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Comparative Study of Neural Network Architectures for Rainfall Prediction

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***Abstract*— Majority of Indian farmers depend on rainfall for agriculture. Thus, in an agrarian country like India, rainfall prediction becomes very important. This paper presents comparative study of neural network architectures namely Back Propagation Neural Network (BPNN), Generalized Regression Neural Network (GRNN) and Radial Basis function Neural Network (RBNN) to predict rainfall in Thanjavur district of southern province Tamil Nadu, India. The different models are trained using the training data set and have been tested for accuracy on available test data. MATLAB has been used for model development. After training all networks and testing them we found that RBNN gives best result for prediction.**

Keywords*— *Rainfall prediction; BPNN; GRNN; RBNN

I. Introduction

In developing countries like India, majority of population is engaged in agriculture. Due to poor irrigation facilities, they depend on rainfall for their agricultural activities. Rainfall has a significant effect on their produce. Effective rainfall prediction can help farmers plan their agricultural activities in advance and avoid losses that are incurred due to erratic rainfall.

Long term monthly rainfall prediction is a challenging task in this era of highly uncertain climate. As we know, climate and amount of rainfall received at a given location are highly non-linear phenomena that depend on many different factors. Rainfall is of the most complex elements of climate to understand and model due to the complexity of atmospheric process that generate it as well as the large range of variation over a wide scale in both space and time [1]. Thus, despite many advances in weather forecasting, accurate rainfall prediction is one of the greatest challenges in operation hydrology [2]. Many different techniques have been applied for the task of rainfall prediction worldwide. But the prediction accuracy obtained still lies below the satisfaction level because of large uncertainties involved in the climatic processes [3].

The concept of artificial neural networks was first introduced in 1943 [4]. But main research of applications of ANNs has begun only after the introduction of the backpropagation training algorithm for feedforward ANNs in 1986 [5]. Thus ANNs may be considered a fairly new tool in the field of prediction and forecasting. Many studies indicate that consideration of statistical principles in the ANN model building might improve model performance [6], [7]. Thus, it is important to adopt a systematic approach in the development of ANN models, taking into account factors such as data pre-processing, the determination of adequate model inputs and suitable network architecture, optimization [8] and model validation. Also, careful selection of a number of internal model parameters is required.

ANNs have gained popularity because of their ability to tolerate noisy data and to predict or classify patterns they have not been trained on [9]. Studies have shown that neural networks are highly suitable for this problem and can be used to accurately forecast rainfall. ANN is capable of modeling the complex relationship between the parameters and rainfall without the knowledge of actual natural processes [10], [11]. Also ANN can learn and generalize different examples to produce a meaningful solution even when the input data contain errors or is incomplete [10]. The self-adaptive nonlinear and nonparametric data driven approach used by ANNs have made it popular among many scientists [4].

Neural networks are of many different types. The most common is Backpropagation Neural Network. Other types are Radial Basis Neural Networks and Generalized Regression Neural Network. The objective of this paper is to compare the various architectures of neural networks that can be used for effective rainfall prediction.

II. Neural Network Architectures

A. Back Propagation Neural Network (BPNN)

Backpropagation algorithm is used for training feed forward neural networks. Nodes in a feed forward ANN are arranged by layers- input layers, zero or more hidden layers and output layer. They allow signal to travel only in one way; from input to output. In backpropagation algorithm, the objective is to achieve global minima. This is a supervised learning method. The actual output of the network is compared with desired output. The error between the two acts as feedback to input to adjust the weights for achieving minima. The term backpropagation is used to imply a

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backward pass of error to each internal node within the network, which is then used to calculate weight gradients for that node. The network learns by propagating the instantaneous errors back from each layer to previous layer. Fig 1 shows BPNN feed forward architecture.

B. Radial Basis Neural Network (RBNN)

Radial basis function (RBF) networks are a special type of feed-forward networks that consist of three layers- input, one hidden layer and an output layer. The single hidden layer is configured with basis functions. These basis functions transform the input features to a higher dimension. The basis functions have parameters center and spread. The Euclidean distance of each input vector from the center is calculated. Output of the hidden layer unit is calculated by applying the basis function on the Euclidean distance. Final output of the network is calculated by a linear combination of hidden layer outputs. RBF networks are mostly used for function approximation. Fig 2 shows RBNN architecture.

C. Generalized Regression Neural Network (GRNN)

GRNN is a variation of the radial basis neural network. It is based on kernel regression networks. The RBF units in the hidden layer are known as kernels. GRNN architecture does not require an iterative training procedure for determining weight. It is mostly used for function approximation. Any arbitrary function between inputs and outputs can be estimated from the training data using GRNN. As the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function. A GRNN consists of four layers: input layer, pattern layer, summation layer and output layer. Fig 3 shows GRNN architecture.

III. Data and Methodology

The main area of study is Thanjavur district of Tamil Nadu. We have used data made publicly available from the website India Water Portal [12]. The data contains monthly averages from 1901-2002 for the following climatic parameters:

- Precipitation (i.e. rainfall)
- Cloud cover
- Vapor pressure
- Average temperature

A. Preprocessing

All data used has been normalised. Normalization factor was 200.

B. Methodology

The cloud cover, vapour pressure and average temperature data from March to July along with rainfall data from March to June has been used for prediction of rainfall for the month of July. Fig 4 shows the model used for rainfall prediction. The MATLAB Neural Network toolbox has been used for simulation of neural network models. The normalized data was used as input for the three neural networks. And normalized output was obtained from the networks.

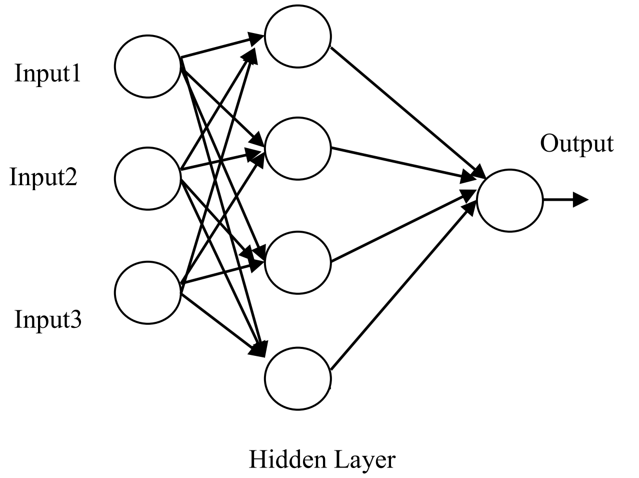

Fig 1 – BPNN Feed Forward Architecture

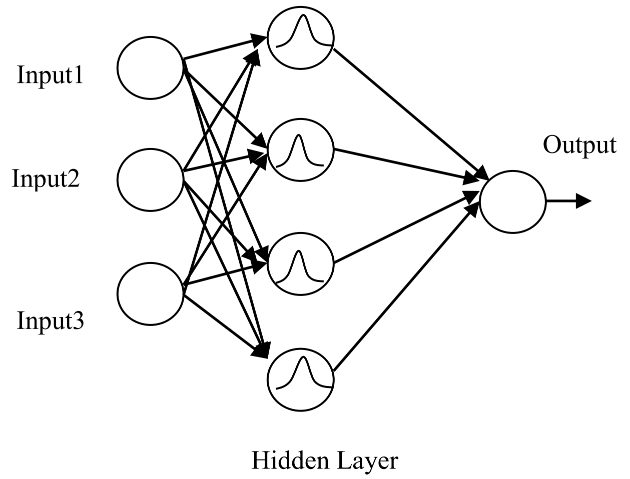

Fig 2 – RBNN Architecture

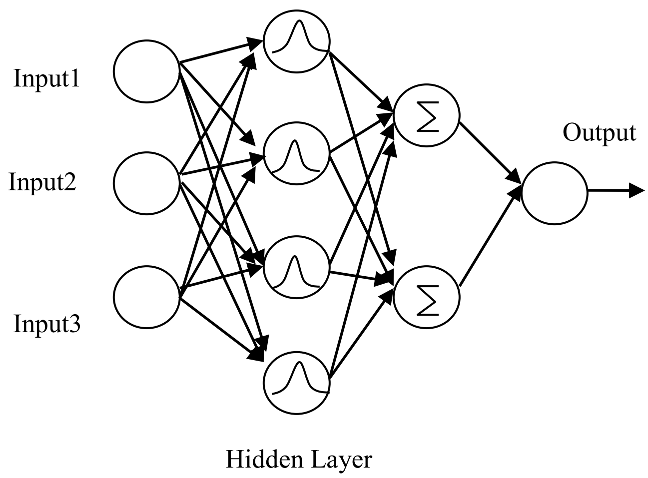

Fig 3 – GRNN Architecture

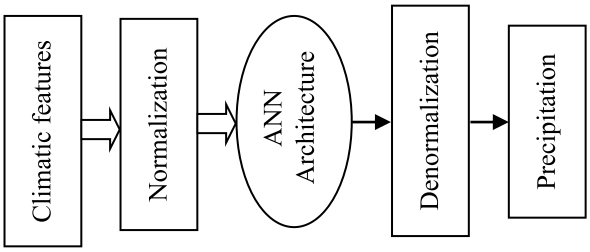

Fig 4 – Model used for prediction

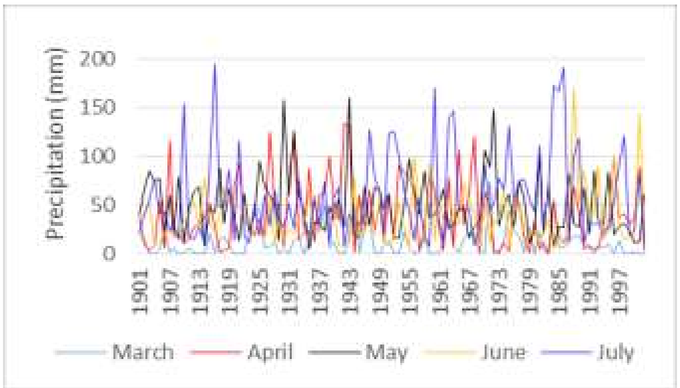

Fig 5 – Percipitation

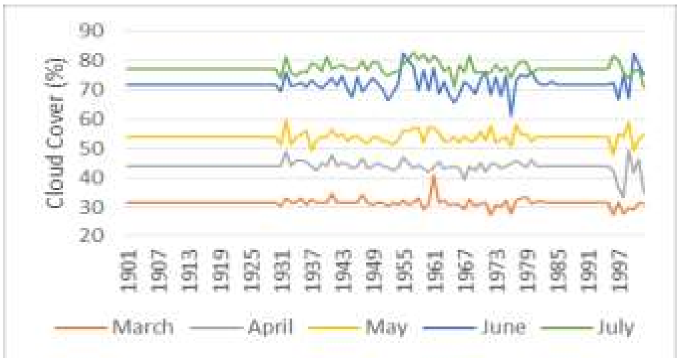

Fig 6 – Cloud cover

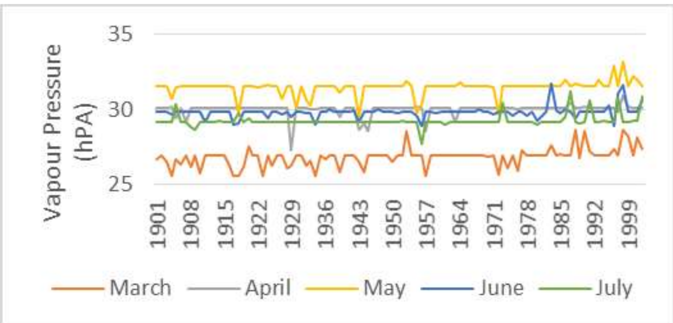

Fig 7 – Vapour pressure

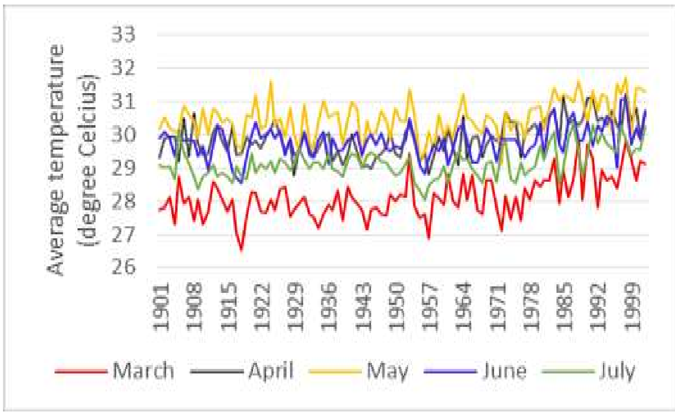

Fig 8 – Average tempearture

Fig 5 shows Precipitation in the months of March-July over a period of 101 years, starting from 1901.

Fig 6 exhibits Cloud cover in the region in the months of March-July from 1901-1999.

Fig 7 shows data of Vapor pressure in Thanjavur in the months of March-July from 1901-1999.

Fig 8 displays Average temperature in the months of March-July through the period from 1901 to 1999.

IV. Result and Discussion

The Neural Networks were trained using data from 1901-1990. The trained networks were used for predicting rainfall in the month of July from the year 1991- 2001. For comparative analysis, we have compared the prediction results of BPNN, GRNN and RBNN. Fig 9 shows the outputs while training the networks. TABLE1 lists the parameters and the normalized root mean square error (RMSE) for all three architectures.

Fig 10 shows actual observed rainfall and the rainfall predicted in the month of July for the years 1991- 2001. It is found that values of normalized RMSE are 45.1447, 41.78305 and 36.30701 for BPNN, RBNN and GRNN respectively. Although GRNN gives least RMSE, its output do not show any significant variations.

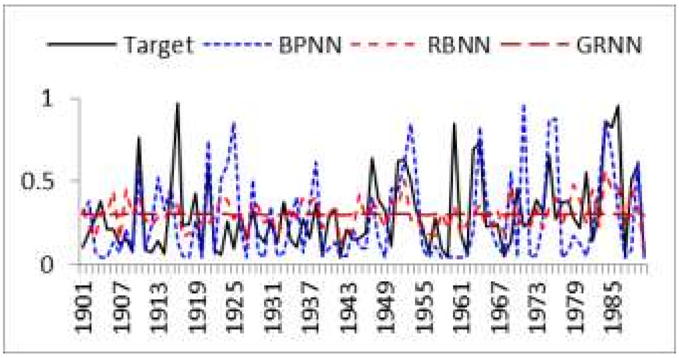

Fig 9 – Training result for years 1901 - 1990

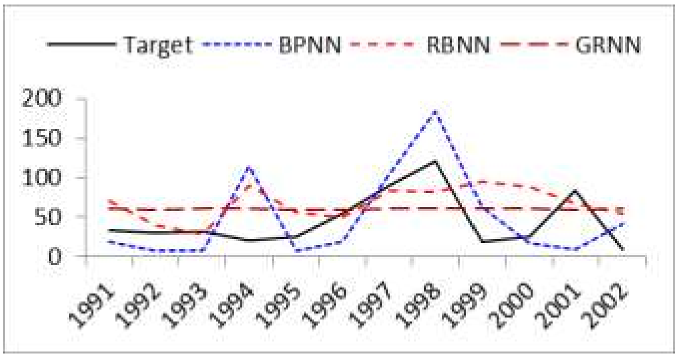

Fig 10 – Extrapolation result for years 1991 – 2002

TABLE 1 Training summary

Type	Neurons in network	RMSE goal for normalized data	RMSE obtained for Trained network
BPNN	10-1	0.2062	0.2786
RBNN	10-1	0.2062	0.2060
GRNN	90-1	0	0.2268

V. Conclusion

With respect to the results obtained, we can conclude that

- RBNN architecture gives the lowest training error and is most suitable for prediction.
- BPNN can also be used but it is not able to follow sharp variations in the output.
- GRNN overfits the data due to large number of neurons.

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