Forecasting rainfall using soft computing techniques – A case study using India rainfall data

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Abstract. In this study, an empirical evaluation of the effectiveness of soft computing techniques in forecasting annual and seasonal rainfalls on a nationwide and regional level is presented. Four different forecasting techniques, namely, Artificial Neural Networks (ANN), Adaptive Network based Fuzzy Inference System (ANFIS), Regression trees and linear regression, and two different techniques for data selection: expanding window and sliding window are considered. India is chosen as the test case mainly because of its immense topographical variations resulting in a highly diverse set of climates. A comparative study between the various techniques is also performed to find the best suited technique for the prediction.

Keywords: Rainfall, Forecasting, Artificial Neural Networks, Regression tree, neuro-fuzzy.

1. Introduction
Accurate rainfall forecasting is of great importance to developing countries that primarily rely on rains as the primary water source for agricultural purposes. This is especially true in case of the SAARC countries where only a fraction of the total arable land is irrigated[1]. A typical case in point is India. Statistics from the World Bank and FAO show that even by the year 2010, only around 36.3% of Arable & Perm. Crop Area (APC) in India was covered by irrigation [2]. With an approximated 799 million people (or 67.2% of India’s population) engaged in agriculture [1], accurate forecast of rainfall is highly desirable. An attempt has been made in this study to empirically evaluate the applicability of different soft computing techniques in generating one-step-ahead rainfall forecasts. Soft computing based systems considered in the present study are trained and validated on Indian rainfall data. India was chosen due to the wide variety of climates observed. It can be seen from the map of Köppen–Geiger (K-G) climate classification system [3] that around seventeen distinct climatic zones can be observed in India, ranging from Tropical Rainforests to Hot Desert to Continental subarctic with dry winter. This wide variety of climatic zones makes the study and forecasting of Indian rainfall patterns an extremely challenging task.

Linear regression [4], non-parametric regression models[5] and adaptive filters[6], have been employed for simulation [7]and prediction of monsoon as well as analysis of rainfall pattern and extreme events during monsoons[6], with good results, however, soft computing based techniques are now being preferred, primarily due to their ability to handle non-linear time series. Since rainfall time series also tend to be nonlinear, such techniques appear ideally suited for rainfall prediction. This has led to widespread use of soft computing techniques for rainfall forecasting. Artificial Neural Networks (ANNs) and their variants appear to be capable of generating good forecast accuracy, e.g. in [10,11,20,12–19]. Other techniques considered include Genetic Algorithms (GA) e.g.[10,11], Adaptive Neuro-Fuzzy Inference Systems (ANFIS)[10,19], support vector machines [21], ensemble methods e.g. [13,21] and multiple linear regression models[10].

In the present study, four different approaches, namely, ANN, ANFIS, regression tree and linear regression based models, are used to generate one-step-ahead rainfall forecasts. A detailed description
of the methodology used for the purpose is presented in the following section.

2. Methodology

In this study, a total of 4 different forecasting techniques are evaluated using two different dataset selection techniques on monthly, seasonal and annual rainfall data for 36 meteorological subdivisions in India as well as for the all-India rainfall data.

Thus, a total of 4 forecasting techniques*2 selection techniques*(4 seasonal+1 annual datasets) *(36 sub-divisional+1 all-India) =1480 systems are evaluated. Block diagram of the proposed system is given in Figure 1. Individual blocks in the block diagram are described in the following sub-sections.

2.1. Data

The Indian Meteorological Department (IMD) classifies India into 36 meteorological subdivisions, as shown in Figure 2. All data used in the present study has been sourced from [22]. Data sourced, consists of monthly, annual and seasonal rainfall for the entire country as well as meteorological subdivision-wise from the year 1951-2012. It was also observed from the surveyed literature that summer monsoons in India are affected by the temperature and pressure in north Indian Ocean[23] and surface temperatures [24]. Hence, in addition to rainfall (annual and seasonal), maximum, minimum and mean temperatures in India [25], number of depressions and deep depressions formed over north Indian Ocean (Arabian Sea and Bay of Bengal) annually and seasonally [26], the number of annual and seasonal cyclonic storms observed over north Indian Ocean [27], are also used as inputs for one-step ahead forecasting.

2.2. Data Segmentation

Two different techniques for segmenting data (selecting the training and testing data) were evaluated. The dataset is divided into training and testing windows (let’s take as \( W_0 \) to \( W_5 \)). In the sliding window technique, the first window \( W_0 \) is used to train the model and the trained model then forecasts the data in the next window \( W_1 \). The model is then re-trained on the window \( W_1 \) and used to forecast data in \( W_2 \) and so on. In the expanding window technique, on the other hand the first window \( W_0 \) is used to train the model which is then used to forecast the data in the next window \( W_1 \) but after that, data in both the windows \( W_0 \) and \( W_1 \) (i.e. the window expands to include both \( W_0 \) and \( W_1 \)) is used to re-train the model and the data in \( W_2 \) is forecast and so on. In the present study, the window slides (or expands, in case of expanding window technique) by one step at a time to enable one-step ahead forecasting. The training and testing timeframes used in the present study are presented in Table I.
Table I Training and testing timeframes considered.

| Testing Period | Training Period - Expanding Window | Training Period - Sliding Window |
|----------------|------------------------------------|---------------------------------|
| 2007           | 1951-2006                          | 1951-2006                       |
| 2008           | 1951-2007                          | 1952-2007                       |
| 2009           | 1951-2008                          | 1953-2008                       |
| 2010           | 1951-2009                          | 1954-2009                       |
| 2011           | 1951-2010                          | 1955-2010                       |
| 2012           | 1951-2011                          | 1956-2011                       |

2.3. Techniques Employed

Please present study attempts to empirically evaluate the effectiveness of three different soft computing techniques, namely, ANNs, regression trees and adaptive neuro-fuzzy systems. Ordinary-least-squares regression is also evaluated. A brief overview of each technique considered is given below. Given the training dataset (as described with \( n \) features and \( m \) samples at time \( t \), the feature set \( X \) can be represented as

\[
X = \begin{bmatrix}
  x_{11}(t) & x_{12}(t) & \cdots & x_{1n}(t) \\
  x_{21}(t-1) & x_{22}(t-1) & \cdots & x_{2n}(t-1) \\
  \vdots & \vdots & \ddots & \vdots \\
  x_{m1}(t-m+1) & x_{m2}(t-m+1) & \cdots & x_{mn}(t-m+1)
\end{bmatrix}
\]

With corresponding one-step ahead rainfall given by:

\[
Y = [y(t+1) \ y(t) \ \cdots y(t-m+2)]^T
\]  

Based on the training data, all the forecasting techniques used, attempt to generate a model that can produce one-step ahead forecast, i.e. estimated rainfall at the time step \( t+1 \), \( \hat{y}(t+1) = f(x) \), where \( f(.) \) is the model obtained from \( X \) and \( Y \).

2.3.1. ANN based forecasting technique. A feed-forward ANN with a single hidden layer was considered. The optimal number of hidden neurons was obtained using trial-and-error method, which was found to vary from dataset to dataset. Levenberg-Marquardt learning algorithm has been found to outperform other back propagation learning algorithms, for example, in [28], [29] and hence considered in the present study.
2.3.2. Regression based forecasting techniques. Regression tree starts with all the data points in a ‘root node’ and then attempts to recursively create binary splits using one of the n input features in X, such that resulting smaller and ‘purer’ partitions (or ‘leaf node’) minimize the overall Mean Square Error (MSE) of the tree [30]. The partitioning stops when the number of samples in the leaf node is below a set threshold. In this technique, the number of folds was selected to be 10. The minimum leaf size was 1 and the minimum number of branch nodes was 10.

2.3.3. Adaptive Neuro-Fuzzy forecasting system. The neuro-fuzzy system considered in this study, ANFIS[31] combines the robustness offered by Sugeno type fuzzy inference systems with the learning capability of neural networks. Forecasting results using ANFIS based systems as reported in [10,19] etc. were found to be good and have been considered in this study as well.

2.3.4. Linear Regression based forecasting system. Linear regression based model serves as the base model against which other models considered in the present study are compared. The linear regression model attempts to fit a linear model to represent the given dataset where the linear coefficients are identified such that the squared error gets minimized. Least Squares technique is used in the present study to estimate the coefficients.

3. Results and Discussions
Based on the data collected from [22] from the period 1951-2012 (time frames are listed in Table I), the annual and seasonal summary statistics for all-India rainfall data, were calculated. The seasonal and annual all-India rainfall summary statistics are presented in the Table II. It can be observed from that a substantial chunk of the total annual rainfall is recorded during the months of June-September. This can be attributed to the monsoons. Average rainfall is observed to be the lowest during the winter months of January-February. It is also observed that standard deviation (as a percentage of the average rainfall) is the highest for January-February followed by October-December. This is indicative of high variation in the rainfall during winter months over the past six decades under consideration. On the other hand, it is observed that the standard deviation for the total annual rainfall as a percentage of the average, is just around nine percent. It is also seen that the maximum and minimum rainfalls recorded, considering India as a whole (see column ‘Annual’ in Table II), happen to fluctuate a lot lesser when compared to the fluctuations in the seasonal rainfall. Over the entire time-frame under consideration (1951-2012), the worst (best) all-India rainfall recorded was just around twenty (twenty four) percent below (above) the average country-wide annual rainfall over the time frame. At the same time, the maximum and minimum rainfalls recorded during January-February were in excess of +/- 70 % of the average rainfall recorded during the season.

For forecasting all-India rainfall, initially only rainfall was used as input. Features such as temperature, depression and cyclonic storms were then added one-by-one and forecasts were generated.

Performance measure used in the present study is the Mean Absolute Percentage Error (MAPE). MAPE, being scale independent[32] was found to be a more intuitive measure compared to, say RMSE, since rainfall in India shows significant variations across regions and seasons and due to this scale dependence. In ANFIS, Sugeno-type fuzzy inference system learning algorithm using least squares method and back propagation gradient descent method for training was used. Figure 3 presents the forecasting results (MAPE) for expanding window technique, Figure 4 results for sliding window technique.

From the results obtained, it is observed that ANN gives best values for both sliding window and expansion windows. On comparing the sliding and expanding window the latter tend to produce better results. Of the four different combinations of parameters used the use of rainfall, temperature and depression has resulted in an more accurate results. Use of cyclones as additional parameter has led to increase in the error, leads to an inference that this parameter is not a good one because this is mostly the outlier scenarios which may not be applicable universally.
Table II Summary statistics for All-India season-wise rainfall.

| Rainfall (mm) | Jan-Feb | Mar-May | Jun-Sep | Oct-Dec | Annual |
|---------------|---------|---------|---------|---------|--------|
| Average       | 41.88   | 127.86  | 887.48  | 121.59  | 1177.48|
| Median        | 40.8    | 124.6   | 894     | 119.7   | 1183.1 |
| Std. Dev.     | 13.66   | 22.18   | 85.6    | 32.35   | 105.93 |
| Max           | 74.9    | 210.7   | 1084.3  | 206.1   | 1463.9 |
| Min           | 11.6    | 83.5    | 674.3   | 52.7    | 947.1  |

Next, meteorological sub-division wise predictions were carried out. Some of the Indian meteorological subdivisions(Figure 2) are composed of two or more climatic regions as defined in [3].

An attempt is also made below to identify if sub-divisions corresponding to same Köppen classification tend to show similar forecast accuracies.

Figure 3. Expanding window MAPE values for (a) ANN (b) Regression Tree (c) ANFIS (d) Linear regression based forecasting system.
Figure 4. Sliding window MAPE values for (a) ANN (b) Regression Tree (c) ANFIS (d) Linear regression based forecasting system

Table III Annual Region-Wise MAPE of forecasts using expanding and sliding window technique.

| Region | Expanding window | Sliding Window |
|--------|------------------|----------------|
|        | ANFIS | Linear Reg. | ANN | Reg. Tree | ANFIS | Linear reg. | ANN | Reg. Tree |
| 1      | 13.5  | 11.4 | 7.1 | 6.1 | 13.9 | 8.9 | 15.3 | 4.8 |
| 2      | 13.4  | 16.3 | 74.7 | 13.3 | 12.3 | 14.5 | 56.5 | 14.6 |
| 3      | 19.4  | 9    | 3.8 | 17.6 | 19.2 | 7    | 11.8 | 17.6 |
| 4      | 17.6  | 17.1 | 0   | 6.5 | 17.3 | 29.3 | 14.1 | 7.4 |
| 5      | 17.2  | 7.3  | 2.5 | 3.6 | 17.3 | 6.2  | 8.6  | 3.6 |
| 6      | 16.7  | 22.1 | 2.3 | 6.6 | 16.6 | 11.1 | 17.2 | 7   |
| 7      | 9.7   | 29.9 | 10.7 | 10.6 | 9.7  | 38.8 | 9.3  | 10.5 |
| 8      | 20.6  | 13.2 | 0.3 | 17.7 | 20.6 | 11.2 | 14.5 | 17.7 |
| 9      | 16    | 10.4 | 0   | 15.4 | 16.5 | 8.8  | 7.8  | 14.8 |
| 10     | 18.1  | 7.9  | 7   | 8.8 | 17.3 | 6.4  | 15.3 | 7.2 |
| 11     | 21.8  | 17.2 | 0.5 | 13.8 | 22.3 | 28.8 | 12.9 | 13  |
| 12     | 21.6  | 7.3  | 0.1 | 13.9 | 20.3 | 5.9  | 18.9 | 14.5 |
| 13     | 33    | 25.4 | 6.3 | 13.5 | 32.6 | 12.3 | 12.5 | 13.5 |
| 14     | 18.2  | 29.4 | 2.3 | 7.2 | 18   | 39   | 23.8 | 7.4 |
| 15     | 13.7  | 20.2 | 0   | 8.7 | 13.9 | 15.6 | 16.3 | 9.3 |
| 16     | 18.9  | 8.9  | 1.4 | 13.1 | 18.4 | 6.9  | 11.7 | 11.1 |
| 17     | 13.6  | 9.3  | 10.3 | 8.4 | 13.4 | 7.2  | 13   | 7.3 |
| 18     | 11    | 16.9 | 8.3 | 6.6 | 10.7 | 28.6 | 11.9 | 6.4 |
| 19     | 8.8   | 8.4  | 5.6 | 13.6 | 9.5  | 6.6  | 15   | 13.9 |
| 20     | 10.9  | 24.9 | 9.5 | 6.7 | 10.8 | 13   | 10.7 | 10.7 |
| 21     | 24    | 28.5 | 25.7 | 12.6 | 24   | 34.7 | 17.5 | 10.1 |
| 22     | 24.7  | 21   | 1.8 | 17.4 | 24.8 | 15.6 | 25.4 | 17.4 |
| 23     | 18.4  | 8.9  | 9.2 | 6   | 18.3 | 8.2  | 18.7 | 7.3 |
| 24     | 7.6   | 7.8  | 6.3 | 8.2 | 7.6  | 6.3  | 13   | 7.6 |
| 25     | 35.8  | 17.3 | 3.8 | 12.4 | 35.5 | 28.4 | 12.8 | 12.1 |
| 26     | 12.7  | 8.4  | 2.4 | 12.6 | 12.5 | 6.2  | 16.4 | 10.6 |
| 27     | 37.7  | 23.9 | 13.7 | 16.7 | 38.4 | 15.5 | 32.2 | 20.6 |
| 28     | 12.5  | 26.7 | 3.3 | 9   | 12.5 | 33.9 | 10.7 | 9.7 |
| 29     | 9.5   | 21.6 | 4.3 | 6.5 | 8.9  | 15.9 | 9.5  | 6.5 |
| 30     | 12.9  | 9.2  | 15.1 | 11.7 | 12.8 | 8.4  | 8.1  | 9.4 |
| 31     | 16.7  | 8.5  | 17.1 | 8.2 | 16.9 | 6.3  | 15.8 | 8.1 |
| 32     | 19.8  | 17.4 | 0.2 | 9.8 | 19.5 | 28.3 | 13.5 | 11.5 |
| 33     | 15.9  | 8.7  | 2.4 | 11.9 | 16.1 | 6.5  | 14.9 | 11.9 |
| Region | Expanding window | Sliding Window |
|--------|------------------|----------------|
|        | ANFIS    | Linear Reg. | ANN | Reg. Tree | ANFIS    | Linear Reg. | ANN | Reg. Tree |
| 34     | 13.4     | 20.9      | 4.5 | 13.9      | 20.1     | 14.9       | 5.4 |           |
| 35     | 23       | 25.8      | 15.5| 11.2      | 23       | 33.1       | 9.7 | 10.2      |
| 36     | 26.4     | 21.4      | 3.2 | 18.1      | 26.1     | 15.6       | 15.2| 18        |

Table IV: Annual Region-Wise RMSE of forecasts using expanding and sliding window technique.
### Table V Seasonal region-wise MAPE of forecasts for different techniques using expanding window.

| Region | ANFIS | Linear Reg. | ANN | Reg. Tree |
|--------|-------|-------------|-----|-----------|
| Jan-Feb | 25.2  | 14.8        | 19.6| 2570.1    |
| Mar-Sep | 11.4  | 10.3        | 11.2| 14.6      |
| Oct-Dec | 8.7   | 10.3        | 11.1| 8.9       |
| Jan-Feb | 10.9  | 10.3        | 11.0| 10.9      |
| Mar-Sep | 10.1  | 10.3        | 11.0| 10.1      |
| Oct-Dec | 10.0  | 10.3        | 11.0| 10.0      |
| Jan-Feb | 10.0  | 10.3        | 11.0| 10.0      |
| Mar-Sep | 10.1  | 10.3        | 11.0| 10.1      |
| Oct-Dec | 10.0  | 10.3        | 11.0| 10.0      |
| Jan-Feb | 10.0  | 10.3        | 11.0| 10.0      |
| Mar-Sep | 10.1  | 10.3        | 11.0| 10.1      |
| Oct-Dec | 10.0  | 10.3        | 11.0| 10.0      |

### Table VI Seasonal region-wise MAPE of forecasts for different techniques using sliding window.

| Region | ANFIS | Linear Reg. | ANN | Reg. Tree |
|--------|-------|-------------|-----|-----------|
| Jan-Feb | 25.2  | 14.8        | 19.6| 2570.1    |
| Mar-Sep | 11.4  | 10.3        | 11.2| 14.6      |
| Oct-Dec | 8.7   | 10.3        | 11.1| 8.9       |
| Jan-Feb | 10.9  | 10.3        | 11.0| 10.9      |
| Mar-Sep | 10.1  | 10.3        | 11.0| 10.1      |
| Oct-Dec | 10.0  | 10.3        | 11.0| 10.0      |
| Jan-Feb | 10.0  | 10.3        | 11.0| 10.0      |
| Mar-Sep | 10.1  | 10.3        | 11.0| 10.1      |
| Oct-Dec | 10.0  | 10.3        | 11.0| 10.0      |
| Jan-Feb | 10.0  | 10.3        | 11.0| 10.0      |
| Mar-Sep | 10.1  | 10.3        | 11.0| 10.1      |
| Oct-Dec | 10.0  | 10.3        | 11.0| 10.0      |
Comparing with Køppen climate classification model of India in Figure 5, it was observed that the meteorological sub-divisions that corresponded to a single climatic region as per Køppen classification, tended to give good annual rainfall forecast accuracy, e.g. the humid sub-tropical
climate regions (sub-divisions 3,4,8,10,11 and 13) and warm semi-arid climate regions (sub-divisions 18,29 and 34) were giving consistent results using ANN technique for expanding window data selection technique. On the other hand, the meteorological sub-divisions, e.g. 21,27,30,35 and 2 show comparatively poorer annual rainfall forecasting results. This could be because of overlap of two or more Köppen regions.

Figure 5. Köppen classification map for India

4. Conclusions
Soft computing techniques were used to forecast the annual and seasonal rainfall on all-India and meteorological sub-division wide basis. It was observed that annual rainfall forecasts were more accurate when compared to seasonal forecasts. ANN technique with rainfall, temperature and depression data as inputs and using expanding window based dataset selection technique, gave the best accuracy for all-India rainfall prediction, while ANN with expanding window based dataset selection technique gave the best result for region-wise rainfall prediction. Cyclone is not a good parameter because it is more like an outlier which is not applicable for all the regions. The possibility of a correlation between geographical spread of the meteorological sub-divisions; their Köppen climate classifications and the accuracy of the forecasting techniques can be taken up as future work.

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