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Optimum Neural Network Architecture for Precipitation Prediction of Myanmar

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Abstract**—**Nowadays, precipitation prediction is required for proper planning and management of water resources. Prediction with neural network models has received increasing interest in various research and application domains. However, it is difficult to determine the best neural network architecture for prediction since it is not immediately obvious how many input or hidden nodes are used in the model.

In this paper, neural network model is used as a forecasting tool. The major aim is to evaluate a suitable neural network model for monthly precipitation mapping of Myanmar. Using 3-layerd neural network models, 100 cases are tested by changing the number of input and hidden nodes from 1 to 10 nodes, respectively, and only one outputnode used. The optimum model with the suitable number of nodes is selected in accordance with the minimum forecast error. In measuring network performance using Root Mean Square Error (RMSE), experimental results significantly show that 3 inputs-10 hiddens-1 output architecture model gives the best prediction result for monthly precipitation in Myanmar.

Keywords**—**Precipitation prediction, monthly precipitation, neural network models, Myanmar.

I. INTRODUCTION

TODAY world is witnessing an ever changing climate conditions. Climate changes have far reaching effects especially in the agricultural sector of a country. Among different aspects of climate changes, precipitation is the main source of water for the hydrological cycle which is important for agribusiness. Since Myanmar is still an agricultural country, the level of precipitation directly affect on the Myanmar agribusiness on which 80 percent of the population depend. In addition, the consequences of precipitation, such as flooding and droughts, can cause serious natural hazard in Myanmar. Under these circumstances, precipitation prediction, in other words, knowing the condition of rainfall in Myanmar in advance can help in managing and dealing with agricultural management and disaster prevention.

Since accurate precipitation prediction is becoming an important issue for the scientific community, many computational methods have been proposed in an attempt to predict precipitation accurately. Among them, forecasting with neural network models has received increasing interest in various research areas.

Adya and Collopy have examined applications of neural network to business forecasting and prediction. Among, 48 studies done between 1988 and 1994, Adya and Collopy found that neural network models produced superior predictions when they are effectively implemented and validated. Compared with Linear Regression, stepwise Polynomial Regression, multiple regression, discriminant analysis, logic models, and rule-based system, their results show that effectively implemented and validated Neural Network models outperformed all comparative methods. [8]

The next section of this paper reviews related works, and section 3 presents data source and geographical background of Myanmar. Section 4 discusses about neural network models, consisting of training and evaluation and followed by conclusion in a final section.

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II. RELATED WORKS

Today, Neural Network (NN) models are being used in many subject areas for prediction purposes. For hydrological problems, NN models are used for prediction of tornados (Marzban & Stumpf, 1996), damaging winds (Marzban & Stumpf, 1998), thunderstorms (McCann, 1992), river-flow (Cannas & Fanni, 2005), inflow into Rivers (Karla & Carlos, 2007), wind-speed (Soteris & Costas). Moreover, NN models are applied on other areas such as electricity load, financial times series, electric power and population of a country [3, 4, 7, 10, and 14]. Some precipitation prediction using NN models are presented as follows.

Chantasut & Charoenjit have built a neural network model for monthly rainfall prediction, by using monthly historical rainfall data in 1941-1999 from 245 rainfall stations in Thailand. They employed Neural network (NN) architecture 10 inputs-5 hiddens-1 output . Their results show that backpropagation neural network used for predictions of rainfall data provide acceptable accuracy. [10]

Yerong et. al have also shown that BPNN (Backpropagation Neural Network) and LR (Linear Regression) approaches produce forecasts of similar quality, but BPNN slightly outperformed the Regression for Short-Range QPF (quantitative precipitation forecasts). Their results show that fewer number of hidden layer nodes will not be able to solve the learning problem but a prediction with too many number of hidden layer nodes will slow the process and produce unreliable output. [5]

McCullagh et. al employ NN to estimate the 6-hr rainfall over the south east coast of Tasmania. Compared with one estimation technique and one forecast technique, their results suggest that NN has potential for successful application to the problem of rainfall prediction. [6]

Recently, Chattopadhyay has built a 3-layered ANN with sigmoid non-linearity to study the number of hidden nodes. Neural network architecture used is 3 input and one output, changing number of hidden nodes from 1 to 19 nodes. The results show that NN with 3 nodes in hidden layer is the best predictive model. [13]

III. Study Area and Data Used

The diamond-shaped Myanmar is situated in Southeast Asia, with an area of 676,577 square kilometers. Generally, Myanmar enjoys a tropical monsoon climate. However, climatic conditions differ widely from place to place due to widely differing topographical situations. In Lower Myanmar, Yangon receives a very high average annual rainfall of approximately 2,500 mm (98 in). [9] In Yangon, when rainfall comes, most of the daily activities are nearly perplexed. Some of the immediate consequences of a heavy rainfall in Yangon are: water clogging in the streets, heavy traffic jams, and direct and indirect economic losses.

In Myanmar, there are 17 rain gauge stations where rainfall data are accurately measured for 17 areas. Using their recorded data, precipitation estimates can be made for 17 areas of Myanmar. In this study, monthly precipitation amounts for only Yangon region are predicted using neural network models. Monthly rainfall series data are obtained from the Department of Meteorology and Hydrology of Myanmar for the periods 1970 to 2006. Total data sets (37 years) are divided into 2 data sets: training and test sets; 75% (1970-1997) and 25% (1998-2006) of total sets, respectively.

IV. Neural Network Models

A neural network (NN) model is composed of many artificial nodes that are linked together. The objective is to transform the inputs into meaningful outputs. NNs have the ability to learn by example. In this study, the most commonly used NN model- the three-layer feed-forward NN model learning with Backpropagation method (BPNN) - is used for precipitation prediction.

In the BPNN architecture, each node at input and hidden layers receives input values, processes and passes to the next layer. This process is conducted by weight which is the connection strength between two nodes. [11] The number of nodes in the input layer and the output layer are determined by the number of input and output parameters.

A. Building Neural Network Models

In modeling non-linear relationships, NN models have recently become important alternative tool to conventional methods such as regression methods. In building our NN models, the model parameters shown in Table 1 are used.

B. Training Neural Network Models

After configuration input parameters of neural network models, next step is to train neural network models with these settings. In present case, the models are trained by using the following train data format:

$$x_t = f(x_{t-1} \ldots x_{t-n})$$

where; x = precipitation amount of one year, n = number of input nodes in the model, t = desired year, f(x) is training function of neural network models.

TABLE I
PARAMETERS OF NN MODELS

Number of Layers	3
Number of Input (or) Hidden Nodes	i ;(i = 1–10)
Number of Output Nodes	1
Input and Output Range	0-1000 (mm)
Maximum Error	0.001
Maximum Iterations	1000000
Learning Rate (Output Layer)	0.1
Learning Rate (Hidden Layer)	0.15
Progress Period	1000

Generally, the number of nodes in the input layer depends on the number of possible inputs we used in the model, while the number of nodes in the output layer depends on the number of desired outputs. The number of hidden layers and how many nodes in each hidden layer cannot be well defined in advance. In general the addition of a node in input or hidden layer could allow the network to learn more complex patterns, but at the same time also affects its performance.

This study, uses June rainfall data of Yangon (1970-1997) and neural network models provided by NuExpert software (V1.0). [1] The major area of the study is how the number of nodes in this model affected to prediction errors of the model. Therefore, changes of the number of nodes in input and hidden layers, respectively, are made in current study. In our experiments, 100 test cases are made with the changes from 1 to 10 input nodes and changes from 1 to 10 hidden nodes. Only one output node is used in all cases.

C. Backpropagation

In training the models, BackPropagation approach is used. This method is implemented steps by steps. The first stage apply the input values to the network with the rainfall data and initialize the input weights for all nodes to some random numbers between 0 and 1. Then, the outputs of the model are calculated, using the Sigmoid function. This function is defined as follows:

$$Pj = \frac{1}{1 + e^{-x_j}}$$

where; Pj = Model Ouput, xj = Model Input

Then, the resulting output and the desired output for the given input are compared to produce the error. Error calculation of each nodes in the output layer is different from hidden layers.

For output layer

$$Ej = Pj * (1 - Pj) * (Dj - Pj)$$

For hidden layer

$$Ej = P_j * (1 - P_j) \sum_{j=1}^{k} (E_j * w_{jk})$$

Using these errors, the weights and bias values for all nodes are modified. The process are required to repeat until the error reaches an acceptable value, which means that successfully trained neural network model has obtained. Otherwise, if training process reaches a maximum count of iterations, this means that the NN training is not successful. [2]

After successfully training the models, trained neural network models are ready to use in forecasting the amount of rainfall data in Yangon for next coming years. Using the test data sets, trained models are validated for determining model performance.

V. Experiments and Results

A. Model Performance Criteria

The performance of each model is evaluated by using root mean square error (RMSE) and Mean Absolute Percent Error (MAPE) criteria. RMSE is the most commonly used performance measure in hydrological modeling and the ideal value is zero. RMSE and MAPE can be expressed as the following equations:

$$\text{RMSE} = \frac{1}{N} \sum_{i=1}^{n} P_t - D_t$$

$$\text{MAPE} = \frac{1}{N} \frac{\sum_{i=1}^{n} |P_t - D_t|}{D_t}$$

where, P_t and D_t are the predicted and observed values of output respectively; N is the number of observations or time periods over which the errors are computed. A model with the minimum error is considered the best choice for prediction.

B. Results

Table 2-11 presents the RMSE and MAPE values of rainfall prediction by using the neural network models for Yangon region in Myanmar.

TABLE II
RESULTS OF YANGON USING 1 INPUT NODES NN MODEL

No. of Hidden Nodes	RMSE	MAPE
1	10.709	1.785
2	10.705	1.789
3	10.711	1.785
4	10.598	1.769
5	10.702	1.787
6	10.619	1.769
7	10.630	1.769
8	10.730	1.779
9	10.738	1.779
10	10.711	1.775

TABLE III
RESULTS OF YANGON USING 2 INPUT NODES NN MODEL

No. of Hidden Nodes	RMSE	MAPE
1	10.253	1.646
2	10.243	1.645
3	13.686	2.113
4	10.615	1.804
5	12.603	2.033
6	14.683	2.389
7	13.032	2.081
8	18.125	2.781
9	20.705	3.427
10	15.629	2.535

TABLE IV
RESULTS OF YANGON USING 3 INPUT NODES NN MODEL

No. of Hidden Nodes	RMSE	MAPE
1	11.522	1.924
2	11.267	1.872
3	10.736	1.789
4	14.564	2.396
5	11.519	1.923
6	11.144	1.877
7	10.628	1.561
8	11.519	1.923
9	9.954	1.472
10	*9.881*	*1.649*

TABLE V
RESULTS OF YANGON USING 4 INPUT NODES NN MODEL

No. of Hidden Nodes	RMSE	MAPE
1	11.240	1.889
2	10.639	1.791
3	13.342	2.359
4	12.696	2.242
5	11.120	1.895
6	11.795	2.048
7	11.240	1.889
8	12.101	2.117
9	11.670	2.022
10	12.502	2.190

TABLE VI
RESULTS OF YANGON USING 5 INPUT NODES NN MODEL

No. of Hidden Nodes	RMSE	MAPE
1	15.019	2.455
2	14.675	2.120
3	11.368	1.977
4	11.961	2.058
5	11.562	1.978
6	11.023	1.835
7	15.839	2.719
8	11.402	1.913
9	11.459	1.942
10	11.373	1.933

TABLE VII
RESULTS OF YANGON USING 6 INPUT NODES NN MODEL

No. of Hidden Nodes	RMSE	MAPE
1	10.847	1.777
2	13.784	2.329
3	17.592	2.795
4	18.275	2.920
5	17.319	2.791
6	14.156	1.908
7	10.440	1.683
8	10.394	1.694
9	10.354	1.641
10	9.944	1.561

TABLE VIII
RESULTS OF YANGON USING 7 INPUT NODES NN MODEL

No. of Hidden Nodes	RMSE	MAPE
1	17.306	3.1190
2	18.494	3.289
3	12.422	2.186
4	16.779	2.626
5	18.380	3.028
6	14.283	2.377
7	16.463	2.696
8	15.593	2.413
9	17.379	2.798
10	16.211	2.550

TABLE IX
RESULTS OF YANGON USING 8 INPUT NODES NN MODEL

No. of Hidden Nodes	RMSE	MAPE
1	18.468	3.175
2	22.855	3.915
3	19.978	3.359
4	20.349	3.552
5	15.685	2.542
6	18.333	3.040
7	17.966	3.023
8	16.847	2.827
9	17.805	2.984
10	16.374	2.605

TABLE X
RESULTS OF YANGON USING 9 INPUT NODES NN MODEL

No. of Hidden Nodes	RMSE	MAPE
1	14.297	2.391
2	20.575	3.367
3	16.821	2.857
4	16.064	2.595
5	16.463	2.806
6	16.205	2.701
7	14.875	2.600
8	14.752	2.517
9	16.429	2.909
10	14.695	2.579

TABLE XI
RESULTS OF YANGON USING 10 INPUT NODES NN MODEL

No. of Hidden Nodes	RMSE	MAPE
1	13.863	2.328
2	22.471	3.705
3	17.247	2.831
4	16.312	2.796
5	16.112	2.827
6	15.975	2.705
7	17.247	2.831
8	16.335	2.878
9	16.519	2.841
10	16.273	2.910

Table 2-11 describes the performance statistics of neural network models by using test data sets. It can be seen that the number of nodes in input or hidden layer significantly influences the performance of a network. This finding shows that Yangon rainfall prediction is sufficiently represented by a 3 inputs-10 hiddens-1 output neural model architecture.

The results reflect that the performance of neural network model is satisfactory and it is feasible for rainfall forecast model in Myanmar regions. Training neural network models takes about 4 minutes on Intel(R) Pentium(R) 4 3.00GHz. In current work, training error is 0.09999.

According to our results, in cases with more input nodes and less number of patterns produce higher error rates and lower accuracy. Small number of input nodes, nearly 1, have higher error rate. While more hidden nodes result higher error rates in 2 input nodes model, the results of our study show that more hidden nodes lower the error rates in 3 input nodes model.

For choosing the optimal architecture of neural network models, 100 test cases are made. Forecast errors of 100 neural models are calculated in the commonly used performance measures: RMSE and MAPE. It can be found that 3 inputs-10 hiddens-1 output architecture is optimal with the minimum

RMSE. Figure 1 shows that the results of the optimal neural network architecture (3-10-1) can predict the rainfall of Yangon with acceptable accuracy.

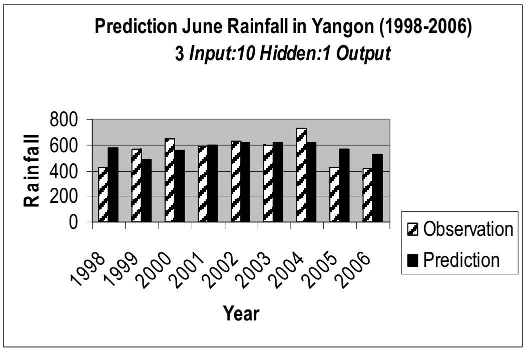

Fig. 1 Yangon Rainfall Prediction using Optimal NN Architecture

VI. Conclusion

In this paper, the potential of neural network models for prediction precipitation of Myanmar has been presented. Forecast experiments were conducted for Yangon region. Several statistics are calculated to examine the performance of these experiments. From experimental results, changes to number of nodes of neural network model affect the performance of the model. And, it can be seen that in cases with more input nodes and fewer number of patterns produce higher error rates and lower accuracy.

Results reflect that the application of neural network models is feasible for precipitation prediction model of Myanmar regions. Obviously, the neural network model has the ability to predict precipitation accurately using the rainfall data as input parameters of the model. Further study can proceed to construct the most suitable neural network models for other regions of Myanmar.

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