Artificial Neural Network Techniques by Using Time Series and Parameterized Rainfall Prediction Models: A Comparative Study

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Abstract- Accurate, timely, area specific forecasts of precipitation are very important in countries thriving on agro based economy. In this aspect, one of the major issue is sudden changes in weather, Weather forecasting is an application of science and technology to predict the atmosphere for a given location.Already so many tools and techniques were introduced, but always there is a need to predict accurate weather information to avoid loss of lives and assets.Due to ease in training, the multilayered Artificial Neural Network learning algorithm is the most common. In this work we have used both Artificial feed forward and feedback(Recurrent) Neural networks forboth parameterized and time series prediction model to predict next month rainfall in mille meter.The feed forward neural network is trained with back propagation algorithm, and feedback neural network is trained with gradient descent strategy .In this work, the data of Extremely severe cyclonic storm Hud-Hud from coastal Andhra Pradesh tested with these four models. The results have been enumerated in this paper.

Keywords- Natural Disasters, Rainfall Prediction, Artificial Neural Networks, Back Propagation, Layer Recurrent network.

I. INTRODUCTION

The implementation of Artificial Neural Network is initiated in 1964[3], an importance is given to Soft Computing methodology in weather forecasting. In the actual complex system, there are multiple variables evolving together and influencing each other, therefore multivariate prediction is much important[3]. A Time Series model can be actually an integration of random and deterministic components [10]. If random components are eliminated then the deterministic components can then be easily modeled. Rainfall is an end product of number of complex atmospheric process which varies both in space and time. Hence time series Prediction is also important.

Most challenging part of flood forecasting is the lack of meteorological observations, particularly precipitation [11]. Precipitation Forecasts using Numerical Weather Prediction models still face difficulties at scales relevant for flood forecasting[12-14]. Indeterminately Parameterized Prediction is important. So many models of Artificial Neural Networks have been developed for rainfall Prediction[17]. There are two models Feed Forward Neural Network and Feedback Neural Network(Recurrent Neural Network). The main difference of Feed Forward Neural Network and Feedback Neural Networkis in each neuron of feed-back network, the output if previous time step is forwarded as input of the next time step. This makes feed-back network be aware of time while the feed forward network has none. On Reading Multiple Papers[3-8] in this domain , come to a conclusion that to compare both Time Series and Parameterized prediction models with Feed Forward and Feedback Artificial Neural Networks.In this paper ANNs are used to obtain a prediction model for the monthly rainfall of Costal Andhra Pradesh.

II. MATERIALS AND METHODS

A. *Hud-Hud Cyclone*

Hud-hud cyclone the biggest disaster to have ever hit Andhra Pradesh.It was a strong tropical cyclone that caused immense loss to both the people and the government[9].It originated from a low pressure system with winds touching a speed of around 180-195 Kmph during landfall and waves surged as high as two to three meters .It all started with a cyclonic circulation in the Andaman sea on October 6 and slowly the furious winds got converted into a devasting cyclone on October 8.It turned out to be too severe on October 9.Hudhud had its major impact on the Jewel of East coast and The city of Destiny that is Vishakapatnam.Hudhud crossed the coast of AndhraPradesh at the noon of October12 over Vishakapatnam,with winds exceeding 185Km/phHudhud caused at least 120deaths within AndhraPradesh. Total damage costs estimated to be at least 10,000 crores.Despite causing extensive damage.

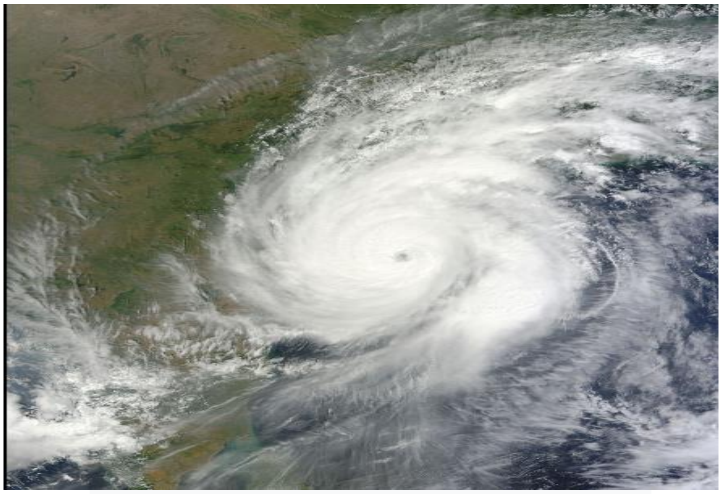

Fig.1: Hudhud nearing landfall at peak strength on October 12, 2014 [9]

B. Artificial Neural Networks

The idea of ANNs is based on the belief that working of human brain can be imitated by making the right connections using silicon and wires as living neurons and dendrites [6].The human brain is composed of 100 billion nerve cells called Neurons. They are connected to other thousand cells by Axons. Stimuli from external environment or inputs from sensory organs are accepted by Dendrites. These inputs create electric impulses, which quickly travel through the neural network. A neuron can either send the message to other neuron to handle the issue or block the message from processing forward.

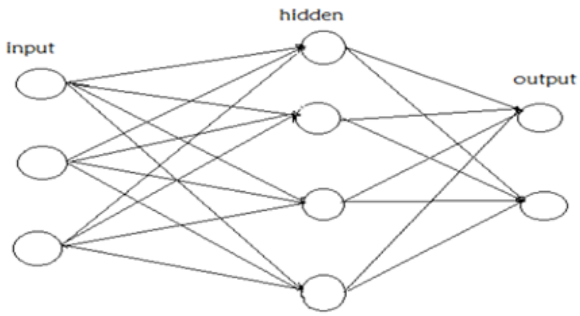

Fig.2: Fully Connected Artificial Neural Network

ANNs are composed of multiple nodes, which imitate the biological neurons of human brain. The neurons are connected by links that interact with each other. These nodes can take input data and perform simple operations on the data. The result of these operations is passed to other neurons. The output at each node is called its activation or node value.Each link is associated with weight. ANNs are capable of learning, which takes place by altering weight values. The following illustration shows a simple ANN

C. Types of Artificial Neural Networks

There are two Artificial Neural Network topologies – Feed Forward and Feedback.

D. Feed Forward ANN

In the Feed Forward ANN the flow of information is unidirectional. A unit sends information to other unit but the vice versa does not take place, that means there are no feedback loops. These types of Artificial Neural Networks are used in pattern generation, pattern recognition or pattern classification. They have fixed inputs and outputs.

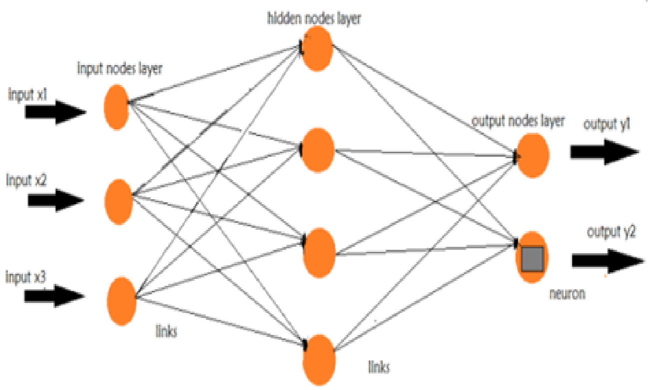

Fig.3: Fully Connected Feed Forward Artificial Neural Network.

E. Feedback ANN

Here, feedback loops are allowed. They are used in content addressable memories.

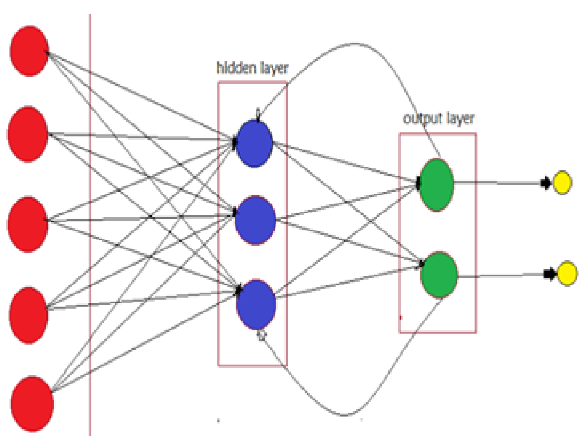

Fig.4: FeedbackArtificial Neural Network

F. Layer recurrent neural networks

Layer recurrent neural networks are equivalent to feed-forward networks, demur that every individual layer has a continual or recurrent connection with a tap delay involved with it. An earlier modest version of the network was introduced by Elman. In the LRN, there exists a feedback loop, with a single delay, around each layer of network except for last layer. The original network had only two layers and employed a tensing transfer function for the hidden layer and purely transfer function for explicit layer. The original Elman network was modified by using an approximation to the back propagation algorithm. The layrecnet command generalizes that the proposed network of Elman to have arbitrary transfer functions in every individual layer. Feedback networks have signals travelling in bidirectional way by introducing loops in network, feedback network change as dynamic. This state changes frequently or continually until they attain an appropriate equilibrium point [7]. They remain at equilibrium point until the input changes and a new equilibrium state need to be found. These networks also called as feedback or Auto associative neural networks.

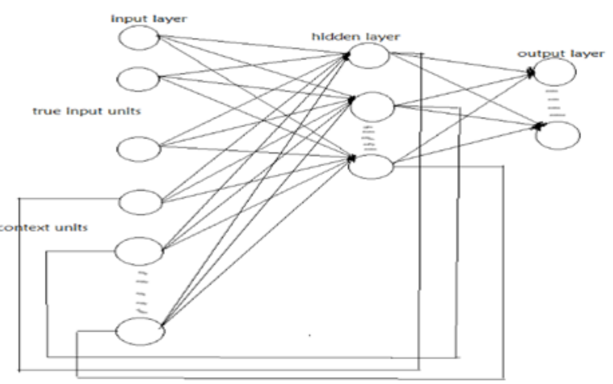

Fig.5: Layer Recurrent Network

RNNs can use their implicit memory to process arbitrary sequence of inputs. This makes them reliable to tasks such as unsegmented connected handwriting recognition or speech recognition. RNNs are recurrent because they perform the same operation or procedure to every individual element of a sequence, with the output depending on previous computations i.e., on previous elements obtained for different inputs.

G. Gradient descent

To minimize the total error, Gradient Descent can be used to change each weight in proportion to the derivative of the error with respect to the weight considered, provided the non-linear activation functions are differentiable. Various methods for minimization of errors were developed in the 1980s and early 1990s by Paul Werbos, Ronald J. Williams, Tony Robinson, Jürgen Schmidhuber, SeppHochreiter,BarakPearlmutter, and others.The standard method is called "Back Propagation Through Time" or BPTT, and is a generalization of back-propagation for feed-forward networks, and it is an instance of automatic differentiation in the reverse accumulation mode or Pontryagin's minimum principle. A more computationally expensive online variant is called "Real-Time Recurrent Learning" or RTRL, which is also an instance of automatic differentiation in the forward accumulation mode with stacked tangent vectors. Unlike BPTT this algorithm is **local in time but not local in space**.
There also is an online hybrid between BPTT and RTRL with intermediate complexity, with variants for continuous time. One of the major problem with gradient descent for standard RNN architectures is that error gradients vanish exponentially quick when compared with the size of the time lag between important events. The long short-term memory architecture together with a BPTT/RTRL hybrid learning method was introduced in an attempt to overcome these problems[7].

H. Back- Propagation Algorithm

Back propagation, an abbreviation for "backward propagation of errors", is a prevailing approach of training artificial neural networks used in conjunction with an optimization method such as gradient descent. For a given set of input patterns with known classifications, this algorithm enlightens a given feed-forward multi layer neural network. The Network examines its output response to each entry of the sample input pattern presented to the network. The error value is calculated when the known and the desired output is evaluated on the evidence of the output response. Based on the error, the connection weights are altered. The Back propagation algorithm is based *on Widrow-Hoff delta learning rule* in which the weight adjustment is done through *mean square error* of the output feedback to the sample input. The set of these sample patterns are repeatedly presented to the network until the error value is curtailed.
The Back propagation learning algorithm can be divided into two phases: propagation and weight update[5-6].

Phase 1: Propagation

Each propagation comprises the following steps:
1. Forward propagation of training pattern's input through the neural network in order to generate the propagation's output stimulation.
2. Backward propagation of the propagation's output activation is achieved via neural network by adopting the training pattern target in order to generate the deltas (the difference between the input and output values) of all output and hidden neurons.

Phase 2: Weight update

For each weight-synapse follow the following steps:

1. To procure the gradient of the weight, multiply its output delta and input activation.
2. Subtract the ratio (percentage) of the gradient from the weight.

This ratio (percentage) esteems the speed and quality of learning; it is called the learning rate. The greater the ratio, the faster the neuron trains; the lower the ratio, the more authentic the training is. The weight must be updated in the opposite direction as the sign of gradient of the weight indicates the increase in error.

I. *Activation Function Used*

Activation function plays a major role in Artificial Neural Networks, introduce non-linear properties to our network. Main purpose is to make input signal as output signal. If we are not using Activation Function then output would be Linear. This model uses Sigmoid Activation Function of form

f(x) = 1 / 1 + exp(-x)

It can easily understand and apply, it vanishes gradient problem, its output isn't Zero Centered, it has slow convergence.

PREDICTION MODELS

To predict Rainfall there are two ways: (1)Time Series Prediction and (2) Parameterized Prediction.

In Time Series Prediction both input and outputs are rainfall (in mm).In parameterized Prediction inputs will be parameters of weather like wind speed, humidity, pressure, Temperature, sea level etc. , output will be the amount of rainfall in mm. Whatever the model, whether it is time series or parameterized, there are 2 phases training and testing.In training phase we need to give both input tuples and output tuples, in testing phase we need to give only inputtuples and get output from the model.

Table 1

Sample Data taken for Time Series Model [18]

Table 2

Sample Data taken for Parameterized Model [18]

For example in Time series, , if there are three inputs in a tuple one output both are amount of rainfall in mm like explained above.

Suppose if , we want to find rainfall of june, 2005 the training tuple will be like following

Input(mm)	output(mm)
May, 2005	June, 2005
June, 2004	
June, 2003	
June, 2002	
June, 2001	

Testing tuple should be following

Input(mm)
May, 2005
June, 2004
June, 2003
June, 2002
June, 2001

For Parameterized prediction

Training set will have tuples like following

Input	output
MaxTemperature	rainfall(mm)
Min. Temperature	
Wind	
Pressure	
Visibility	

Testing tuple like following

Input
Max. Temperature
Min. Temperature
Wind
Pressure
Visibility

For both Time Series and Parameterized Prediction the network should be trained with data, that means we need to to give both inputs and outputs at training phase. After Training we need to give test data which contains only inputs, thentrained network gives outputs. Then we need to compare outputs predicted from network compared with Actual Data. If we get very less error then we can use this model for further prediction, otherwise we need to change the network parameters like activation function, learning rate etc. After these modifications we need to train the network, this process will be continued till we get the efficient network which generates less error.

III. RESULTS& DISCUSSION

By using above process, the four network is trained and tested, the following are test results for both time series and parameterized prediction by using both Feed Forward Neural Network and Recurrent Neural Network.

A. Regression Graph for Time Series Feed Forward Neural Network

This network is Feed Forward Neural Network with 8 neurons in hidden layer, input given to this model is time series data. The network is trained with training algorithm, after testing average error rate is -0.1326, Root Mean Square Error is 1.6918

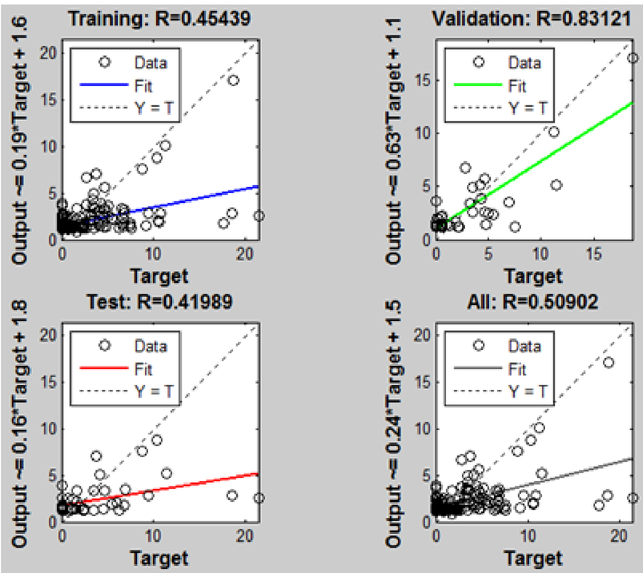

Fig.6: Regression Graph for Time Series FFN

B. Regression Graph for Time Series Feedback Neural Network

This network is Feedback Neural Network with 8 neurons in hidden layer,input given to this model is time series data. The network is trained with training algorithm, after testing average error rate is -0.0523, Root Mean Square Error is 0.762

C. Regression Graph for Parameterized Feed Forward Neural Network

This network is Feed Forward Neural Network with 8 neurons in hidden layer, input given to this model is Parameterized data. The network is trained with training algorithm, after testing average error rate is -0.1076, Root Mean Square Error is 1.6862

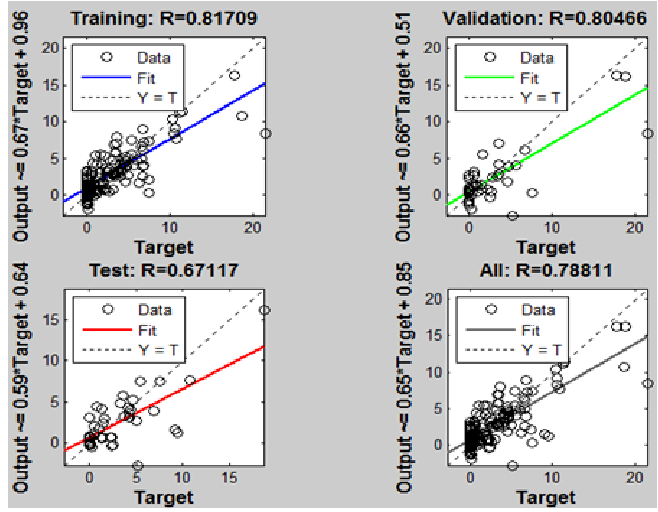

Fig.7: Regression Graph for Time Series RNN

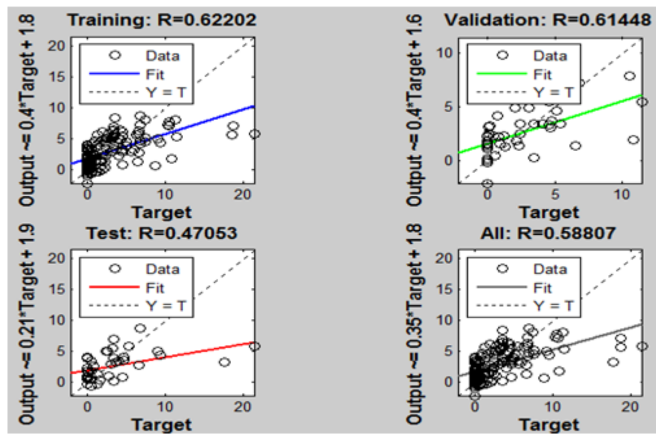

Fig.8: Regression Graph for Parameterized FFN

D. *Regression Graph for Parameterized Feedback Neural Network*

This network is Feedback Neural Network with 8 neurons in hidden layer, input given to this model is parameterized data. The network is trained with training algorithm, after testing average error rate is 0.6270, Root Mean Square Error is 1.2725

E. Comparison Table of Testing Results using four Models

From all above specified Models, Time Series Recurrent Neural Network trained with Backpropagation algorithm with 8 neurons in hidden layer is giving best results

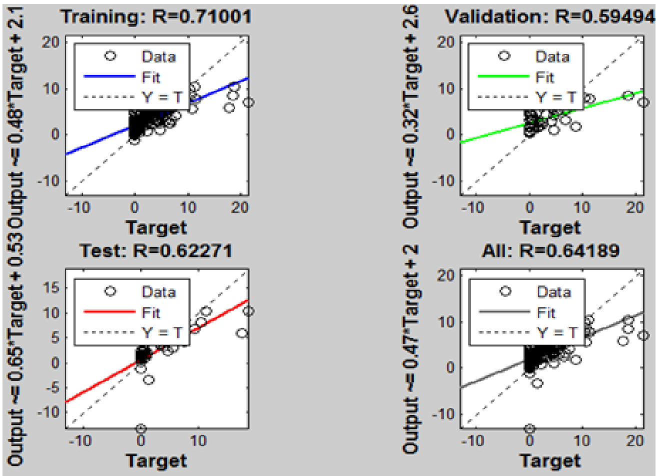

Fig. 9. Regression Graph for Parameterized RNN

Table 3
Testing Results

Neural Network Model	Prediction Model			
	Time Series		Parameterized	
	Average Error	No. of Neurons Used	Average Error	No. of Neurons Used
Feed Forward Network	-0.1326	8	0.1011	8
Feed Back Network	-0.0523	8	0.6320	8

IV. CONCLUSIONS

Weather forecasting using neural networks is a complex Application, we may not know, what is the best model for the corresponding dataset. A major limitation of every data analysis technique, including neural networks, is the need for a training data set that suitably represents the behavior of the system. In this paper an attempt has been made to forecast next month Average rainfall.From four models Feedback Artificial Neural Network using time series model giving best results, and also noticed that when neurons in the hidden layer is increased the results are slightly better. From all training algorithms Backpropagation Algorithm is giving better results. . In results, there are some deviations from the actual rainfall. This may be due to various reasons like delay in commencement of monsoon, occurrences of cyclones etc..

The Limitation of Parameterized Prediction is that it can predict rainfall when actual values of weather parameters are available. By using time series we can predict next month rainfall, so we can use use time series to predict weather parameter values, parameterized to predict rainfall. The present work can be improved by using a hybrid model which is a combination of both timeseries and parameterized predictions in future. This study has demonstrated that multilayered feed forward and Feedback neural networks trained using the error back propagation algorithm can be effectively used to predict rainfall.

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TABLE.1:

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2001	75	0	6	582	890	1381	2771	267	839	1905	1218	267
2002	582	0	25	140	385	730	530	1435	590	2305	614	16
2003	27	8	251	2	58	806	1733	1260	1421	2642	123	990
2004	146	17	4	65	1049	990	1245	809	1511	2158	542	1
2005	29	44	10	61	445	522	1127	797	3910	4077	753	159

TABLE.2:

Date	1/1/2000	1/2/2000	1/3/2000	1/4/2000	1/5/2000	1/6/2000	1/7/2000	1/8/2000	1/9/2000	1/10/2000
Temp Max	0.282	0.28	0.275	0.28	0.274	0.27	0.272	0.28	0.27	0.28
Temp Min	0.205	0.21	0.204	0.2	0.195	0.201	0.193	0.196	0.186	0.185
Wind	0.048	0.067	0.051	0.042	0.042	0.05	0.066	0.069	0.045	0.021
Pressure	0.10138	0.10143	0.10141	0.1013	0.10136	0.10137	0.10133	0.10139	0.10139	0.10132
Visibility	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Rain Fall	0	0	22	5	0.7	0	0	0	2	19