Time Lag recurrent Neural Network model for Rainfall prediction using El Niño indices

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Abstract- Indian summer monsoon rainfall is a process which is dependent on number of environmental and geological parameter. This makes it very hard to precisely predict the monsoon rainfall. As India is agriculture based country, a long range monsoon rainfall prediction is crucial for proper planning and organization of agriculture policy. Severe hydrological events, such as droughts, may result in decline of agricultural output, affecting both inhabitants and national economy of the country. El Niño and Southern Oscillation (ENSO) play an important role in the success or collapse of Indian monsoon development. The year-to-year variability in monsoon rainfall could cause extreme droughts and floods in the country. El Niño is an oscillation of the ocean-atmosphere system in the tropical Pacific having important consequences for weather around the globe. Understanding the relationship between ENSO and Indian monsoon rainfall is crucial to reduce negative impact or to take benefit of positive conditions. In this paper, a focused time lag recurrent neural network model has been proposed in order to determine the temporal relationship between ENSO and Indian summer monsoon rainfall.

Index Terms- Recurrent Neural network, Rainfall, prediction, El Niño

I. Introduction

India is an agriculture based country where the major population is dependent on agriculture. Due to lack of irrigation system, most of the farming is dependent on rainfall. The all-India summer monsoon rainfall (ISMR), is defined as the rainfall received during the month of June to September over India. The ISMR has a huge impact on not only the agriculture growth but also related economic activities of the country, and prediction of the interannual variability of ISMR is thus a matter of great concern for the economic growth of country. If a drought year is predicted well in advance, proper agriculture planning and management can be done so that the losses are less. Rainfall is a random process which is dependent upon various ecological and geographical parameters hence it is very difficult to predict it. Researchers have been working on this problem since the late 1800s. Much research work has been undertaken to predict ISMR variation[1][2]. El Niño and Southern Oscillation (ENSO) has been known to exert the most important external forcing on ISMR [3][4][5][6].

El Niño is an oscillation of the ocean-atmosphere system in the tropical Pacific having important consequences for weather around the globe. As Walker noticed long ago, the anomalous high pressure over the western Pacific–eastern Indian Ocean and anomalous low pressure over the eastern and central Pacific associated with El Niño do influence the ISMR. Krishna Kumar *et al*. [7], propose that El Niño/La Niña results in deficit/excess of rainfall by suppressing/enhancing the convection over the Indian region.

Reason *et al*. [8] showed that when an El Niño occurred during the summer, the Indian Ocean was characterized by a slight warming of sea surface temperature (SST) as compared to normal, which was associated with weaker wind magnitudes than normal and reduced cloudiness. After the summer monsoon season, they observed a clear influence of El Niño over the Indian Ocean; the SST over the entire basin was significantly warmer than normal. At this time, large negative wind speed anomalies around the equator were seen in the Indian Ocean, with an increase in cloudiness over the western Indian Ocean, and a decrease over the eastern Indian Ocean. They also demonstrated that the opposite configuration occurred during La Niña events. Work conducted by Kripalani and Kulkarni [9] concluded that the state of ENSO does not explain all the inter annual variability of ISMR. For example, in spite of the occurrence of strong El Niño events in 1914, 1963, 1976, 1983, and 1997, these years did not experience deficiencies in ISMR (Figure 1). Kripalani and Kulkarni pointed out the existence of the inter decadal variability of ISMR and found that when ISMR was in the above normal inter decadal phase, even strong El Niño events did not bring severe droughts to India.

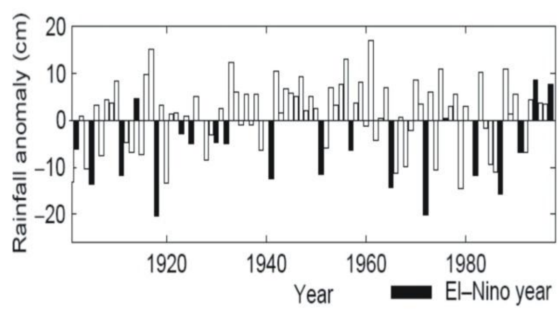

Fig.1. Year of El Niño

Prediction of Indian monsoon rainfall is an important matter for Indian economy. For a proper prediction of rainfall, a better understanding of the ENSO related factors, affecting monsoon rainfall is required. It can improve the ability to forecast rainfall in the country thereby allowing to manage things with greater

ISSN 2250-3153

success. Assessing this relationship with climate modeling could be a useful tool to comprehend processes in El Niño

Artificial Neural Networks (ANN), which replicate the parallel distributed processing of the human nervous system, have proven to be very powerful tool in dealing with complicated problems, such as pattern recognition and function approximation. Hornik et al. [10] has shown that an ANN with adequate complexity is capable of approximating any function to a greater accuracy. In addition, ANNs are computationally robust, in the way that they have the ability to learn and give correct output even if the input contains error [11]. For prediction based upon past input, a time delay recurrent neural network model is more efficient [12].

In this paper a time lag recurrent neural network model is proposed which can be used as tool to comprehend processes in El Niño teleconnection with Indian Summer Monsoon. A time lagged recurrent network has the static Processing elements (PEs) substituted by PEs with short term memories, such as the gamma, the Laguarre or the tap delay line. Memories can be appended to any layer in the network, producing very sophisticated neural topologies very useful for time series prediction and system identification.

II. DATA

The following data sets are used in this study:

(1) All India monthly Rainfall data : All-India rainfall during 1950–2006 is acquired from www.iitromset.com. Out of which 60 percent is used for training the neural network model and 15 percent for cross validation and 25 percent for testing the model.

(2) ENSO index: we have taken NINO index time series for a period of 1950-2006,

i. Nino 1+2 i.e. the Sea surface temperature (SST) anomaly averaged over the region (90–150°W, 5°N–5°S).

Data of Nino1+2 SST was taken from Ocean Observations Panel for Climate (OOPC) site, http://ioc-goos-oopc.org/.

III. NEURAL NETWORK MODEL

To determine the temporal relation between the El Niño and ISMR a focused time lag neural network with gamma memory has been used. Time is an essential dimension of learning. We may incorporate time into the design of a neural network implicitly or explicitly [13]. A straightforward method of implicit representation of time is to add a short-term memory structure in the input layer of a static neural network [14] (e.g., multilayer perceptron). This memory structure is used to store the past information, which can be used to analyze the data in a more efficient way. The element in the memory structure can be varied as per requirement. The resulting configuration is called as focused time lagged feedforward network (TLFN). teleconnection with Indian Summer Monsoon.

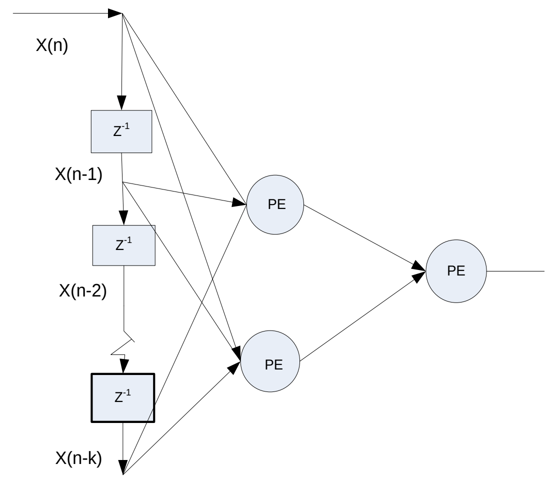

Fig 2. A focused TDNN with one hidden layer and a tap delay line with k+1 taps

The short-term memory structure may be implemented in one of two forms, as described below:

1. Tapped-Delay-Line (TDL) Memory: This is the most commonly used form of short-term memory. It consists of p unit delays with (p + 1) terminals, which may be viewed as a single input–multiple output network. A focused TLFN network using the combination of a TDL memory and multilayer perceptron. The unit-delay is denoted by $z^{-1.}$ The memory depth of a TDL memory is fixed at p, and its memory resolution is fixed at unity, giving a depth resolution constant of p.

2. Gamma Memory: We may exercise control over the memory depth by building a feedback loop around each unit delay, as illustrated in Fig.3 .Effectively, the unit delay z^{-1} of the standard TDL memory is replaced by the transfer function[15]

$$G(z) = \frac{\mu Z^{-1}}{1-(1-\mu)Z^{-1}}$$

where μ is an adjustable parameter. For stability, the only pole of $G(z)$ at $z = (1 - \mu)$ must lie inside the unit circle in the z plane. This, in turn, requires that we restrict the choice of μ to the following range of values:

$$0 < \mu < 2$$

The overall impulse response of the gamma memory, consisting of p sections, is the inverse z transform of the overall transfer function.

ISSN 2250-3153

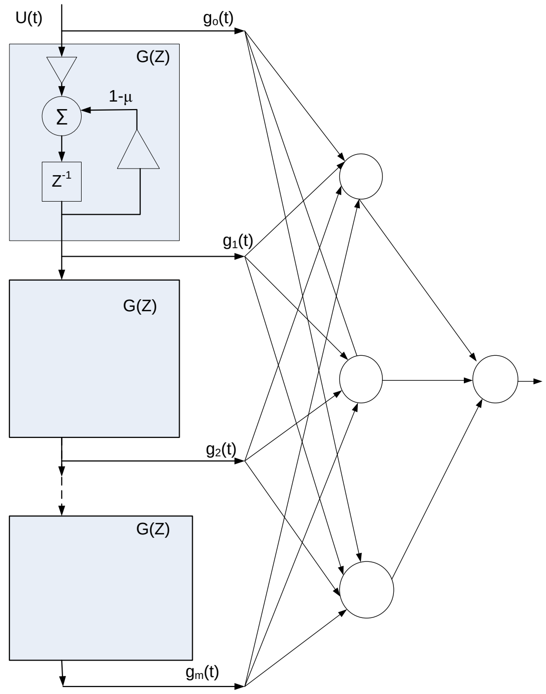

Fig 3.Time lag recurrent neural network with gamma memory.

IV. Development of Neural network model

A focused time lag recurrent neural network is developed to determine the temporal relationship between Indian monsoon rainfall and historical value of El Niño. El Niño has a great impact on the Indian monsoon rainfall. We have tried to develop a neural network model to predict the rainfall one month ahead based upon historical El Niño indices.

A three layer Focused Time Lag Recurrent Neural network(2-16-1) model has been designed with Gamma memory and conjugate gradient back propagation learning algorithm. The training of a neural network model is usually accomplished by using a backpropagation (BP) algorithm. Input data presented to the system was monthly values of El Niño and average monthly rainfall, The system was designed to predict rainfall over one month period based upon the rainfall and El Nino indices for past few months. The amount of past data used for predicting the rainfall for next month is dependent upon the number of lags and Gamma parameter of the model. Data was partitioned into three parts with 60 percent for training, 15 percent as cross validation for evaluating the model performance and 25 percent for testing the model on data not seen before. Model was designed and tested rigorously for various number of lag, number of neuron at hidden layer and with different values of gamma parameter.

Performance of the model is evaluated on the basis of correlation coefficient, root mean square error and maximum absolute error.

Correlation coefficient (R^2) is defined as

$$R^2 = \frac{\sum_{i=1}^{N}\left(x_{act}(i) - \bar{x}_{act}\right)\left(x_{pre}(i) - \bar{x}_{pre}\right)}{\sqrt{\sum_{i=1}^{N}\left(x_{act}(i) - \bar{x}_{act}\right)^2 \sum_{i=1}^{N}\left(x_{pre}(i) - \bar{x}_{pre}\right)^2}}$$

Normalized Root Mean Square Error (NRMSE) is defined as

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_{act}(i) - x_{pre}(i)\right)^2}}{\left(Max\left(x_{pre}\right) - Min\left(x_{pre}\right)\right)}$$

Maximum Absolute error is defined as

$$MAE = Max(Abs(x_{act}(i) - x_{pre}(i)))$$

Where $x_{act}(i)$ is actual rainfall and $x_{pre}(i)$ is predicted rainfall value at point i

$\bar{x}_{act}$ and $\bar{x}_{pre}$ are the mean value of actual and predicted rainfall series.

N is the sample size.

$Max\left(x_{pre}\right)$ is maximum value of predicted rainfall ,

$Min\left(x_{pre}\right)$ is minimum value of predicted rainfall.

V Result and Discussion

During the development of the alternative ANNs, various network configurations were explored in order to determine the effect of number of neuron in hidden layer., number of lags and various values of gamma parameter. Numbers of neurons in hidden nodes were varied were from 4 to 32 and NMSE was calculated. The result is shown in table.1. Eight number of neuron in the hidden are found to be optimum in order to have best performance. Number of lags was varied from 4 to 24 and the best result was found at sixteen lag as shown in table.2. Number of tap decides the amount of delay required i.e. data from previous inputs. Table.3 shows the variation in the performance parameter of the model with the changes in gamma parameter. Minimum NMSE is found at gamma parameter equal to 0.8. Gamma parameter decides the amount of feedback to be taken from the various taps. The results are shown in the table given below. A plot between actual rainfall and predicted rainfall is shown in the fig.4. The plot is linear with residual given in the below figure.

Number of Taps	NMSE	Max Abs Error	Correlation Coefficient
4	0.14685	0.07201	0.93733
8	0.13298	0.06966	0.94084
12	0.14557	0.07403	0.93861
16	0.17348	0.07863	0.92301
24	0.17686	0.07513	0.93097
32	0.16601	0.07380	0.92773

Table 1. Performance parameter at different Number of neuron in the hidden layer

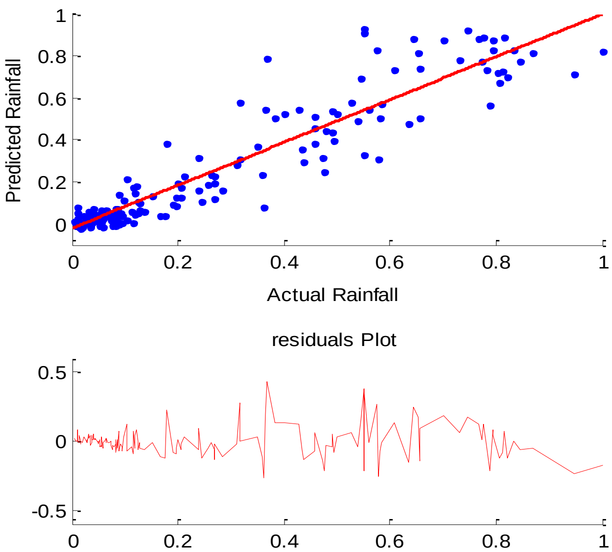

Fig 4. Scatter plot between actual and predicted rainfall and residual plot

Number of Lag	NMSE	Max Abs Error	Correlation Coefficient
4	0.20911	0.08376	0.89842
8	0.13794	0.06934	0.93245
12	0.13813	0.06932	0.93687
16	0.13298	0.06966	0.94084
18	0.16869	0.07540	0.92507
20	0.20620	0.08993	0.91550
24	0.16629	0.08015	0.92719

Table 2. Performance parameter at different Tap number

Gamma Parameter	NMSE	Max Abs Error	Correlation Coefficient
0.20	0.24665	0.09502	0.88780
0.40	0.18667	0.08427	0.91519
0.60	0.15908	0.07429	0.92897
0.70	0.17163	0.07371	0.94222
0.80	0.14386	0.07027	0.94052
0.90	0.13946	0.06946	0.94038
1.00	0.16600	0.08151	0.92128
1.20	0.19806	0.09441	0.92692

Table 3. Performance parameter at different values of Gamma Parameter

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ISSN 2250-3153

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