International Journal of Engineering Innovation & Research
Volume 2, Issue 1, ISSN: 2277 – 5668

Rainfall Rate Analysis from One Hour Statistics Measurements

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***Abstract* – The rain-rate analysis is a realization from a random process. Observed rain-rate realization change from year to year. A complete description of the rain-rate process must include information on year-to-year variability. The rain-rate realization itself would contain this information if the number of independent rain-rate samples in each year were known. This paper presents a new algorithm that provides both annual and monthly rain-rate distribution predictions. The parameters for the model are derived from long term climate data. The scheme not only provides a fast and efficient way to build a new neural network rainfall estimation model but also can provide a way to maintain an existing neural network rainfall estimation model [1].**

***Keywords* – Rainfall, SSE, Rain Rate.**

I. Introduction

The ground rainfall estimation technique includes two stages, namely, 1) the training and validation stage and 2) the application stage. In the training stage, the neural network learns the potential relationship between the rainfall rate and the radar measurements from a training dataset. When a radar measurement set is applied to the neural network, the network yields a rainfall-rate estimate as output. This output is compared with the rain gauge measurement, and their difference or the error is propagated back to adjust the parameters of the network. This learning process is continued until the network converges. Once the training process is complete, a relationship between the rainfall rate and the radar measurements is established and the network is ready for operation. The adaptive neural network is use for the analysis of rain rate , the adaptive neural network can adjust itself whenever new rain gauge data are available. To start with, the network can be built by initial training using all the available data. The network is in the application mode after the initial training. Once new rain gauge data are collected, the network switches into an updating mode. By using an adaptive updating algorithm, the network adjusts some of its parameters, adding or removing some neurons so as to fine-tune its structure with the new information. The scheme not only provides a fast and efficient way to build a new neural network rainfall estimation model but also can provide a way to maintain an existing neural network rainfall estimation model and make it evolve gradually. In this paper we presents a new algoritham that provides both annual and monthly rain-rate distribution predictions. The parameters for the model are derived from long term climate data. The output vector consists of one variable namely the rain rate measured by a rain gauge on ground level. The two available rain gauges provided the rain rate in milli metres every one hour. The efficiency of ANN network in the estimation of the rain rate on the ground in comparison with that supplied by the weather radar is evaluated.

II. Propose Algorithm

Recent research has shown that neural network techniques can be used successfully for ground rainfall estimation from radar measurements. The neural network is a nonparametric method for representing the relationship between radar measurements and rainfall rate. The relationship is derived directly from a dataset consisting of radar measurements and rain gauge measurements. The results of the evaluation show that the neural network can be successfully applied to obtain rainfall estimates on the ground based on radar observations. The rainfall estimates obtained from neural network are shown to be better than those obtained from several existing techniques. The neural network based rainfall estimate offers an alternate approach to the rainfall estimation problem, and it can be implemented easily in operational weather radar systems [3][4].

The back propagation algorithm is an involved mathematical tool; however, execution of the training equations is based on iterative processes, and thus is easily implement able on a computer.

Weight changes for hidden to output weights just like Widrow-Hoff learning rule.

Weight changes for input to hidden weights just like Widrow-Hoff learning rule but error signal is obtained by "back-propagating" error from the output units[5].

Back propagation is a form of supervised learning for multi-layer nets, also known as the generalized delta rule. Error data at the output layer is back propagated to earlier ones ,allowing incoming weights to these layers to be updated. It is most often used as training algorithm in current neural network applications. The back propagation algorithm was developed by Paul Werbos in 1974 and rediscovered independently by Rumelhart and Parker. Since its rediscovery, the back propagation algorithm has been widely used as a learning algorithm in feed forward multilayer neural networks [6][1].

1. Initialize the weight to small values
2. Chooses an input pattern x_i with rain data for last five years
3. Propagate the signal forward through 6the network.
4. Compute the weight sum of inputs to the neurons.
5. Add bias to the sum.
6. Feed the sum as an input to the activation function

$$\mathbf{A(x) = \; 1/\,1 + e^{-x}}$$

$$Output = A \sum_{k=0}^{n} W_k * I_k + bias$$

Where, Wk is weight of the K^th in edge
Ik is input carried across K^th in edge .

7. Pair of set of inputs and outputs
(xi, yi) = (x1,x2,x3,x4,-----)(y1,y2,y3,y4,-------)
The sum of square error
$$SSE = \sum_{k=1}^{n} (yi - Zi)^2$$
Where Zi is set of output of the neural network for the set of input xi
8. Calculate the Zi , the output of network
9. Yi is the desired value of Zi , so when there is error (difference) , we have to compute the 'blame' value by (yi- Zi) . This can be done by using partial derivative which are needed for the gradient descent.
10. Now adjust the weight of neural network by
Wij= Wij + r*ej* Aj * (Ij)*Oj
Where , r is the learning rate (between 0 and 1) Here is 1.
ej is blame of neuron j , j = 1,2,3,----
Aj is derivative of activation function at neuron j
Ij is input fed to neuron during calculation of output in the first step.
Oi is the output of neuron I during the first step.
11. The bias is adjusted as bias-I = bias-I + r * ej

III. Working Operation

The radar rainfall estimation based on neural networks is applied to the full coverage area. Rainfall events could be very widespread in some cases, and we would receive large amount of data streams from both radar and rain gauge stations. A neural network training process would be computationally intensive in those cases. The first objective is to assess the feasibility of adaptively updating NNs on daily basis for a large dataset within observation range of radar. It would be desirable that the ground rainfall rate estimation be computed within the time frame for each radar volume scan. Otherwise, a computational delay will accumulate and can never catch up for real-time operations. A representative training data set consisting of the radar data and corresponding ground rain gauge data are needed to develop a multilayer perception for the rainfall estimation problem. Radar data and other related information are applied to the network as the input and the corresponding rain gauge data are used as the target or desired output. The connectional weights are updated during the backward error propagation according to the learning algorithm. This process is repeated until the error between the network output and desired output (rain gauge measurement) meets the prescribed requirement. When the training process is complete, the network is ready for application. Rainfall estimates can be obtained if radar data are applied to the network at this stage.

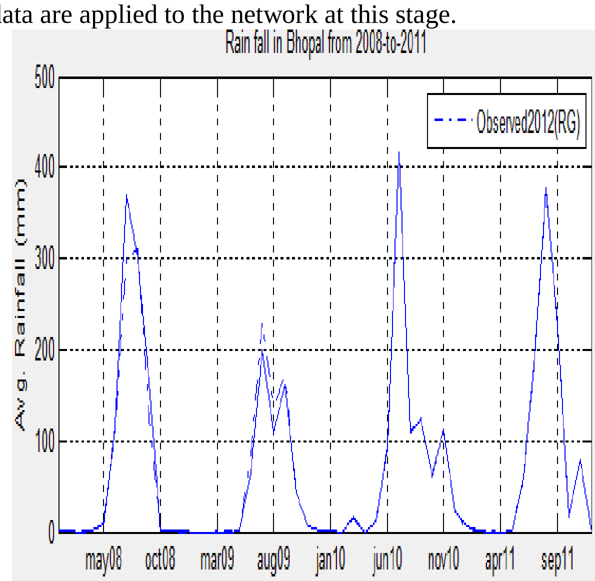

Fig.1. The graphical analysis of rain fall yearwise.

Table 1: Rain data use by year wise from in mm.

YEAR	J	F	M	A	M	J	J	A	S	O	N	D
2012	4	0	0	0	0	114	295	320	N/A	N/A	N/A	N/A
2012 NN	2.53	2.19	0	0	1.13	95.28	289.37	310.98	162.7	38.97	22.65	24.77
2011	1	0	0	0	15	0	180	380	220	18	42	19
2010	1	0	0	0	0	10	95	405	100	110	70	0
2009	0.5	0	0	0	0	80	220	130	170	35	10	0
2008	0	0	0	0	0	105	300	305	110	10	2	0

In this paper we are taking the last five years data at Bhopal in M.P. Region, India. With the help of this data we are trained the neural network which estimating the five years rainfall data month wise basis.

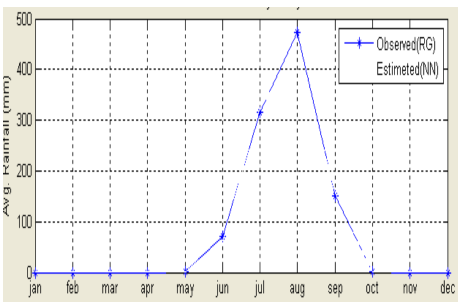

Fig.2. The graphical analysis of rain fall month wise.

International Journal of Engineering Innovation & Research
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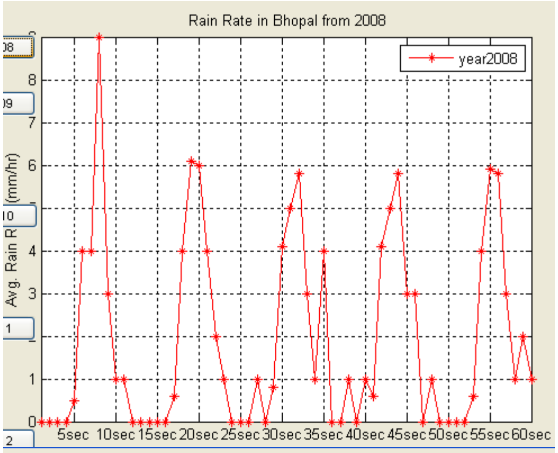

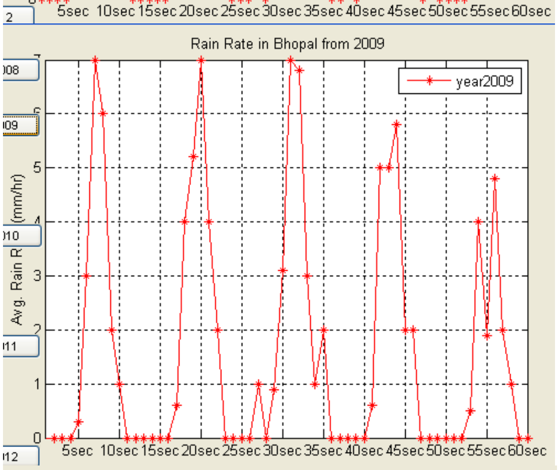

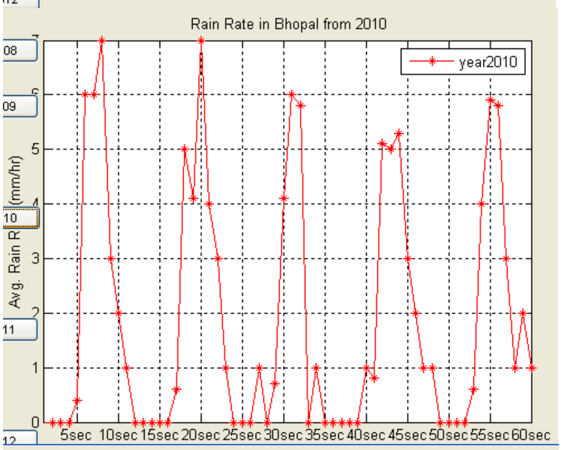

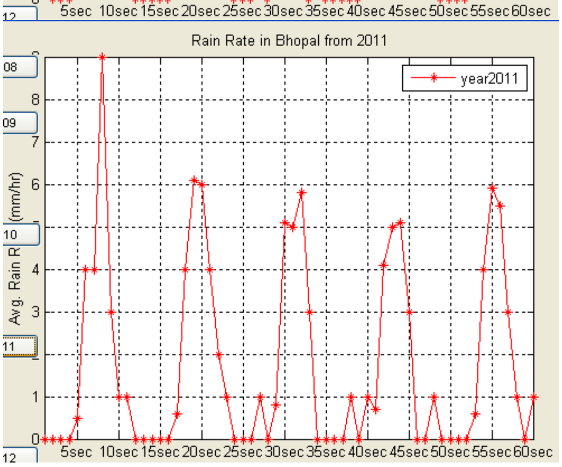

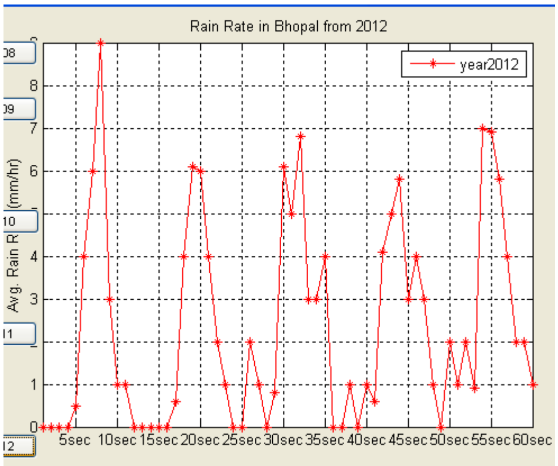

Fig.3. The graphical analysis of rain rate hourwise.

Year 2008 Rain rate in mm per hour
from 0 sec to 10 sec= (0 0 0 0 0.5 4 4 9 3 1 1 0);
from10 sec to 20 sec= (0 0 0 0 0.6 4 6.1 6 4 2 1 0);
from20 sec to 30 sec = (0 0 1 0 0.8 4.1 5 5.8 3 1 4 0);
from40 sec to 50 sec = (0 1 0 1 0.6 4.1 5 5.8 3 3 0 1);
from50 sec to 60 sec = (0 0 0 0 0.6 4 5.9 5.8 3 1 2 1);

Year 2009 Rain rate in mm per hour
from 0 sec to 10 sec= (0 0 0 0 0.3 3 7 6 2 1 0 0);
from10 sec to 20 sec= (0 0 0 0 0.6 4 5.2 7 4 2 0 0);
from20 sec to 30 sec = (0 0 1 0 0.9 3.1 7 6.8 3 1 2 0);
from40 sec to 50 sec = (0 0 0 0 0.6 5 5 5.8 2 2 0 0);
from50 sec to 60 sec = (0 0 0 0 0.5 4 1.9 4.8 2 1 0 0);

Year 20010 Rain rate in mm per hour
from 0 sec to 10 sec= (0 0 0 0 0.4 6 6 7 3 2 1 0);
from10 sec to 20 sec= (0 0 0 0 0.6 5 4.1 7 4 3 1 0);
from20 sec to 30 sec = (0 0 1 0 0.7 4.1 6 5.8 0 1 0 0);
from40 sec to 50 sec = (0 0 0 1 0.8 5.1 5 5.3 3 2 1 1);
from50 sec to 60 sec = (0 0 0 0 0.6 4 5.9 5.8 3 1 2 1);

Year 2011 Rain rate in mm per hour
from 0 sec to 10 sec= (0 0 0 0 0.5 4 4 9 3 1 1 0);
from10 sec to 20 sec= (0 0 0 0 0.6 4 6.1 6 4 2 1 0);
from20 sec to 30 sec = (0 0 1 0 0.8 5.1 5 5.8 3 0 0 0);

```
from40 sec to 50 sec = (0 1 0 1 0.7 4.1
5 5.1 3 0 0 1);
from50 sec to 60 sec = (0 0 0 0 0.6 4
5.9 5.5 3 1 0 1);
```

Year 2012 Rain rate in mm per hour

```
from 0 sec to 10 sec= (0 0 0 0 0.5 4 6
9 3 1 1 0);
from10 sec to 20 sec= (0 0 0 0 0.6 4
6.1 6 4 2 1 0);
from20 sec to 30 sec = (0 2 1 0 0.8 6.1
5 6.8 3 3 4 0);
from40 sec to 50 sec = (0 1 0 1 0.6 4.1
5 5.8 3 4 3 1);
from50 sec to 60 sec = (0 2 1 2 0.9 7
6.9 5.8 4 2 2 1);
```

The analysis performed in above figure is done using data collected from last year. The rainfall rate graphical analysis shows using an adaptive neural network the period of one hour. For the Convenience of evaluation, the rain rate observation is shown by a solid red line in figure. The ANN system with reflectivity values as input variables was trained to predict the rain rate on the ground. Rainfall rates may vary by tens of millimeters per hour in one minute and over distances of few hundred meters. The average rain rate over the rain area is calculated using volume rain rate and dividing by the convection rain area. The neural network algorithm estimates the one hour rain rate fall.

V. Conclusion

The radar rainfall estimation based on neural networks is applied to the full coverage area. Such large-scale application of the rainfall estimate poses several questions in the context of operational applications. i.e the feasibility of adaptively neural network models on a daily basis and the ability of neural network radar rainfall estimation at high spatial resolution within reasonable and practical time frame for operational applications. Using the datasets collected it is demonstrated that radar-based rainfall estimation using an adaptive RBF neural network is feasible.

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