Development of Artificial Neural Network for Lightning Prediction under Malaysia Environment

Jeremy Anak Stewart Bedimbap
Faculty of Electrical Engineering
UiTM Shah Alam

***Abstract* - In recent years, lightning strike on building has become a major concern. Many researchers have to search for the best solution and method to predict lightning activity. It will be easier for them to minimize the effect of lightning strike on building. This paper presents the development of Artificial Neural Network (ANN) for lightning prediction under Malaysia environment. The system was implemented using the data from Malaysia Meteorological Service (MMS) and Tenaga National Berhad (TNB) for weather data and lightning data respectively. In the proposed method, a three layer back-propagation neural network with Levenberg Marquardt algorithm has been developed and predict the output data for four hours in advanced. Through training, ANN will able to recognize the pattern of input data and predict for the future output. The Levenberg Marquardt technique has been used to train ANN that receive input data and select the best output with the smallest error between output data and target data. Lastly, testing process is a stage that used developed network to predict lightning for four hours in advanced. Moreover, single ANN and modular ANN have been developed in order to compare the performance of both ANN for lightning prediction. All the simulation was done using the Matlab software.**

***Index Terms*- Artificial Neural Network (ANN), back-propagation, Levenberg Marquardt (LM), lightning prediction, training, testing**

1.0 INTRODUCTION

According to Group Health, Safety Environment, Malaysia lies near the equator which is located in the region that has high lightning and thunderstorms activities [1]. It ranks as one of the highest lightning activities in the world, where the average-thunder day level for Kuala Lumpur the capital of Malaysia, is between 180 - 300 days per annum [2]. Eighty percent of the lightning discharge currents to the ground in Malaysia exceed 20 kA with potentials approaching 50 to 100 million volts. On average, fifty percent of Kuala Lumpur strokes exceed 36 kA, where it is only 28 kA worldwide. Not only is the energy of the surge very high in Malaysia, but the frequency of occurrence as well [2].

Artificial Neural Network (ANN) is a system programming based on human brain activities that is able to learn by example and do tasks based on training experience [11]. In other words, it is an emulation of the biological neural system that is best at identifying patterns or trends in data. In previous research Frankel et al have used ANN to predict lightning at Kennedy Space Center [3]. Their paper describes the effort to construct and train neural net architectures to generate spatio-temporal maps of predicted probabilities of lightning over the Cape Canaveral Air Force Station and Kennedy Space Center [3]. In other research, Choudhury et al used ANN for classifying the occurrence and non-occurrence of seasonal thunderstorms over the eastern coastal region of India [5, 6]. They used five data such as low pressure area, moisture difference, vorticity and highest gust as an input for ANN to forecast thunderstorm at Kolkata [5].

This paper presents the development of ANN for lightning prediction under Malaysia environment. It describes the construction and process in ANN system that is able to predict lightning activity. Based on that, the accuracy of the ANN in lightning prediction will be determined by linear regression analysis, **R**=1.0.

2.0 METHODOLOGY

This study explains the structure of ANN that is able to predict lightning activity for four hours in advanced. The structure of ANN consists of data collection, network architecture, training, testing and results. Data from the MMS were used as input data and data from TNB were used as target output. TNB data consists of lightning occurrence and lightning strength. From that, ANN can be formed to predict lightning occurrence and lightning strength. ANN can also be trained with modular ANN by using different network in one ANN system which predicts lightning occurrence and current strength separately. From that, this study shows the comparison and performance of each network.

Fig 1 shows the overall ANN system for each network. Modular network consist of ANN 1 and ANN 2. Network that predicts lightning occurrence denoted as ANN 1 and network that predicts lightning strength denoted as ANN 2. On the other hand, network that predict both at once represent the single ANN.

2.1 Data Collection

There are two types of data used in this study. There are data from MMS and data from TNB. Data from MMS has ten parameters and data from TNB recorded the occurrence and the lightning strength. Both data were taken from Subang (3°7' N, 101°33' E), a city in Selangor state, Malaysia which has the highest lightning activity within a year [4].

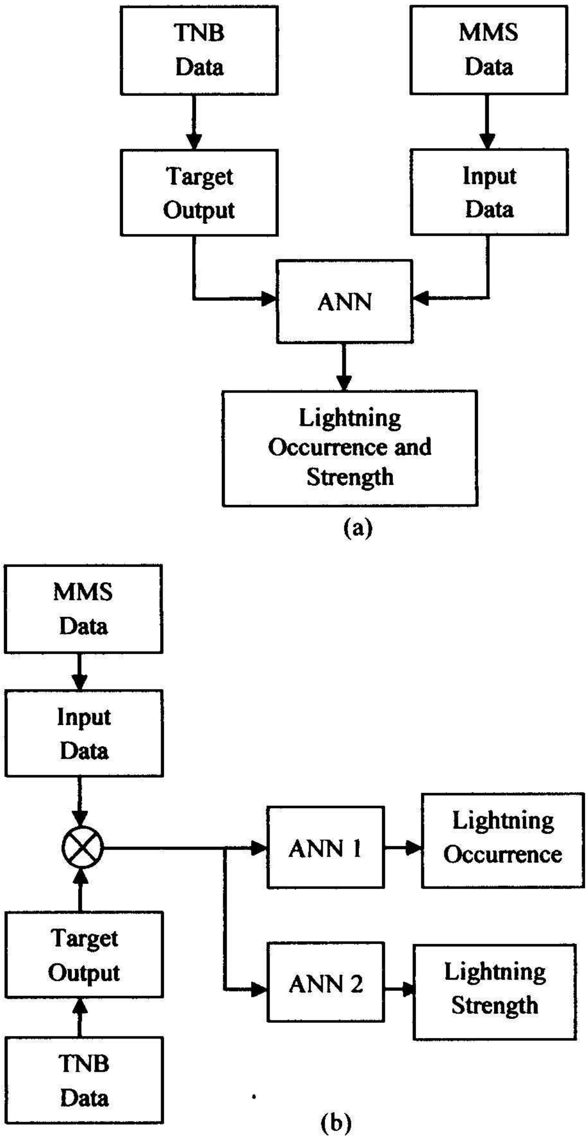


Fig 1: Overall ANN System. (a) Single ANN. (b) Modular ANN (ANN 1 and ANN 2).

MMS data consists of mean sea level pressure, dew point temperature, relative humidity, surface wind direction, surface wind speed, rainfall duration, rainfall amount, cloud height, dry bulb temperature and moisture difference [5, 6]. Therefore, TNB data recorded the occurrence and the lightning strength in term of current (A) that depending on the parameters of MMS data. These data were compiled in Microsoft Excel. The arrangement of these data in Microsoft Excel must be in correct order due to the Matrix dimension and calculation used in Matlab software. Fig 2 shows the example of data arrangement in Microsoft Excel which Fig 2(a) for input data and fig 2(b) for target data.

	X
Y	p_1
Y	p_2
Y	p_3
Y	p_4
Y	p_{n+1}

(a)

	X
Y	t_1
Y	t_2
Y	t_3
Y	t_4
Y	t_{n+1}

(b)

Fig 2: Data arrangement in Microsoft Excel.

From Fig 2, '*X*' represent the parameter of MMS while '*Y*' represent the variables of parameters '*X*'. All the variables are in figure numbers from MMS and TNB. The syntax to call all the data from Microsoft Excel to ANN system is written in the following form.

p = xlsread ('data input') ... (1)
t = xlsread ('target') ... (2)

Where: p = symbol for input data
t = symbol for target data

From the data in Microsoft Excel, '*X*' is in column and variable '*Y*' is in row. In ANN, '*X*' must be in row and the variables '*Y*' must be in column to avoid the mistakes in matrix dimension. To overcome that, transpose the matrix by using the syntax in the following form.

p = p' ... (3)
t = t' ... (4)

The input data denoted as *p* and target data denoted as *t* will be set in the following form:

$$p = [p_1\ p_2\ p_3 \ldots\ldots p_{n+1}] \quad \ldots (5)$$
$$t = [t_1\ t_2\ t_3 \ldots\ldots t_{n+1}] \quad \ldots (6)$$

Before entering the network architecture and training process, all the data from Microsoft Excel must be normalized so that they always fall within a specified range which the data is preprocessed using their min and max values giving the data in the range of *[-1, 1]*. From that, the training process would be more efficient. The syntax used to normalize data of *p* and *t* is:

[pn, ps] = mapminmax (p) ... (7)
[tn, ts] = mapminmax (t) ... (8)

Where: pn = normalized input data
tn = normalized target data

2.2 Neural Network Architecture

In this ANN structure, there are three layer feedforward back-propagation ANNs developed with Levenberg Marquardt technique. The first layer is called input layer followed by second layer called hidden layer and the third layer is called output layer [6, 7]. Fig 3 shows the diagram Neural Network Architecture.

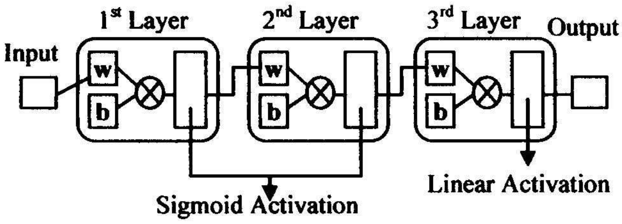


Fig 3: Neural Network Architecture

From the diagram, '*w*' represents the weight matrices defined as the interactions between neurons and '*b*' defined as the bias vectors [8]. The sum of '*w*' and '*b*' will be used in sigmoid and linear activation that represents the transfer function for layer *1*, *2* and *3*. The syntax to represent the network architecture is given in the following form.

net= newff (minmax, [α β γ], {T1, T2, T3}, 'λ') ... (9)

Where: α = number of neurons in the 1st layer
β = number of neurons in the 2nd layer
γ = number of neurons in the 3rd layer
T1, T2, T3 = transfer functions for layer 1, 2, 3 respectively
λ = training technique

2.3 Training and Testing Process

In order to get the best and accurate results, collected data in the first place must be first trained before proceeding into testing process. From all the collected data, set data for training and testing process. It is better to set more data for network training than network testing as 70% data from collected data is set for network training and 30% data is set for network testing process.

2.3.1 Data Generalization

One of the problems that occur during neural network training is called overfitting. The error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The network has memorized the training examples, but it has not learned to generalize to new situations [10]. In this study, regularization method is used to avoid over fitting during training process and improve the network. This method will cause the network to have smaller weights and biases, and this force the network response to be smoother and less likely to overfit.

2.3.2 Training Process

In training process, first select the training technique that will be used in training process. In this study, the training technique is Levenberg Marquardt (LM). Then, the following task is to prepare the training parameters for Levenberg Marquardt technique [9]. Parameters that will be used in training process are learning rate (lr), momentum constant (mc), the result of mean square error in each iteration (show), limit of iteration process (epoch), and stopping criterion based on mean square error goal (goal) [9]. Set all the parameter, next train the network with the following syntax.

net = train(net, pn, tn) ...(10)

Training launches the neural network training window. After training, simulate the network to see if it has learned to respond correctly.

2.3.3 Testing Process

Testing process is the step to measure the performance of the developed network. The performance of the developed network will be determined by performing a linear regression analysis. The highest value of **R** (near to 1) determines the accuracy of the network. Then, to achieve the best value of R, adjust the ANN architecture and LM parameter in training process by using the heuristic technique. This process will continue until the results perform a linear regression analysis with **R** $\approx$ 1. The system algorithm for this study is illustrated in Fig 4.

2.3.4 Heuristic technique

Heuristic technique is a trial and error technique. This technique was applied in order to find the best value of parameter in ANN and the value of R. For ANN architecture design, the learning rate was set to be 0.5 while the momentum constant 0.7 (random value between 0 and 1). These values were kept constant so that the effect of having different number of neurons and transfer functions could be observed.

The best ANN architecture design can be formed with the best value of transfer function and number of neurons. Then, this technique will proceed with the searching of LM parameter value. Keep the best ANN architecture design and vary the value of LM parameter between 0.001 and 1.00. As a result, the highest value of **R** will be achieved. Keep all the best parameters with the highest value of **R** as a final result. This technique will be applied in each ANN. Each ANN will perform different architecture design and parameters value with the highest **R**. From the results, compare each ANN and make a conclusion which ANN is better for the lightning prediction under Malaysia environment.

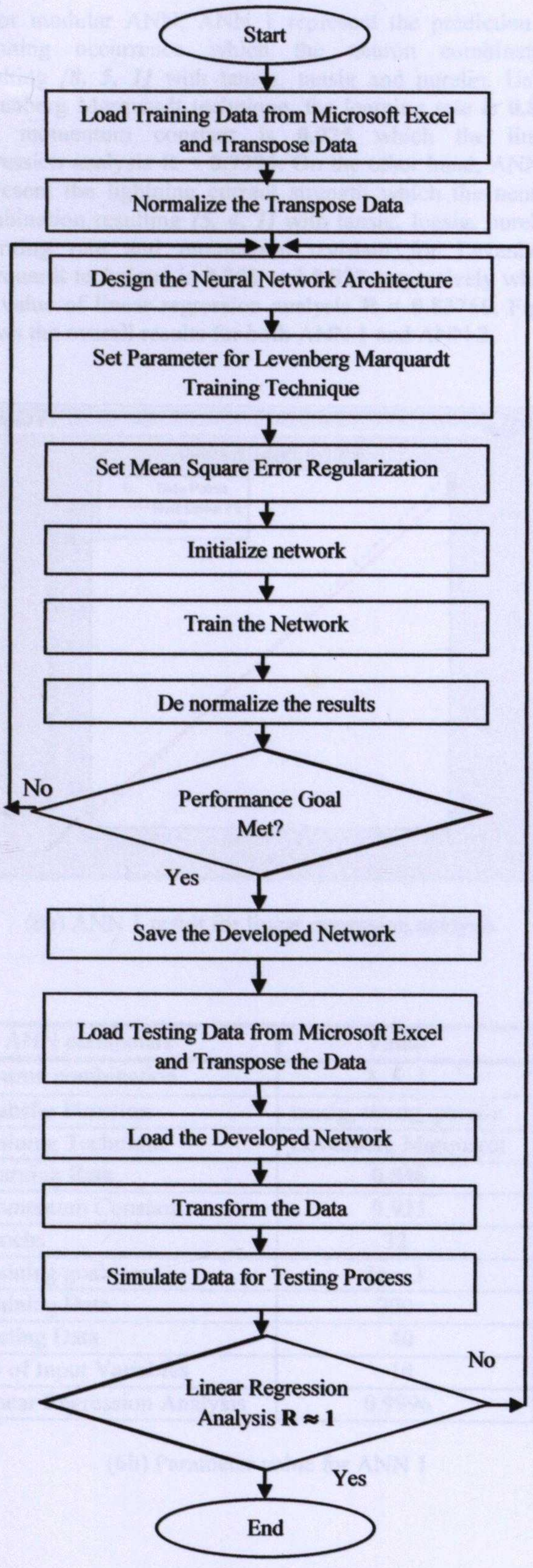
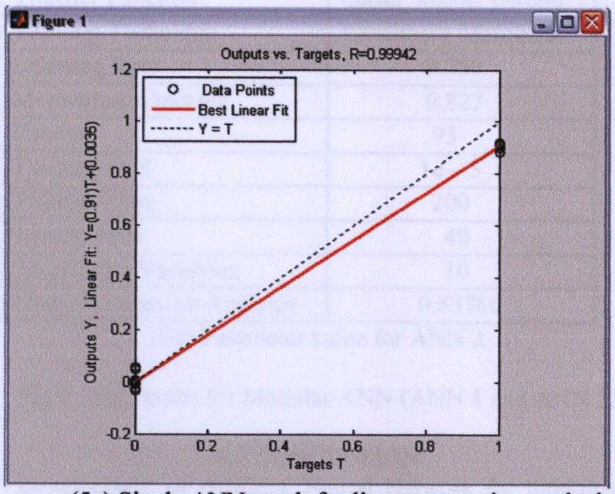


Fig 4: System Algorithm

3.0 RESULTS AND DISCUSSION

The data was randomly selected from MMS and TNB data. 200 patterns of data were selected for training process while 40 patterns data were selected for testing process. Each pattern has 10 variables. From that, 83% of data was selected for training process and 17% of data was for testing process. After training process, the developed network has recognized the pattern and ready for testing process.

Heuristic technique was applied to find the best parameter value for ANN. For single ANN, the network architecture showed the best combination of neuron *[9, 3, 2]* with tansig, logsig and purelin as the transfer functions using Levenberg Marquardt technique for training process. The 9 and 3 represent the number of neurons for the first and second hidden layer respectively and 2 represent the number of output for the ANN as this single ANN has two targets for lightning occurrence and lightning current strength. For Levenberg Marquardt technique, the parameter of learning rate is **0.875** and momentum constant is **0.925** which the linear regression analysis **R = 0.99942**. The results for single ANN can be summarized in Fig 5.



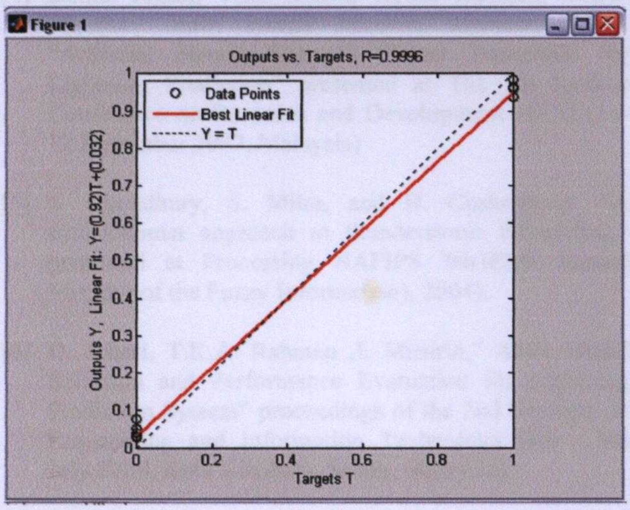
(5a) Single ANN result for linear regression analysis

ANN parameters	Value
Neuron combination	9, 3, 2
Transfer Function	tansig, logsig, purelin
Training Technique	Levenberg Marquardt
Learning Rate	0.875
Momentum Constant	0.925
Epochs	15
Training goal	1e – 3
Training Data	200
Testing Data	40
No of Input Variables	10
Linear Regression Analysis	0.99942

(5b) Parameter value for single ANN

Fig 5: The results for single ANN

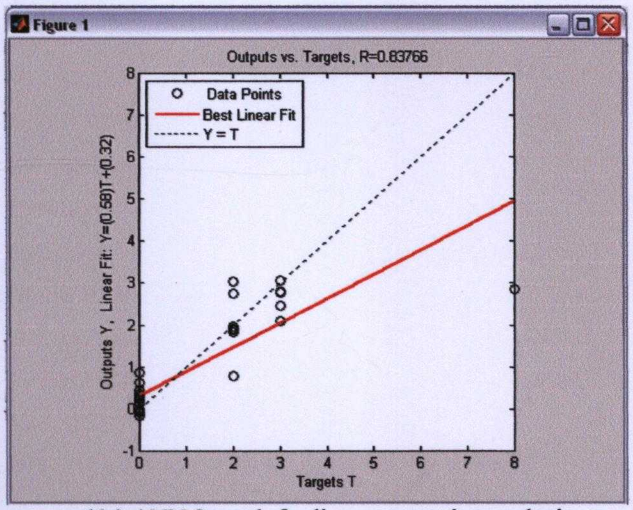
For modular ANN, ANN 1 represent the prediction of lightning occurrence which the neuron combination resulting ***[8, 5, 1]*** with tansig, tansig and purelin. Using Levenberg Marquardt technique, the learning rate is **0.846** and momentum constant is **0.925** which the linear regression analysis **R** = **0.9996**. On the other hand, ANN 2 represent the lightning current strength which the neuron combination resulting ***[5, 4, 1]*** with tansig, logsig, purelin. Learning rate and momentum constant for Levenberg Marquardt technique is **0.750** and **0.827** respectively which the value of linear regression analysis **R** = **0.83766**. Fig 6 shows the overall results for both ANN 1 and ANN 2.



(6a) ANN 1 result for linear regression analysis

ANN parameters	Value
Neuron combination	8, 5, 1
Transfer Function	tansig, tansig, purelin
Training Technique	Levenberg Marquardt
Learning Rate	0.846
Momentum Constant	0.925
Epochs	32
Training goal	1e – 3
Training Data	200
Testing Data	40
No of Input Variables	10
Linear Regression Analysis	0.9996

(6b) Parameter value for ANN 1



(6c) ANN 2 result for linear regression analysis

ANN parameters	Value
Neuron combination	5, 4, 1
Transfer Function	tansig, logsig, purelin
Training Technique	Levenberg Marquardt
Learning Rate	0.750
Momentum Constant	0.827
Epochs	93
Training goal	1e – 3
Training Data	200
Testing Data	40
No of Input Variables	10
Linear Regression Analysis	0.83766

(6d) Parameter value for ANN 2

Fig 6: The results for Modular ANN (ANN 1 and ANN 2)

4.0 CONCLUSION

Development of Artificial Neural Network for lightning prediction under Malaysia environment was presented and can be used as one of the alternative in lightning prediction. By evaluating the past meteorological data and lightning data with ANN, the developed network is able to recognize the pattern of past data and predicts the future outcome. This can be achieved after carefully testing different ANN architecture, transfer functions and training algorithms, all of which were determined using a heuristic technique. As the result, single ANN and modular ANN that consists of ANN 1 and ANN 2 has results the different architecture design and LM parameter value. Consequently, single ANN performs the best result to predict lightning occurrence and lightning strength. Although ANN 1 for lightning occurrence have the highest value of **R** but in the same network ANN 2 that predicted lightning strength have the lowest value of **R**. In conclusion, single ANN has better performance than modular ANN.

5.0 REFERENCES

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