forecasting.

In this implementation, sigmoid activation function ($f(x) = (1 + \exp(-ax))^{-1}$) is used to execute the learning. Prior to the implementation, the raw data are converted to [0.1, 0.8] to avoid the asymptotic effect

$$x_{\text{transformed}} = 0.1 + 0.8 \times \left(\frac{x_{actual} - x_{min}}{x_{max} - x_{min}} \right) \quad (3)$$

The whole dataset is divided into training and test sets. The first 75% of the whole dataset is taken as the training set and the last 25% of the data are taken as the test set. Using Conjugate gradient descent Descent algorithm, the data are trained three times up to 1000 epochs. After training the ANN is tested over the test set. The association between the actual and predicted rainfall amounts for the test cases presented as line plot in Fig. 2. The percentage errors of prediction are presented in Fig. 3. It is observed that in 7 out of these 28 cases, the prediction error is below 5%, and in 17 test cases the error is below 10%. This means that if 10% error is allowed, then prediction yield is 0.61. But, it is further observed that in the years 1972, 1974, and

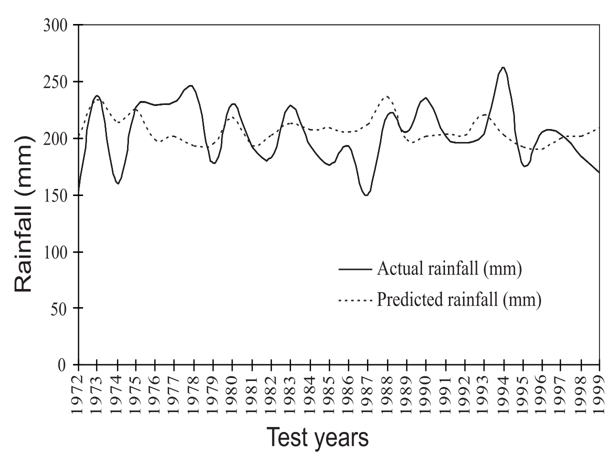

Fig. 2. Line diagram showing the actual and predicted summer monsoon rainfall obtained by backpropagation neural network trained through scaled conjugate gradient descent. This figure displays the test cases.

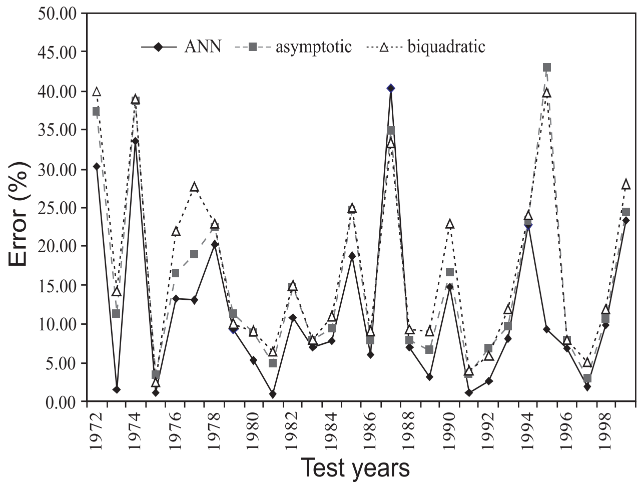

Fig. 3. Percentage errors of prediction for the three competitive models.

1987 the prediction errors are too high (above 30%). Now, the results are viewed statistically. Using the formula for overall prediction error (PE) percentage computed as

$$\text{PE} = \frac{\left\langle \left| x_{predicted} - x_{actual} \right| \right\rangle}{\left\langle x_{actual} \right\rangle} \tag{4}$$

The symbol ⟨ ⟩ implies the average over the test cases. The ANN model presented above is found to produce a prediction error (PE) 10.21% for the test cases. Thus, it can be said that the overall performance of the model is acceptable. But, it has failures too. This might have occurred due to absolute lack of persistence in the dataset as explained through autocorrelation structure.

3.2 Prediction by Regression

In this section a non-linear regression model are developed and their predictive abilities are compared with that of ANN. The non-linear regression equations are formed as biquadratic regression and exponential regression. The regression equations are found to be as follows:

$$\hat{Y}(n+1) = a + b^* \text{ June}(n) + c^* \text{ (July}(n))^2 + d^* \text{ (August }(n))^3 + e^* \text{ (Average }(n))^4 \tag{5}$$

$$\hat{Y}(n+1) = a^*\exp(b^*\text{June}(n)) + c^*\exp(d^* \text{ July}(n)) + e^*\exp(f^*\text{July}(n)) + g^*\exp(h^*\text{Average}(n)) \tag{6}$$

The $\hat{Y}(n+1)$ in the left hand side is the estimated predictand, where the variables are the same as in the ANN. The same sets of training and test data sets are chosen for the regressions presented in the last two equations. The regression coefficients are initialized at 0.001. The regression parameters and constants derived above are now presented to the test sets and the corresponding predicted values are obtained.

3.3 Statistical Skill Assessment

In the present paper the comparison is made with both asymptotic regression and biquadratic regression models. When the percentage errors of prediction from the asymptotic regression and biquadratic regression models are compared, it is found that asymptotic regression performs significantly better than biquadratic regression as far as percentage error of prediction in the individual test cases is concerned. Now, a closer look is given to the bar diagram of Fig. 3. In the test cases numbered 3 and 24 the error percentages produced by asymptotic regression are the highest among all the error percentages produced by all the models in the test cases. Therefore, in spite of better prediction performance by asympototic regression than biquadratic regression in some test cases, the overall comparison requires some other statistical tools used in judging prediction models.

Willmott (1982) advocated an index to measure the degree of agreement between actual and predicted values. This is given as:

$$d = 1 - \left[\sum_i \left| P_i - O_i \right|^2 \right] \left[\sum_i \left(\left| P_i - \bar{O} \right| + \left| O_i - \bar{O} \right| \right)^2 \right]^{-1} \tag{7}$$

The index (d) is a descriptive measure, and it is both a relative and bounded measure, which can be widely applied in order to make cross comparison between models (Willmott 1982). Willmott's index d is calculated for the scaled CGD based ANN model and the regression models as well. It is found that for scaled CGD based ANN model, the value of d is 0.49, for asymptotic regression it is 0.43, and for biquadratic regression it is 0.22. Thus, it is found that the maximum degrees of agreement between predicted and observed average rainfall amounts are occurring for scaled CGD based ANN and asymptotic regression respectively. Thus, on the basis of Willmott's index, it can be said that scaled CGD based ANN and asymptotic regression models are almost equally skillful in predicting average summer monsoon rainfall in India with one-year lead-time. Now, PE is computed for both of the regression models and for asymptotic and biquadratic regression they come out to be 18.01% and 22.34% respectively. Both of the values are significantly greater than the PE (10.21%) produced by ANN model. Thus, as far as PE is concerned, ANN with scaled CGD learning can be identified as a better predictive model than the proposed regression models.

4. CONCLUSION

In the study presented above, the possibility of predicting the average summer-monsoon rainfall amount has been judged using three predictive problems. First of all, the autocorrelation structure of the average monsoon rainfall time series has been analyzed. It has been proved by the small autocorrelation values that the monsoon rainfall time series is not characterized by serial dependence. The neural network based predictive methodology has been adopted with scaled conjugate gradient descent learning. To compare the performance with statistical methodologies, the biquadratic and asymptotic regressions have been implemented as competing predictive tools. All of these three predictive models have been trained and tested over the same sets of data. The average monsoon month rainfall amounts of a given year have been used as predictors to forecast the average summer monsoon rainfall of the next year. After appropriate training and testing, the results have been assessed statistically to view the relative potential of the predictive models. Observing the percentage errors of prediction for the test cases, it has been understood that the scaled conjugate gradient descent learning based backpropagation neural network is producing less errors than the biquadratic and asymptotic regression models in maximum number of cases. The overall prediction error and Willmott's index computed over the entire test set further support the better prediction performance of the scaled conjugate gradient descent learning based backpropagation neural network.

Thus, the final conclusion is that the conjugate gradient descent learning based backpropagation neural network is a better predictive model than the regression techniques in predicting the average summer monsoon rainfall amount with one-year lead time. But, the model is still not up to the mark in its prediction capacity.

In the test years of 1972, 1977 and 1984, the prediction errors are above 40%. Whereas, in the test years of 1973, 1975, 1978, 1979, 1980, 1983, 1984, 1986, 1988, 1989, 1994, 1995, 1996 and 1998, the prediction errors are below 10%. It is, therefore, understandable that in spite of high prediction capacity of the proposed ANN model, it failed to create a good forecast in a few cases. However, in all of the cases, the prediction errors are below the corresponding prediction errors produced by asymptotic and biquadratic regressions. To get rid of the high prediction errors, the ANN model may be further improved by means of incorporation other soft computing tools. This may be proposed as a future study.

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