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Comparative study among different neural net learning algorithms applied to rainfall time series

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ABSTRACT: The present article reports studies to identify a non-linear methodology to forecast the time series of average summer-monsoon rainfall over India. Three advanced backpropagation neural network learning rules namely, momentum learning, conjugate gradient descent (CGD) learning, and Levenberg–Marquardt (LM) learning, and a statistical methodology in the form of asymptotic regression are implemented for this purpose. Monsoon rainfall data pertaining to the years from 1871 to 1999 are explored. After a thorough skill comparison using statistical procedures the study reports the potential of CGD as a learning algorithm for the backpropagation neural network to predict the said time series. Copyright © 2008 Royal Meteorological Society

KEY WORDS multilayer perceptron; backpropagation learning; momentum; conjugate gradient descent; Levenberg–Marquardt; asymptotic regression; monsoon rainfall

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1. Introduction

In the last few decades, ideas from the theory of non-linear dynamical systems and chaos have been applied to various atmospheric problems (e.g. Fraedrich, 1986; Elsner and Tsonis, 1992; Tsonis *et al.*, 1993; Varotsos, 2005; Chattopadhyay and Chattopadhyay, 2007 and many others). Limitations of numerical weather predictions (Richardson, 1922), the foremost conventional methodology of atmospheric prediction, have been discussed by Thompson (1957), Mary Selvam (1988) and Maqsood *et al.* (2002) in the context of intrinsic chaos of atmospheric phenomena. Mathematical tools based on theoretical concepts underlying the methodologies for detection and modeling of dynamical and chaotic components within hydrological time series have been studied extensively by various scientists such as Islam and Sivakumar (2002), Khan *et al.* (2005) and Jayawardena and Lai (1994). Phase space reconstruction and artificial neural networks (ANN) are non-linear predictive tools that have been proposed in modern literature as potent mathematical methodologies to be applied to hydrological time series characterized by chaotic features (Elsner and Tsonis, 1992; Khan *et al.*, 2005 and references therein). Several studies have identified the existence of deterministic chaos within rainfall time series (e.g. Rodriguez–Iturbe *et al.*, 1989; Sharifi *et al.*, 1990). Applications of fractal theory to rainfall-time series conducted thus far have produced positive evidence regarding the existence of fractal behaviour in rainfall-time series (Sivakumar, 2001).

In recent times, the competence of ANN (Rojas, 1996) in forecasting chaotic time series has been established by several authors (e.g. Principe *et al.*, 1992; Oliveira *et al.*, 2000; Silverman and Dracup, 2000). Prediction of atmospheric events, especially rainfall, has benefited significantly by voluminous developments in the application field of ANN, and rainfall events and quantities have been predicted statistically (e.g. DelSole and Shukla, 2002; Mohanty and Mohapatra, 2007). The advantages of ANN over traditional statistical and numerical weather prediction approaches have been discussed by McCann (1992); Kuligowski and Barros (1998) and Silverman and Dracup (2000). Several research papers are available where the suitability of the ANN approach has been established quantitatively over conventional statistical rainfall prediction procedures (e.g. Hastenrath *et al.*, 1995; Toth *et al.*, 2000; Ramirez *et al.*, 2005; Chattopadhyay, 2007).

The Indian economy is based on agriculture, and the summer monsoon (June, July, and August) is the period which is of highest importance for agricultural practices. Considering the significance of monsoon rainfall in this country, various attempts have been made to develop predictive models using statistical procedures (e.g. Hastenrath, 1988; DelSole and Shukla, 2002; Mohanty and Mohapatra, 2007). During the last two decades ANN has been put into practice by some authors to forecast monsoon rainfall over India. Navone

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and Ceccatto (1994) implemented an ANN method to Indian monsoon rainfall time series using pre-season predictors and derived better forecasts than conventional approaches. Sahai *et al.* (2000) applied backpropagation ANN to predict the average summer-monsoon rainfall amount in India with data from the previous five years 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 the performance of the ANN was better than existing methods to understand the long-term behaviour 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 gave a better forecast than a forecast based on multiple linear regression and persistence.

In the present article an attempt has been made to forecast average summer-monsoon rainfall over India with 1 year lead time using ANN technique applied in the form of multilayer perceptron (MLP). The MLP has been learned through three advanced backpropagation learning algorithms, namely, momentum learning, conjugate gradient descent (CGD) learning, and Levenberg–Marquardt (LM) learning. The novelty of this study lies in the fact that instead of using classical backpropagation learning some advanced backpropagation learning algorithms have been chosen and a statistical prediction skill comparison has been carried out. Another originality is that the ANN forecasts have been compared with an asymptotic regression-based forecast, whereas in the available literature the comparisons have been made mostly with multiple linear regressions (e.g. Hastenrath *et al.*, 1995; Chattopadhyay, 2007).

1.1. A brief review of the MLP learning algorithms used in this article

Since the advent of the backpropagation algorithm a vast variety of improvements has been made to the technique for supervised learning of MLP. The backpropagation algorithm looks for minimum error function in weight space using the method of gradient descent. The combination of weights, which minimizes the error function, is considered to be a solution of the learning problem (details are in Rojas, 1996). To remove some of the inherent problems of the classical gradient descent approach to backpropagation, some adaptive learning methodologies have been proposed by neural network experts (Salomon, 1990). In the present article, three adaptive backpropagation learning methods have been studied with respect to their potential to predict average summer-monsoon rainfall over India.

The momentum learning (Dalmi *et al.*, 1998) is a simple modification to the classical backpropagation in the sense that in this learning procedure the past increment to the weight is used to stabilize the convergence. The weight increment is then adjusted to include some fraction of the previous weight update. Thus in momentum learning in a network with n different weights $w_1, w_2, \ldots\ldots, w_n$, the i-th correction for weight w_k is given by:

$$\Delta w_k(i) = -\gamma \frac{\partial E}{\partial w_k} + \alpha \Delta w_k(i-1) \quad (1)$$

where γ and α are the learning and momentum rate respectively, and E denotes the error.

In CGD learning (Kramer and Vincentelli, 1989; Medsker and Jain, 2000) the step size is adjusted at each of the iterations. A search is made along the conjugate gradient direction to determine the step size, which minimizes the performance function along that line. The conjugate gradient method can move to the minimum of an N-dimensional quadratic function in N steps. The search direction at each of the iterations is determined by:

$$\mathrm{d}(t+1) = -\nabla E(t+1) + \beta^* d(t) \quad (2)$$

where, search direction $d(t) = -\nabla E(t)$ and

$$\beta = \frac{(\nabla E(t+1) - \nabla E(t))\nabla E(t+1)}{(\nabla E(t))^2}$$

The LM algorithm is a higher-order adaptive algorithm known for minimizing the MSE of a neural network. It is a member of a class of learning algorithms called 'pseudo second-order methods'. The LM utilizes the Gauss–Newton approximation that keeps the Jacobian matrix and discards second order derivatives of the error (Maqsood *et al.*, 2002). In this algorithm, the function to be minimized is of the form $f(x) = \frac{1}{2}\sum_{j=1}^{m} r_j{}^2$ where $x = (x_1, x_2, \cdots, x_n)$ is a vector and each r_j is a function from R^n to R. The gradient of f is of the form $\nabla^2 f(x) = J^T J$, where $J(x) = \frac{\partial r_j}{\partial x_i}$.

2. Methodology

2.1. Data analysis

In this article, three predictors have been used with one predictand. The three predictors are: homogenized Indian rainfall in June (x_1), homogenized Indian rainfall in July (x_2), and homogenized Indian rainfall in August (x_3) of a given year n. The predictand is the average Indian summer-monsoon rainfall (y) of the next year ($n+1$). The data have been collected from the website of IITM (Pune) (http://www.tropmet.res.in). The study period is the years from 1871 to 1999. The predictors are considered for the year n to predict the average summer-monsoon rainfall in India in the year ($n+1$). To view the degree of persistence within the time series pertaining to the predictand time series under study, the autocorrelation function is computed up to lag 10 and is presented in Figure 1.

This figure shows that all the autocorrelation coefficients are very low (below 0.2) in their numerical values. Thus it can be interpreted that the data series have

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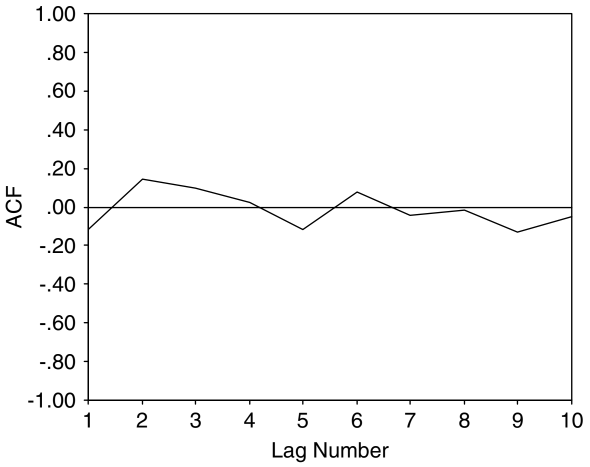

Figure 1. Autocorrelation function (ACF) for the average monsoon rainfall amount time series pertaining to the years from 1871 to 1999.

Table I. Correlation matrix for rainfall amounts in the months of June (x_1), July (x_2), August (x_3) of a given year and average monsoon rainfall amount of the very next year(y).

	x_1	x_2	x_3	y
x_1	1.00	−0.06	−0.01	−0.04
x_2	−0.06	1.00	−0.01	−0.11
x_3	−0.01	−0.01	1.00	−0.04
y	−0.04	−0.11	−0.04	1.00

no serial dependence (Wilks, 1995). This observation supports the necessity of implementing some non-linear approach for its prediction.

The correlation matrix for the variables under study is presented in Table I. It is apparent from the correlation matrix that rainfall amounts in the months of June (x_1), July (x_2), and August (x_3) have very small Pearson correlation coefficients with the predictand (y), which is the average monsoon rainfall amount of the next year. Since the Pearson correlation coefficient is the measure of the degree of linear association between a pair of variables, it can be inferred from the above correlation matrix that the predictors x_1, x_2, and x_3 are non-linearly associated (as implied by very small Pearson correlation coefficient values) with the predictand y. Thus on the basis of the above discussions it can be concluded that some non-linear approach is required for the present prediction problem.

2.2. ANN model formulation

Since the present dataset contains 129 years of rainfall data and the prediction is to be made with 1 year lead time, the initial input matrix would have 128 rows, and 4 columns; where the first 3 columns correspond to the three predictors x_1, x_2, and x_3 and the fourth column corresponds to the desired output y. From these 128 rows, the first 64 rows (i.e. first 50%) are used as training patterns, and the last 64 rows (i.e. last 50%) are used as test patterns.

The prediction problem can be symbolically expressed as:

$$y_{(n+1)} = f(x_{1n}, x_{2n}, x_{3n}) \tag{3}$$

where the bracketed terms x_{1n}, x_{2n}, and x_{3n} on the right side imply the monthly rainfall amounts in the months of June, July, and August, respectively, in the year n. The term $y_{(n+1)}$ implies the average monsoon rainfall in the next year ($n + 1$). The form of this function is obtained after adjusting a set of parameters that defines it. If the function f were a linear function of a linear combination of the inputs, then a linear regression could be obtained, but due to proven non-linearity within the data series, it is necessary to allow for non-linearity, which would be introduced by a set of hidden nodes and an activation function.

With 64 training patterns, the maximum number of hidden nodes can be 13 (Chattopadhyay, 2007). To impose non-linearity in the ANN model, the non-linear activation function is chosen as the sigmoid function (McCann, 1992):

$$f(z) = (1 + \exp(-z))^{-1} \tag{4}$$

To avoid complexity, only one hidden layer is chosen. In all cases, the perceptrons are learned thrice up to 1000 epochs. The minimization of the minimum squared error (MSE) is taken as the stopping criterion. In all cases, the threshold value is fixed at 0.01 and a batch-learning procedure is adopted.

After training the MLP with all the learning algorithms mentioned above, the predicted average monsoon rainfalls are available for the test cases. The actual and predicted summer-monsoon rainfall amounts for the test cases are schematically presented as time series plots in Figure 2(a) and (c) respectively. It is discernible from the figure that in some test cases the predicted values are greater than the actual values and sometimes they are below the actual values. The differences are the prediction errors. In some test cases the predicted values have almost coincided with the actual values. Observing Figure 2(a)–(c) it can be roughly said that there is somewhat a close association between the actual monsoon rainfall amounts and those predicted by ANN models. In Section 3, the prediction skill of the models are judged statistically using a scatterplot matrix and different summary statistics.

2.3. Prediction using asymptotic regression

This section aims to predict average Indian summer-monsoon rainfall using a non-linear regression technique. A literature survey shows that there are some significant contributions towards regression-based forecasts of summer monsoon rainfall over India. Hastenrath (1987) analysed the correlations between the various precursors and the rainfall anomalies in the course of 1939–81 and used a stepwise multiple regression to extract from the

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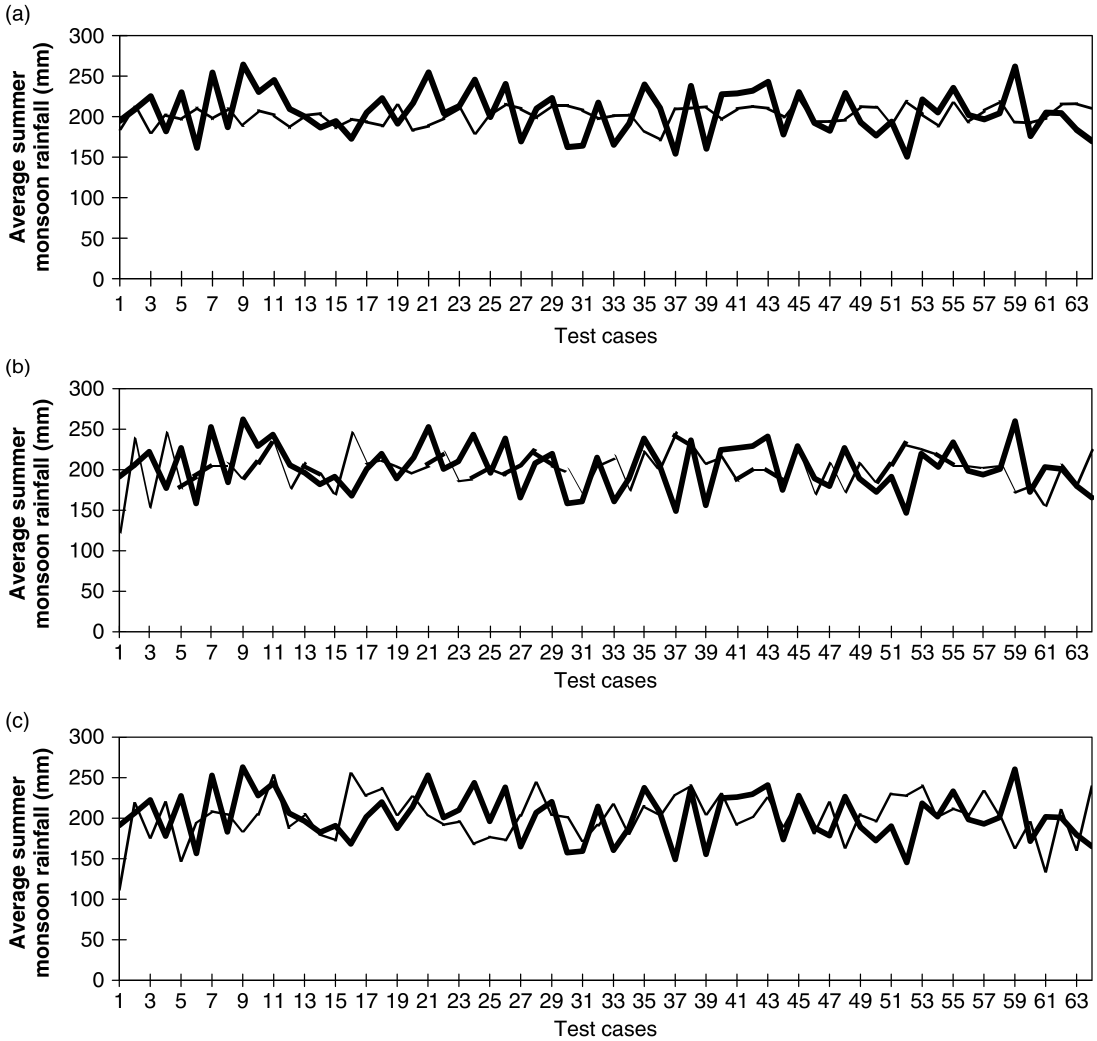

Figure 2. (a)–(c) Schematic of the actual average monsoon rainfall (bold line) and the average monsoon rainfalls (thin line) predicted by MLP with momentum, conjugate gradient descent (CGD), and Levenberg–Marquardt (LM) learning respectively.

'anomaly complex' the variance, which is most pertinent to the interannual variability of southwest monsoon (summer) rainfall. Hastenrath (1988) developed regression models for prediction of monsoon rainfall anomalies over India for various base periods. Singh *et al.* (1995) revealed that the average lowest mean sea-level pressure of heat low over central Pakistan and adjoining northwest India of the month of May had the potential for predicting all of India's summer monsoon rainfall. DelSole and Shukla (2002) indicated the necessity of non-linear models for predicting summer monsoon rainfall over India. Mohanty and Mohapatra (2007) implemented statistical procedures to predict the occurrence/non-occurrence and daily summer-monsoon rainfall quantity over Orissa, a state of India.

The present study deviates a little from the earlier regression studies on Indian monsoon rainfall. In this study no predictors other than monsoon rainfall have been used and the yearly rainfall amount has been predicted. Since non-linearity is a major issue behind adopting the ANN technique, a non-linear regression in the form of asymptotic regression (Chatpattananan, 2006) has been generated and whether the ANN can perform better than regression technique for the prediction problem under consideration has been examined. A multiple asymptotic regression equation is fitted as:

$$\hat{y}_{(n+1)} = \mathrm{a}_0 + \mathrm{a}_1\exp(b_1x_{1n}) + \mathrm{a}_2\exp(b_2x_{2n}) + \mathrm{a}_3\exp(b_3x_{3n}) \quad (5)$$

where, $y_{(n+1)}$, x_{1n}, x_{2n}, and x_{3n} carry the meaning explained after Equation (3). The symbol '$\wedge$' over $y_{(n+1)}$ in the left hand side of Equation (5) implies the estimated value of $y_{(n+1)}$. The constant a_0 is the regression constant, and the other a_is and b_is are regression parameters. The asymptotic regression constants and parameters are computed by iterating up to 100 steps using the LM algorithm. Training over the same set of patterns as in an ANN, the asymptotic regression equation finally comes out as:

$$\hat{y}_{(n+1)} = 208.032 + 0.001\exp(0.043x_{1n}) - 0.797\exp(0.008x_{2n}) + 0.008\exp(0.014x_{3n}) \quad (6)$$

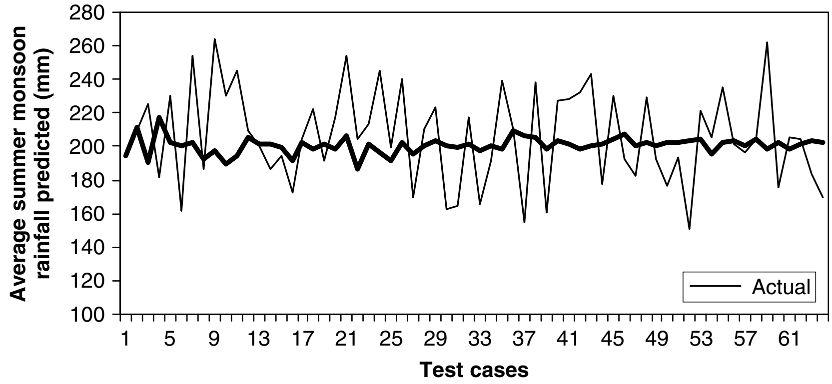

Figure 3. Schematic of the actual (thin line) summer monsoon rainfall *versus* the prediction (thick line) from asymptotic regression.

Applying the asymptotic regression Equation (6) to the same test cases as that of the ANN models it is found that there is a close association between actual and predicted average monsoon rainfall. The results are displayed in Figure 3, but a noteworthy feature is also available here. If the predicted value curve is examined carefully it is seen that throughout the test cases it has maintained a specific pattern, which is close to a straight line. Consequently, for the years with smaller amount of average rainfall, the prediction has come in close agreement with the observations, but the predicted values deviate notably from the observed values in the cases where a high or very low amount of average rainfall has been observed. It is therefore felt that the regression approach is not as appropriate for the extreme cases as they are in the normal cases. A statistical appraisal of the prediction performance of all the techniques is made in the following section.

3. Performance assessment

Willmott (1982) recommended computation of some 'summary measures' to assess the degree to which a model output fits an observed dataset. These measures are: the mean of the model-predicted variable ($\overline{P}$), the mean of the observed variable ($\overline{O}$), the standard deviation of the predicted variable (S_p), the standard deviation of the observed variable (S_O) and the estimated values of the predicted variable ($\hat{P}_i$) under the least-squares regression $\hat{P}_i = a + bO_i$. According to Willmott (1982), these measures are more illuminating than the measure of coefficient of determination and correlation. Fox (1981) recommended the use of mean square error (MSE), but, Willmott (1982) described the limitations of the MSE, and alternatively proposed and used an 'index of agreement' (d) of the form:

$$d = 1 - \left[\sum_{i=1}^{N} (P_i - O_i)^2 / \sum_{i=1}^{N} (|P_i - \overline{O}| + |O_i - \overline{O}|)^2 \right], \quad 0 \le d \le 1 \quad (7)$$

where, N is the number of observations. 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; Yarnal and Draves, 1993). Since a model intends to explain most of the major trends or patterns present in the observed data, it is important to know how much of the root mean square error (RMSE) is systematic in nature. For a good model, the systematic error should tend to 0, and the unsystematic error should approach the RMSE. Willmott (1982) proposed systematic (MSE_s) and unsystematic (MSE_u) errors as:

$$MSE_s = \frac{1}{N} \sum_{i=1}^{N} (\hat{P}_i - O_i)^2 \quad (8)$$

$$MSE_u = \frac{1}{N} \sum_{i=1}^{N} (P_i - \hat{P}_i)^2 \quad (9)$$

Thus while comparing several models, those having lower systematic errors would be identified as better predictive models. Similarly, for such models, the unsystematic errors would be nearer to the RMSE (Willmott, 1982). On the basis of the earlier discussion it can be said that models having higher Willmott's indices would be more efficient predictive models than those with lower Willmott's index values.

In the present problem all the summary measures described above and the forecast yields are computed to judge the performance of the predictive models described in the preceding sections. Values of these measures are presented in Table II. This table shows that the statistics $\overline{O}$ and $\overline{P}$ are very close to each other in all the models. Statistics S_o and S_p differ significantly for momentum learning-based MLP and the asymptotic regression models, but they have higher degree of agreement in the case of CGD and LM learning-based MLP models, whilst the ratio $\frac{RMSE_u}{RMSE}$ is much closer to 1 than the other two models. This implies that the momentum learning and asymptotic regression models are better than the other two because the unsystematic error is much closer to the RMSE than the other two models.

Willmott's index values (d) indicate that CGD and LM-based MLP models have almost equal values. It is further observed that in these two MLP models

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Table II. Statistical judgment of the forecast accuracy of the four prediction models.

	Regression	Momentum	Conjugate gradient descent	Levenberg–Marquardt
$\overline{O}$	203.01	203.01	203.01	203.01
$\overline{P}$	201.37	203.69	203.91	205.64
S_o	28.33	28.33	28.33	28.33
S_p	5.07	11.34	21.86	26.63
d	0.13	0.24	0.35	0.34
$\frac{RMSE_u}{RMSE}$	0.15	0.26	0.42	0.47
FY	0.45	0.53	0.50	0.44

Willmott's index has significantly higher values than those in the case of the momentum learning-based MLP and the asymptotic regression model. It can, therefore, be inferred that CGD and LM learning-based MLP models are of very similar nature. Because of higher values of Willmott's index of agreement in these two cases, it can be interpreted that these two models are producing forecasts in better agreement with the actual average monsoon rainfall than the momentum learning-based MLP and the asymptotic regression models. Thus for the prediction problem under consideration an ANN in the form of MLP can be trained by either CGD or LM learning and they would produce a better forecast than an MLP with momentum learning or an asymptotic regression.

Another statistic, forecast yield, defined as the percentage of test cases where the prediction error percentage is below some pre-determined limit, is computed over the entire test set for all the four prediction models. To compute this statistic, the prediction error percentages are calculated for each test case for all the models under study. For the present problem, 10% prediction error is taken as the limit because of the small numerical value of the corresponding absolute prediction error. It is observed that if a maximum 10% error level is allowed, then 53.12% and 50% of the test cases support the ANN in the form of MLP trained through CGD and LM learning respectively. Thus it can be said that in these two cases, the forecast yields are 0.53 (approximately) and 0.50 respectively, whereas, for MLP with momentum learning it is only 0.45 and for asymptotic regression it is only 0.44. This result also favours the CGD and LM-based MLP models. To make the relationship between actual and predicted rainfall amounts more comprehensible a scatterplot matrix is presented in Figure 4, where all the ANN model outputs for the test years are presented against the corresponding actual average rainfall values. From the first column of the scatterplot matrix it is perceptible that there are points, which are situated away from the linear trend lines. This happened due to the test cases having relatively large prediction errors, but in all the cases dense data pair clouds are available in the vicinity of the trend line. It should be noted that the trend lines are having negative slopes in all the cases. From this study, the existence of large prediction errors has become very prominent. This has happened due to the immense non-linearity in the data sets. The ANN models could make predictions to a considerable extent, but further study is needed to reduce the number of cases with large prediction errors.

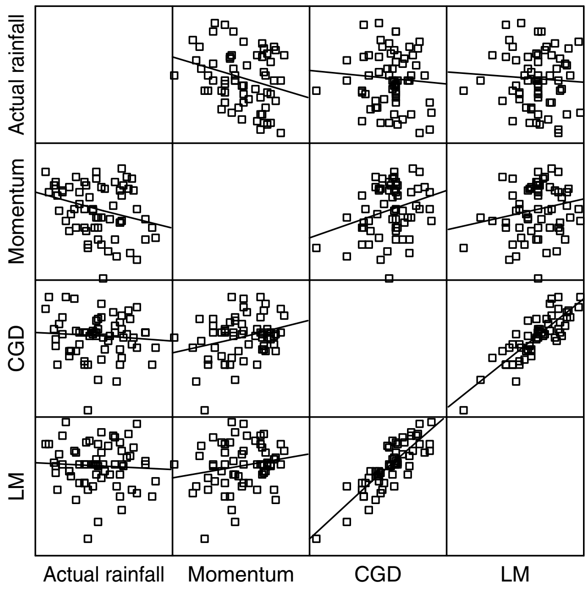

Figure 4. Scatterplot matrix for the actual rainfall and the predictions by multilayer perceptrons (MLP) trained through momentum, conjugate gradient descent (CGD) and Levenberg–Marquardt (LM) learning.

Thus far, the entire test set has been considered, and CGD and LM-based MLP models have been proven to dominate the other two models with respect to their prediction ability. In this paragraph, all the models under consideration are judged for a subset of the test set whose elements would be the test cases corresponding to high observed average rainfall amounts. For this purpose 200 mm is taken as the lower boundary for high average rainfall amounts. Those test cases having 200 mm or more average rainfall were identified and the corresponding absolute prediction errors observed for all of the four models. The results are displayed as a line diagram in Figure 5. This figure shows that in these high observed rainfall cases, the errors produced by the asymptotic regression and MLP trained through LM learning have significantly dominated the errors produced by MLP trained through CGD learning and momentum learning. Thus, it is revealed that in extreme rainfall cases ANN in the form of MLP trained through CGD learning and momentum learning predict with significant efficiency.

4. Conclusion

In the preceding sections different advanced backpropagation techniques have been tested for predicting average

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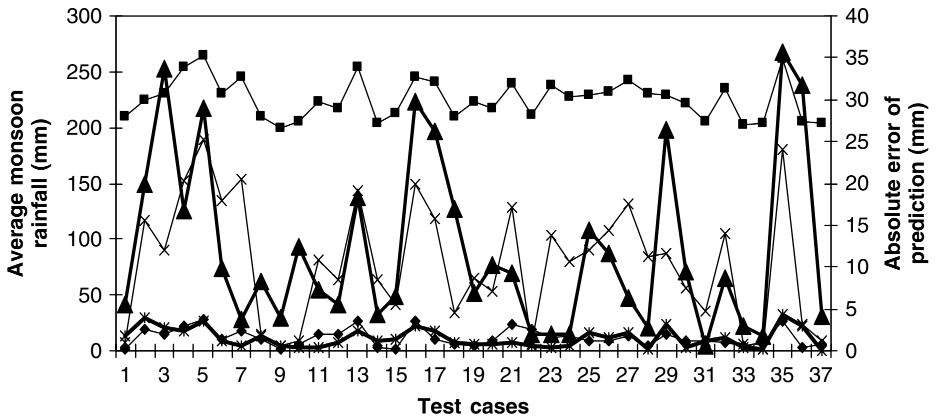

Figure 5. Performances of different MLP learning algorithms and asymptotic regression in the prediction of average summer-monsoon rainfall are judged in this figure for the extreme cases. The absolute prediction errors for different prediction models are presented here for the test cases where the observed average monsoon rainfall amounts are above 200 mm. Actual observations ■, MLP ♦, CGD learning MLP *, LM-learning MLP ▲ and asymptotic regression ♦.

summer monsoon rainfall with the previous year's rainfall amounts in the months of June, July, and August as the predictors. While analyzing the available data sets it has been observed that the data series are not exhibiting any serial correlation. From this it can be concluded that there is no persistence within the time series of average summer monsoon rainfall over India. This implies that the average monsoon rainfall time series does not have any tendency to be in the same pattern for a considerable period of time. Moreover, the very small autocorrelation coefficients indicate that there is no linear association between the past and present values of the time series under study. From the very low entries of the correlation matrix for the rainfall amount time series pertaining to the different monsoon months it can be further observed that the months have no linear association among themselves with respect to the average summer-monsoon rainfall amounts.

From the application of an artificial neural network model in the form of MLP with different backpropagation learning rules it is found that the perceptron models with CGD and LM learning perform almost alike while predicting the time series. It is further observed that the perceptron with momentum learning performs similarly to the asymptotic regression model. The predictions generated by these two models are somewhat inferior to the predictions generated by perceptron models with CGD and LM-learning algorithms.

From a graphical appraisal of the test cases having high amounts of average monsoon rainfall, it is visualized that the CGD and momentum learning perform significantly better than the other two models.

Thus the conclusion is that the artificial neural network is a suitable predictive tool for average monsoon rainfall over India, but a non-linear regression in the form of asymptotic regression also has considerable prediction ability for this problem. CGD, giving good prediction in normal as well as extreme cases, is identified as the best learning procedure for the predictive artificial neural network generated for this purpose.

In this article, the predictions were made using advanced backpropagation learning rules, but the overall prediction has been affected by the existence of a few large prediction errors. Because of such errors the Willmott's indices were not very high and the scatterplots did not give a linear patter. Removal of such errors with the aid of some other soft computing techniques such as Genetic Algorithm and Fuzzy Logic can be a future work to make more accurate forecast.

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