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On The Rainfall Time Series Prediction Using Multilayer Perceptron Artificial Neural Network

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Abstract— **In this paper, Multilayer Perceptron Neural Network is proposed as an intelligent tool for predicting Rainfall Time Series. A Rainfall samples have been collected from the authorized Government Rainfall monitoring agency in Yavatmal, Maharashtra state, India. Rainfall percentage rise and fall with an irregular cycle.Multi-step ahead (1, 5, 10, 20) predictions of this Rainfall Data series have been carried out using the proposed Multilayer Perceptron Neural Network. It is seen that the performance measures such as MSE (Mean square error), and NMSE (Normalized mean square error) on testing as well as training data set for short term prediction are found as optimal in comparison with other network such as Jordon Elmann Neural Network, SOFM (Self organized feature map), RNN (Recurrent neural network).Out of all these networks, the results for Jordon Elman and MLP network were by far the closest. Hence, in this paper the analysis of these two networks is shown. The different results Parameters are calculated by using software, "Neurosolution 5.0". Neurosolution is an object oriented environment for designing, prototyping, simulating, and deploying artificial neural network (ANN) solutions. It is also evident that estimated neural network model closely follows the actual outputs for desired outputs for multi step ahead predictions [1].**

Keywords—**ANN (Artificial Neural Network), k (Number of step ahead), MSE (Mean square error), MLP (Multilayer Perceptron), NMSE (Normalized mean square error).**

I. INTRODUCTION

The main motivation for analysis and research of Rainfall time series is to predict the future and understand the fundamental feature and effects on human life. Artificial neural network used for solving the real world problem. This is mainly due to their ability to deal with nonlinearities, non-stationary and non guassianity [4]. The modeling and analysis of chaotic time series has also attracted the attention of many researchers [4]. In this paper different NNs are compared and an optimal Neural Network is found for prediction of Rainfall time series [2]. In this paper, Multilayer Perceptron Neural Network is found as an optimal NN as compared to Jordon Elman NN, SOFM NN, & RNN for Rainfall time series [1].

Multilayer Perceptron Neural Network is trained for multi step ahead prediction and the results are compared with reference to the MSE (mean square error), and NMSE (normalized mean square error) against various Neural Networks. On testing as well as training data sets for short term prediction. The number of experiments is carried out by changing various parameters like Error criterion (L1, L2, L3, L4, L5, and L∞), number of iterations, learning rule, percentage of Training & Testing data sets and Transfer functions [1]. Thus the optimum neural network model is proposed for short time prediction of Rainfall time series.

II. NEURAL NETWORKS FOR PREDICTION

The beginning of the prediction of the time series was made in 2-'s of the past century with the introduction of the autoregressive model for the prediction [13]. Time series are samples of system's behavior over discrete time values. The neural networks ability to cope with the nonlinearities, the speed of computation, the learning capacity and the accuracy made them valuable tools of prediction [11]. To predict the evolution over time of a process implies the prediction of the future values of time series describing the process [1], [4].Time series prediction with classical methods relies on some steps to be followed in order to perform an analysis of the time series, including here modeling, the identification of the model and finally parameter estimation. The most difficult systems to predict are a) those with insufficient amount of data in the data series (for instance chaotic signals); b) the systems whose data series are obtained through observation and measurements, in this case data being possibly affected by measurement errors; c) systems whose behavior varies in time[7].The artificial neuron for prediction receives at its inputs the delayed signal y(k-i), i=the number of inputs, the inputs are transmitted through i+1 multipliers for scaling, then the scaled inputs are linearly combined to form an output signal that is also passed through an activation function in order to obtain an output signal. The model of the neuron is schematized as shown in figure 1, [2].

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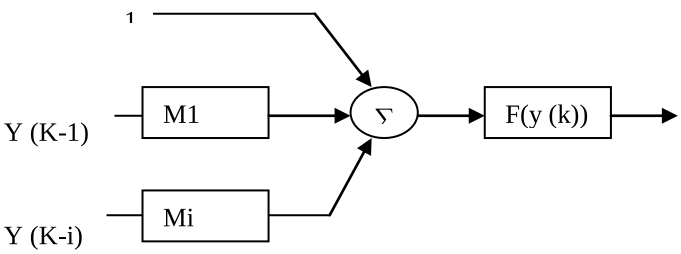

Figure1. The artificial neuron for prediction (M1….i are multipliers)

Consider x (t) the time series data collected in order to build a model. The data in the data series are samples of x(t) with a time step k. the prediction of the time series values can be made single step ahead, in this case one looking for a good estimation X1(t+1) of X(t+1) or multi step ahead prediction, in this case looking for a good estimate X1(t+nk) of X(t+nk), n being the number of steps ahead[9].The first and most common method for the prediction of time series consist in using M past values or M-tuples as inputs and one output.

III. MULTILAYER PERCEPTRON

The multilayer perceptron (MLP) is one of the most widely implemented neural network topologies MLPs are normally trained with the back propagation algorithm. The back propagation rule propagates the errors through the network and allows adaptation of the hidden PEs.

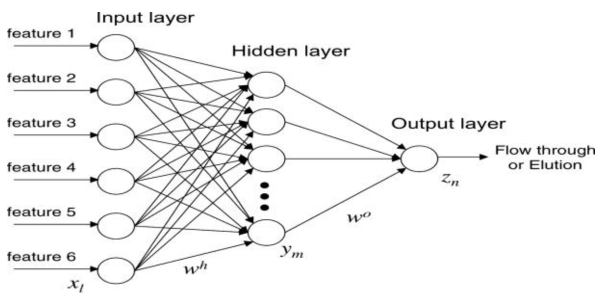

Figure2. Multilayer Perceptron Network

Two important characteristics of the multilayer perceptron are: its nonlinear processing elements (PEs) which have a nonlinearity that must be smooth (the logistic function and the hyperbolic tangent are the most widely used); and their massive interconnectivity (i.e. any element of a given layer feeds all the elements of the next layer).The multilayer perceptron is trained with error correction learning, which means that the desired response for the system must be known .

Error correction learning works in the following way: From the system response at PE i at iteration n,yi(n), and the desired response di(n) for a given input pattern an instantaneous error ei(n) is defined by -

$$ei(n)= di(n) - yi(n)$$

Using the theory of gradient descent learning, each weight in the network can be adapted by correcting the present value of the weight with a term that is proportional to the present input and error at the weight, i.e.

$$Wij(n+1)= Wij(n)+ \eta\, di(n)Xj(n)$$

The local error di(n) can be directly computed from ei(n) at the output PE or can be computed as a weighted sum of errors at the internal PEs. The constant h is called the step size. This procedure is called the backpropagation algorithm. [3], [7].

IV. PERFORMANCE MEASURES

The generalization performance of the network is validated on the basis of the following parameters.

A.MSE (Mean Square Error)

It is the average of the square of the difference between each output processing element and the desired output. It is used to determine how well the network output fits the desired output, but it doesn't reflect whether two sets of the data move in same direction [1].

Yij = network output for exemplar i at PE j
P = number of output PEs(processing elements)
N = number of exemplar in datasheet
Dij = desired output for exemplar I at PEj

B.NMSE (Normalized Mean Square Error)

NMSE is given as -

$$NMSE = \frac{p.n.MSE}{\sum_{j=0}^{p}\left[\frac{N\sum_{i=0}^{N} dij^2 - \left(\sum_{i=0}^{N} dij\right)^2}{N}\right]}$$

P = number of output PEs(processing elements)
N = number of exemplar in datasheet
dij = desired output for exemplar I at PEj [1].

V. NEUROSOLUTION 5.0

Neurosolution is an object oriented environment for designing, prototyping, simulating, and deploying artificial neural network (ANN) solutions. This environment is inherently modular, as a neural network breaks down into a fundamental set of neural components.

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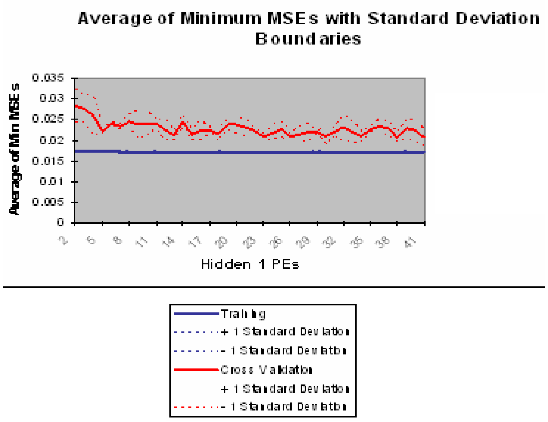
Individually simple, these components combine to form networks that can solve complex problems. Neurosolution supports a practically infinite number of neural models. It provides the user with an icon-based interface from which the neural components are arbitrarily interconnectable [1].

VI. CASE STUDY

The different neural network models like Jordan Elman ,MLP (Multi layer perceptron), time lag recurrent network and self organizing feature map are trained for multi step ahead [1,5,10,20] predictions and the results are compared with reference to MSE (Mean square error),and NMSE (Normalized Mean Square Error) on testing as well as training data set for short term prediction[6] ,the number of experiments are carried by changing various parameters like no. of possessing elements ,number of hidden layers, no. of iterations, transfer function learning rule[3]. On the Rainfall time series number of experiments is carried out for the multi step ahead prediction. Here we are varying number of processing elements and finding out the number of processing elements for which the network gives minimum MSE



Best Networks	**Training**	**Cross Validation**
Hidden 1 PEs	22	41
Run #	3	3
Epoch #	1000	57
Minimum MSE	0.01711896	0.018418431
Final MSE	0.01711896	0.025432078

Figure3. Graph and Table showing optimal parameters

Figure 3.shows the graph obtained by varying parameters giving the number of processing elements for which the network gives minimum MSE.

Here in this Rainfall time series prediction we have used 60% samples as training, 25% samples as testing, and 15% samples are used as cross validation. The optimum parameters are decided of the NN model on the test data set, and by processing element graph as listed in following table.

TABLE I: PROCESSING ELEMENTS TABLE

Sr. no	Parameter	Hidden Layer	Output Layer
1	Processing elements	22	1
2	Transfer function	tanh	tanh
3	Learning rule	momentum	momentum
4	Step Size	1	0.1
5	Momentum	0.8	0.7

It is found that the performance of the selected model is optimal for 22 neurons in the hidden layer with regard to the MSE, and NMSE for the testing data sets. Next the proposed model is trained with different error criterion L1, L2, L3, L4, L5 and L∞ the best combination network is then trained and test for different transfer functions such as Tanh, sigmoid, linear sigmoid and all different transfer functions. Then the proposed Multilayer Perceptron NN model is trained for the best combinations resulted for training and testing exemplars and it is experimented for 1000 to 20000 iterations for getting an optimum results for each multi step (k=1, 5, 10, 20) of chaotic Rainfall time series .The number of epochs are varied from 1000 to 20000 in the step 2000 and the graphs are plotted for all the steps.

TABLE II: TYPE OF NETWORK-JORDAN ELMAN NN

SHIFT (LOOK AHEAD)	**MSE**	**NMSE**
1	0.029853	0.317395
5	0.054582	0.593164
10	0.080943	0.878603
20	0.110404	1.977274

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TABLE III: TYPE OF NETWORK MULTILAYER PERCEPTRON NEURAL NETWORK

SHIFT (LOOK AHEAD)	MSE	NMSE
1	0.070474	0.766414
5	0.081301	0.883524
10	0.062007	0.781608
20	0.064779	0.828212

The best combination network is then trained and test for different transfer functions such as a) Tanh axon b) Sigmoid c) Linear Tanh axon d) Linear Sigmoid. And then various combinations of training & testing samples for obtaining Optimal combinations of training & testing samples. Then the proposed Multilayer Perceptron NN model is trained for the best combinations resulted for training and testing exemplars and it is experimented for 1000 to 20000 iterations for getting an optimum results for each multi step (k=1, 5, 10,20) of chaotic Rainfall time series .

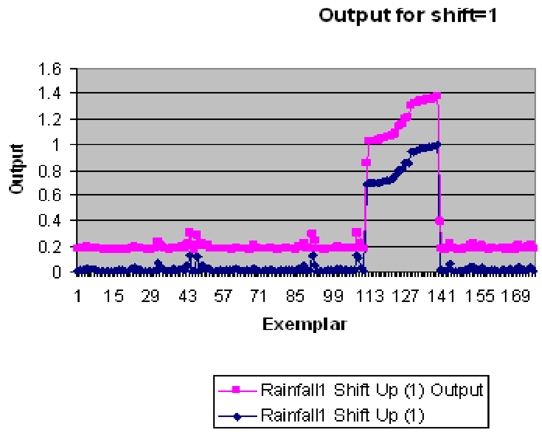

Figure4. Graph for (K=1)

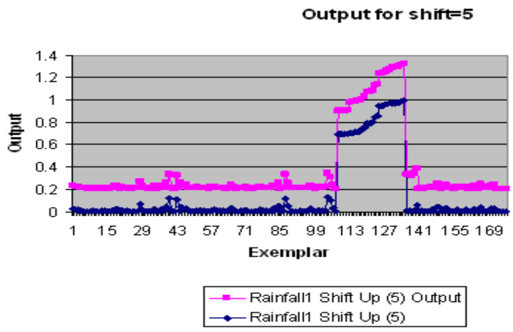

Figure5. Graph for (K=5)

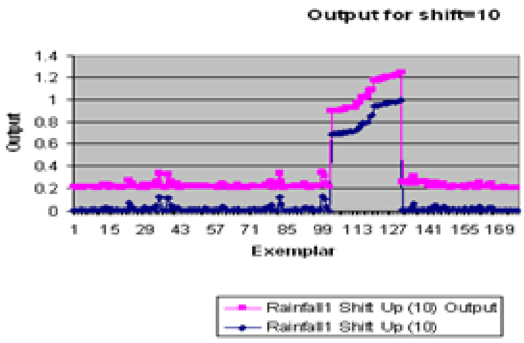

Figure6. Graph for (K=10)

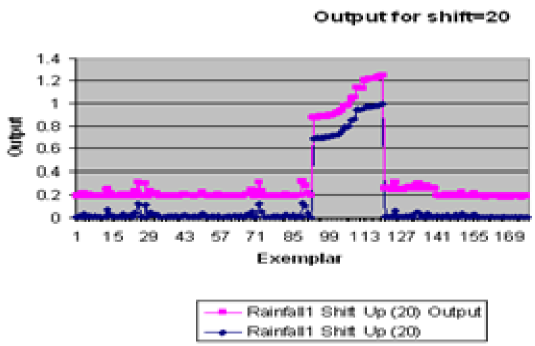

Figure7. Graph for (K=20)

Then, the number of epochs is varied from 1000 to 20000 in the step 2000 and the scatter plots are plotted for all the steps.

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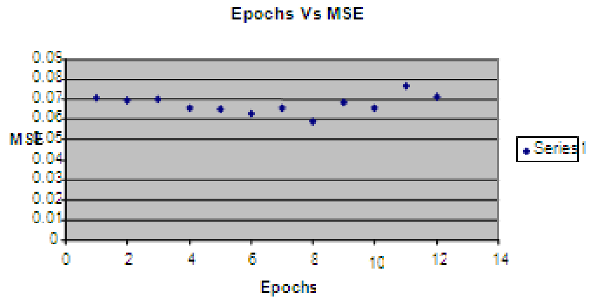

Figure8. Scatter plot (K=1)

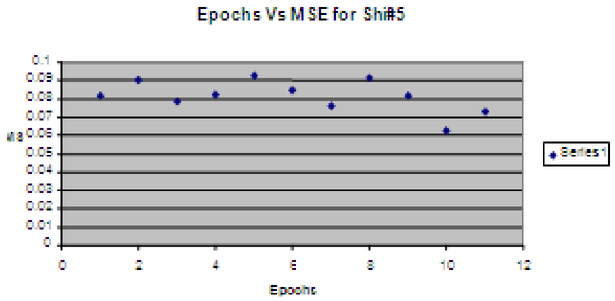

Figure9. Scatter plot (K=5)

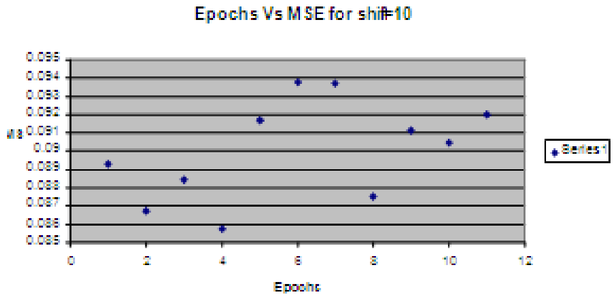

Figure10. Scatter plot (K=10)

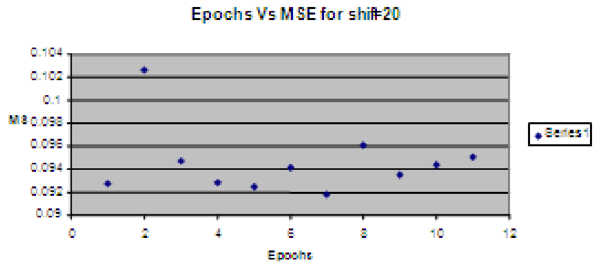

Figure11. Scatter plot (K=20)

VII. RESULTS

Comparison Tables of JENN, and Multilayer Perceptron Neural Network for Rainfall time series Prediction for K=10 and k=20 are as below.

TABLE IV: FOR (K=10)

SR. NO.	NN MODEL	MSE	NMSE
1	MLP	0.062007	0.781608
2	JORDAN ELMAN NN	0.080943	0.878603

TABLE V: FOR (K=20)

SR. NO.	NN MODEL	MSE	NMSE
1	MLP	0.064779	0.828212
2	JORDAN ELMAN NN	0.110404	1.977274

Tables 4 and 5 shows comparison between Jordn-Elman NN, and Multilayer Perceptron Neural Network for shift(k=10,20).Thus here we have compared various NN on the basis of MSE,and NMSE. And an optimal NN for prediction of Rainfall time series is found.

VIII. CONCLUSION

It is seen that Multilayer Perceptron Network is able to predict Rainfall time series quite well in comparison with other networks. It is seen that MSE, and NMSE of the proposed dynamic model for Testing data set as well as Training data set are significant than other neural models. The network is analyzed for different step ahead (k=1, 5, 10, 20).The better results can be obtained for maximum 20step ahead by using this network. The following parameters are obtained for 10 step ahead; MSE=0.062007, NMSE=0.781608, and for 20 step ahead; MSE=0.064779, NMSE=0.828212. Initially we find that for small step ahead values the Jordon Elman Network was giving good results, but as soon as we go for the larger step ahead values then the performance of Multilayer network is better than all the other networks. Also, by looking at the response illustrated in figures 4 to 7, the shadowing technique can also be applied here for the analysis of the graphs. In this paper, we have also studied the variation of error with the number of epochs, and this variation is illustrated by the scatter plots from figures 8 to 11.

References

[1] Rohit R. Deshpande and Athar Ravish Khan *"On The Sunspot Time Series Prediction Using Jordon Elman Artificial Neural Network (ANN)".*International Journal of Advances in Engineering & Technology, Jan 2012. ISSN: 2231-1963

[2] Sanjay L. Badjate, Sanjay M.Gulhane *"Multi-Step Ahead Prediction Of Chaotic Time Series Using Recurrent Neural Network Models ".* International Journal Of Computer Science And Applications Vol. 4, No. 1, April / May 2011 ISSN: 0974-1003

[3] Tuevo kohonen *"self organizing feature map"*, third edition , Springer 2001,p.28

[4] D.Hammerstram, *"Working with neural network*", IEEE spectrum, 1993, pp46-53.

[5] Hecht-Nielsen R. NeuroComputing. Addison Wesley, 1990.

[6] Hertz J., Krogh A. and Palmer R. Introduction to the Theory of Neural Networks. Addison Wesley, 1991.

[7] Hopfield J. "Neural networks and physical systems with emergent collective computational abilities." Proc. Natl. Acad. Sci. (USA) 79, 2554-2558, 1982.

[8] Jacobs R. "Increased rates of convergence through learning rate adaptation." Neural Networks 1, 295-307, 1988.

[9] Jordan M. "Attractor dynamics and parallelism in a connectionist sequential machine." Proc.8th Annual Conf. on Cognition Science Society, pp 531-546, 1986.

[10] Kohonen T. "The self-organizing map." Proc. IEEE 78, 1464-1480, 1990.

[11] Lang K., Waibel A. and Hinton G. "A time delay neural network architecture for isolated word recognition." Neural Networks 3(1), 23-44, 1990.

[12] LeCun Y., Denker J., Henderson D., Howard R., Hubbard W. and Jackel L. "Handwritten digit recognition with a backpropagation network." In Advances in Neural Information Processing Systems 2, (ed. Touretsky), pp 396-404, 1990.

[13] Lippman R. "An introduction to computing with neural nets." IEEE Trans. ASSP Magazine 4,4-2, 1987.

[14] Makhoul J. "Pattern recognition properties of neural networks." Proc. 1991 IEEE Workshop on Neural Networks for Signal Processing, pp 173-187, 1992.

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