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LIGHTNING STRIKE MAPPING FOR PENINSULAR MALAYSIA USING ARTIFICIAL INTELLIGENCE TECHNIQUES

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ABSTRACT

This research focuses on artificial intelligence (AI) techniques on mapping the lightning strike area in Peninsular Malaysia. Three AI techniques such as fuzzy logic, neural network and neuro-fuzzy techniques are selected to be explored in classifying the characteristics of lightning strike which are based on; level of strike (high, medium, low) and category of lightning (positive cloud-to-ground, negative cloud-to-ground, flash). Nine predefined areas in Peninsular Malaysia were chosen as a case study. The analysis was carried out according to twelve months lightning data strikes which had been made available by Global Lightning Network (GLN). All three AI techniques have successfully demonstrated the ability to mapping and classify lightning strikes. Each technique has shown very good percentage of accuracy in term of determining the area and characterizing the lightning strikes. The finding of this research can be made use in risk management analysis, lightning protection analysis, township planning projects and the like.

Keywords: *Lightning Strike, Classification, Fuzzy Logic, Neural Network, Neuro-Fuzzy*

1. INRODUCTION

Lightning strike comes about every day in the world. The lightning strike towards the surface on earth has been estimated at 100 times every second. Thus, almost every governments suffer major loses because of this phenomenon every year. It also would cause horrific injury and fatality to humans and animals. The lightning may affect almost every organ system as the current passes through the human body taking the shortest pathways between the contact points. There are 25.9% of lightning strike occurrences for victims who have sheltered under trees or shades, whereas 37% at open space area. Head and neck injury are two common areas which have an effect on the lightning strike victims with 77.78% and 74% respectively. Only 29.63% of the cases presented with ear bleeding [1]. United State National Lightning Safety Institution reported that Malaysia has highest lightning activities in the world whilst the average-thunder day level for Malaysia's capital Kuala Lumpur within 180 - 260 days per annum [2, 3]. The isokeraunic level is approximately 200 thunderstorm days a year. The lightning ground flash density is about 15-20 strike per km^2 per year.

Lightning has an extremely high current, high voltage and transient electric discharge. It is transient discharge of static electricity that serves to re-establish electrostatic equilibrium within a storm environment [1]. Malaysia lies near the equator and therefore it is categorized as prone to high lightning and thunderstorm activities [2]. Observations performed by the Malaysian Meteorological Services indicate that thunders occur 200 days a year in Malaysia. Thunderstorms have been suspected to have caused between 50% and 60 % of the transient tripping in the transmission and distribution networks for Tenaga Nasional Berhad (TNB), Malaysia's electric power provider. The main reason could be short of precise and consistent

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lightning data in Malaysia to enable through studies on lightning and its mitigation [5].

Lightning discharge occurs when the electric current flows due to exert a pull on charged particles of positive and negative. There are three types of lightning discharge (i) cloud-to-ground (ii) cloud-to-cloud (intercloud) (iii) intracloud. Cloud-to-ground denoted as C2G happens when the charge at the cloud strike the ground surface. About 25% of lightning strikes are C2G. Majority of C2G lightning will appear as growing ball [5, 6]. Cloud-to-cloud (intercloud) denoted as C2C occurs when the negative charge and positive charge of different clouds attracted. Meanwhile, intracloud lightning discharge happens when some charge at the base of the cloud attract the positive charge at the top of the cloud.

Positive lightning take places when the positive charge flows instead of electrons. About 5% of lightning is positive in nature and tend to come about during the peak of severe thunderstorm or as the storm is decaying [6]. Positive lightning travels outside the cloud and strikes the ground where there is a pool of a negative charge. As more and more negative charge builds at the base of the cloud, more and more positive charge builds in the upper part of the cloud and on the ground beneath the cloud. The separation between the cloud and the ground creates an electric field. The pull towards positively charged particles and negatively charged particles arise as charge continues to build up. The air prevents the electric current from flowing. However, if this insulator of air is overcome, a discharge will go off. This discharge is known as the negative lightning.

The development of lightning strike mapping area for Peninsular Malaysia with regards to lightning characteristic is an effort to provide government assessment for any housing and industrial ventures. Such valuable assessments are; protector design, prone area identification, housing development, theme park construction and industrial suitability locations and et cetera. The lightning strike is classified according to level of strike (high, medium, low) and types of lightning (positive cloud-to-ground, negative cloud-to-ground, flash). The chosen classification techniques are (i) fuzzy logic (ii) neural network and (iii) neuro-fuzzy.

2. METHODOLOGY

2.1 Predefined region for Peninsular Malaysia

The predefined region of Peninsular Malaysia has been divided into nine as illustrated in Figure 1. Each column and row is characterized as follows:

1. A1 and B1 is South West denoted as (SW).
2. A1 and B2 is South denoted as (S).
3. A1 and B3 is South East denoted as (SE).
4. A2 and B1 is West denoted as (W).
5. A2 and B2 is Central denoted as (C).
6. A2 and B3 is South East denoted as (E).
7. A3 and B1 is North West denoted as (NW).
8. A3 and B2 is North denoted as (N).
9. A3 and B3 is North East denoted as (NE).

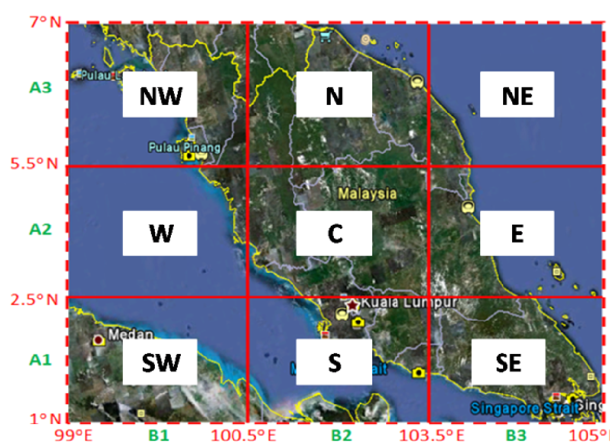

Figure 1: Predefined Area of Peninsular Malaysia with the

Although, there are regions which cover part of Indonesia (SW) and Singapore (SE) and regions that may not be meaningful such as W and NE but the idea of this research is to justify the capability of AI techniques in lightning classification for mapping purposes.

The lightning data was acquired from the Global Lightning Network (GLN). The data consists of (i) time (ii) latitude (iii) longitude (iv) strike current. The structure of lightning characterization and mapping system is shown in Figure 2.

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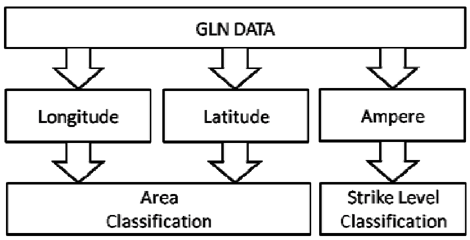


Figure 2: The Structure of Lightning Characterization System

The data was divided into (i) longitude and (ii) latitude to identify the exact location of lightning strike and (iii) lightning strike current to classify the level of strike current in ampere.

2.2. Classification of Lightning Category

Lightning strike can be categorized into three different types which are positive lightning (+C2G), negative lightning (-C2G) and flash. C2G is stands for cloud to ground discharge. Thus, the main input is the current flow of lightning strike. The value is between -180 kA and 180 kA. The basic 'IF rule' used for this classification is tabulated in Table 1.

Table 1: Classification of lightning

Input: Current (A)	Category of Lightning
< 0	Negative lightning (-C2G)
= 0	Flash
> 0	Positive lightning (+C2G)

Once the category is identified then the system will classify the level of lightning current (low, medium or high). The strike current levels are in amperes between -180 kA to 180 kA as tabulated in Table 2.

Table 2: Strike level definition

Class	Range
Low	[-60 kA,+60 kA]
Medium	[-120 kA, -60 kA] and [+60kA, +120 kA]
High	[-180kA, -120 kA] and [+120 kA, +180 kA]

2.3 AI Classification Techniques

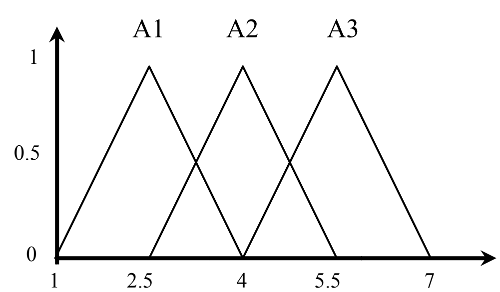
i) Fuzzy Logic

The area of lightning strike is identified according to it latitudes and longitudes number. *'IF rule'* has been used to categorize the lightning and levels of lightning current because the system has single input single output (SISO). It is simpler to use *'IF rule'* rather than fuzzy logic. If the system is dealing with a multiple inputs such as multiple inputs multiple output (MIMO) system, then fuzzy logic method is most preferable for the characterization.

The input membership function for latitude, longitude and output are displayed in Figure 3 and 4. The output membership function is normalized for the purpose of simplicity. The equation used for the normalization is:

$$Z_{(true)} = zX0.52631578$$

where $Z_{(true)}$ is the actual value for the output of x-axis and z is the value represented in the output membership function. Based on the membership functions the fuzzy rules are developed. For instant, when the latitude is A1 and the longitude is B1, the output is declared as Region North West or NW. All combinations from both input membership function will be mapped into selected region based on it lightning characteristics. All the fuzzy rules used for the region classification are summarized in Table 3.



Input Variable "Latitude"

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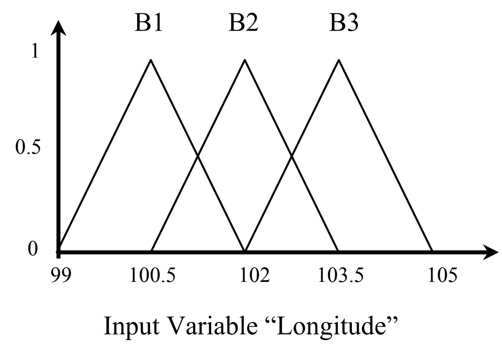

Figure 3: Input membership function for fuzzy logic technique

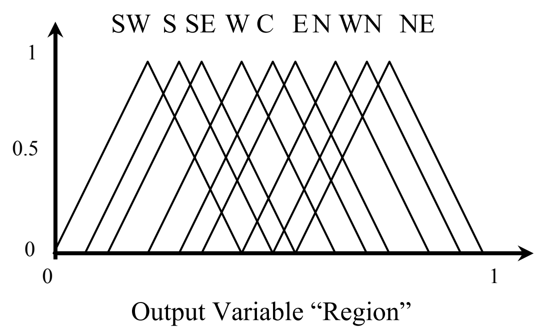

Figure 4: Output membership function for fuzzy logic technique

Table 3: Fuzzy rules for the region classification

No. of Rule	Input		Output
	Latitude	Longitude	Region
1	A1	B1	North West (NW)
2	A1	B2	North (N)
3	A1	B3	North East (NE)
4	A2	B1	West (W)
5	A2	B2	Central (C)
6	A2	B3	East (E)
7	A3	B1	South West (SW)
8	A3	B2	South(S)
9	A3	B3	South East(SE)

ii) Neural Network

The implementation of neural network for classification problems is dependable on their structure and functions. By considering a set of classes, the objective in classification is an assignment of a random sample to one of this class with minimum probability error. Each sample is described by a set of parameter which then forms a vector, usually referred as the feature vector. The development of such classification system can be achieved as a result of neural network training so that it produces the output which corresponds to one of these classes. However, the training sample must have similar form as its input that is belong to the same class.

The ability of neural network to correctly classify the test sample is subjected to it generalization ability. Back propagation method has been used to train the data from Global Lightning Network (GLN) database. The network consists of an input layer, one hidden layer and an output layer. The input layer consists of 2 input neurons which represent the longitude and latitude as it input, hidden layer with 16 hidden neurons while the output layer represent the 9 output regions that need to be classified their distributions. Each neuron in the hidden layer and output layer has a bias which is connected via weight matrix to the previous layer. The number of hidden layer depends on the performance index of the system. Trial and error approached has been implemented to get an accurate number of hidden layers for the system. It begins with a modest number of hidden neurons and gradually increasing the number if the network fails to reduce the error. A much used approximation for the number of hidden neurons for a three layered network is;

$$N = 1/2(j + k) + P, \quad (2)$$

where N is the number of neuron, j and k are the number of input neurons and P is the number of patterns in the training set. As the pattern is set to 1 the number of hidden layer begins with 6 and amplifies to 16.

Optimum weight was calculated using Widrow-Hoff Rule. The algorithm of the Widrow-Hoff Rule shows that the network weights are moved along the negative of the gradient of the performance function. The derivative of the

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sigmoid function evaluated as the net output value for that neuron which can be expressed mathematically as:

$$= (t_k - y_k).f'\,(y_{k\text{-}in}) \quad (3)$$

where, t_k target output for the k^{th} output neuron. These deltas values of are used to fine-tune their input connection weights according to the following formula:

$$W_{ik\ new} = w_{ik\ old} + \alpha.\delta_k.z_j \quad (4)$$

In this technique, the initial weight for all connection is initialized to 1.0. There are 176 connections weight, which is the input to hidden connection (32 weights) and hidden to output connection (144 weights). The connection of all layers is illustrated in Figure 5 below.

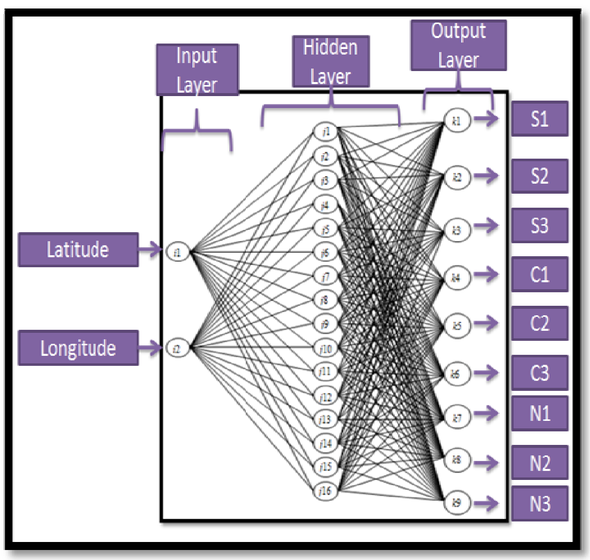

Figure 5: Mapping of lightning strike system with neural network

The layers are well connected whilst every neuron in each layer is connected to every other neuron in adjacent forward layer. Learning rate, α effectively controls the size of the step is needed in multidimensional weight space when each weight is modified. If the selected learning rate is too large then the local minimum may be over stopped constantly, resulting in oscillations and slow convergence to lower error state. If the learning rate is too low, the number of iterations requires may be too large, resulting in slow performance. Usually the default value of most commercial neural network packages are in the range 0.1-0.3 providing a satisfactory balance between the two reducing the learning rate may help improve convergence to a local minimum of the error surface. For this project, the initial learning rate is set at 0.1. The difficulty arises when training internal layer weights as no target is available. The solution lies in propagating the error back, layer by layer, from the output successively to backwards layer. The j^{th} hidden neuron receives an error signal as the weighted sum of the following layer error signals, and then multiplies this summation with the derivative of input to the neuron by using equation (5):

$$\delta_j = f'\,(z_k\text{-}in) \text{ x } \delta_k.w_{ik} \quad (5)$$

Then, this signal will be used to adjust the input weight w_{ij} to the hidden neuron z_j which is computed using the following equation

$$W_{ij\ new} = w_{ij\ old} + \alpha\ .\ \delta_i \quad (6)$$

Finally, neuron uses its error signal to train it associated weight, then passes it back to all neurons to which it is connected in the previous layer. This two step process is repeated over the training set elements until the network converges and produces the desired response. It must be noted that all weight wet set to 1.0 initially.

iii) Neuro-fuzzy

Neuro-fuzzy algorithm is derived from two reliable artificial intelligence technique known as fuzzy logic and neural network algorithm. Therefore, the performance of neuro-fuzzy classifier is certainly reliable. Similar to fuzzy, there are two types of neuro-fuzzy models, (i) Sugeno and (ii) Mamdani. Sugeno model is derived to generate fuzzy rules from a given input-output data set and it has the form of "*If x is A and y is B, then z is f(x,y)*", which is a typical fuzzy rule in a model. Where *A* and *B* are fuzzy sets in the antecedent. The order of Sugeno model is represented by the output of the system, *z*. The output is normally presented in a polynomials form of input variables x and y. The coefficient of x and y of Sugeno output model is known as weighted average of consequents. The weight will provide a smooth effect, mature and

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efficient gain scheduler [4]. Thus, the weight will minimize the defuzzification process in Mamdani model.

The Sugeno model increases computational efficiency and suitable for linear and adaptive techniques. It also guarantees a constancy of the output surface, which is a complementary for mathematical examination. Due to this advantage, the Sugeno model offers the best preference for computation modelling. There are quite a number of neuro-fuzzy classification applications worldwide; one of them is numeral handwritten recognition which was carried out by Al-Alawi [9]. The system has successfully achieved 98.5% of accuracy. Another neuro-fuzzy classification method which combined fuzzy-gaussian neural network is applied in face recognition system [10]. The system scored 100% accuracy on 100 images with 10 classes. For lightning classification, there are researches using the artificial intelligence method to classify the area and the level of strikes for multifractal characterization, and fuzzy classification of lightning strike maps [11]. The classifier used K-means classifier which described a novel approach for measurement of physical lightning strike mapping. The data was accumulated from Canadian Lightning Detection Network (CLDN). The lightning strike mapping was modeled and characterized to 15 classes through Davis-Bouldin criterion for statistical purposed [12,13,14].

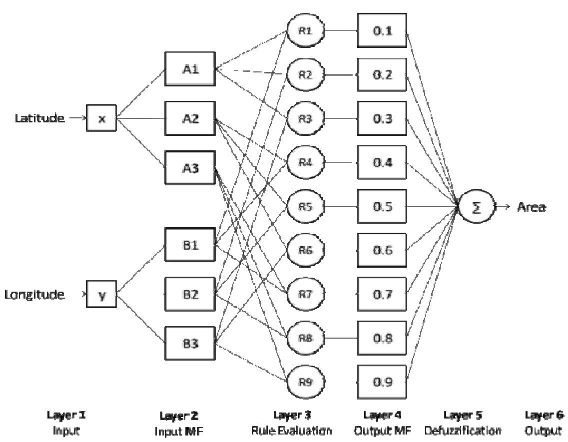
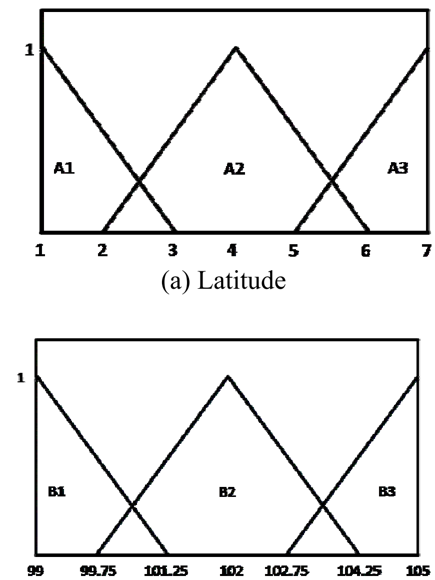


Figure 6: Structure of neuro-fuzzy classifier

The neuro-fuzzy classifier (NFC) in the system is structured as multi-layer neural network. The NFC has input output layers and three hidden layers. That represents its membership functions and fuzzy rules. As shown in Figure 6, the neuro-fuzzy Area Classifier has several layers.

The first layer or *Layer 1* is the crisp inputs, where each inputs; *x* (latitude) and *y* (longitude). The latitude input is represented by fuzzy sets A1, A2 and A3, while the latitude input is represented by fuzzy sets B1, B2, and B3. *Layer 2* is the layers of Input Membership Function or the fuzzification layer. In this layer, the node represents the fuzzy set used in the antecedents of fuzzy rules. The fuzzification determines the input is fit to which fuzzy sets. The membership function used is the triangular type as shown in Figure 7.



(a) Latitude

(b) Longitude

Figure 7: Input membership function for neuro-fuzzy

Each triangular membership functions can be defined by two parameter (a,b) as ;

where *a* and *b* are the parameters that control the center and the width of the triangle.

The next layer is the *Layer 3,* is the fuzzy rules. Each node in this layer represents the rules of the system. The rule for each node is listed under Table 4.

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Table 4: List of Rules

Node	Antecedent	Consequent
1	If x is A1, and y is B1	Then the area is North West (NW)
2	If x is A1, and y is B2	Then the area is North (N)
3	If x is A1, and y is B3	Then the area is North East (NE)
4	If x is A2, and y is B1	Then the area is West (W)
5	If x is A2, and y is B2	Then the area is Central (C)
6	If x is A2, and y is B3	Then the area is East (E)
7	If x is A3, and y is B1	Then the area is South West (SW)
8	If x is A3, and y is B2	Then the area is South(S)
9	If x is A3, and y is B3	Then the area is South East(SE)

It is also important to mention that between layer 3 and layer 4, there are weights located in each node as to establish learning mechanism. The layer 4 also has option to have several hidden layers in order to obtain better result for learning.

After the rules evaluation, the output of *Layer 4* is fed into *Layer 5* which is known as defuzzification layer. The method of defuzzification layer is the *Weight Average (WA)* method with equation as below:

where k is the constant as the singleton spike in the output membership function as shown in Figure 7, while the n is the number of output membership function in the system. For this system the n number is 9 since the area classified has 9 areas can be classified, they are; NorthWest (NW), North (N), Northeast (NE), West (W), Central (C), East (E), Southwest (SW), South (S) and Southeast (SE).

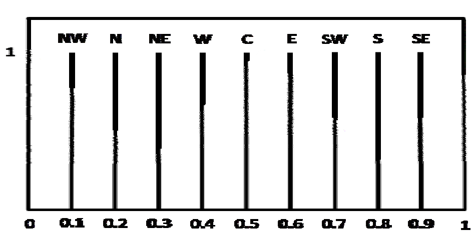

Figure 7: Output membership function

The learning method of neuro-fuzzy basically apply standard back-propagation algorithm. The back-propagation algorithm will compare the input-output and calculates the difference as known as error. The error then is propagated backwards throughout the network in reversed direction which means from the output layer to the input layer. During the propagation, the neuron nodes will be affected by changing the neuron activation functions. In determining the necessary modifications, the activation neuron function will be differentiated and only then it will be modified. They are three ways of neuro-fuzzy learning process: (i) membership function shapes may adjust during training (ii) the bias or weight between layer 3 to layer 4 may be formed or terminated (iii) the weight between layer 3 to layer 4 behave adaptively by changing its values. However, in this particular study, the membership function shapes is fixed and no additional or terminated weight. The learning process is only allowed to changes the weight in between layer 3 and layer 4. The performance of neuro-fuzzy can be measured with many methods such as Mean Percentage Error, Root Mean Square Error and Mean Squared Error. In this report, the neuro-fuzzy classifier performance is determined by Mean Squared Error as equation below:

(8)

where t is the target values, o is the output of the system and N is the total record involved. In other word, The MSE measures the average of the square of the differences between the estimator (o) and the quantities to be estimated (t).

3. RESULT AND DISCUSSION

Each technique has been analysed and the results is described on the following section:

3.1 Fuzzy Logic Analysis

It is clearly shown in Figure 8 that majority of the lightning level is in LOW level which ranging from 0 to 60 kA. Meanwhile, HIGH level of current has the least percentage. In May 2010, the percentage of all three level of current are quite similar. The highest percentage in May for HIGH level current which was 27%.

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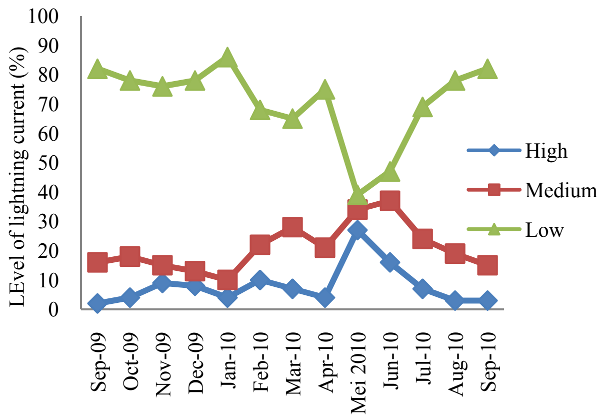

Figure 8: Percentage of lightning's level current for 12 month

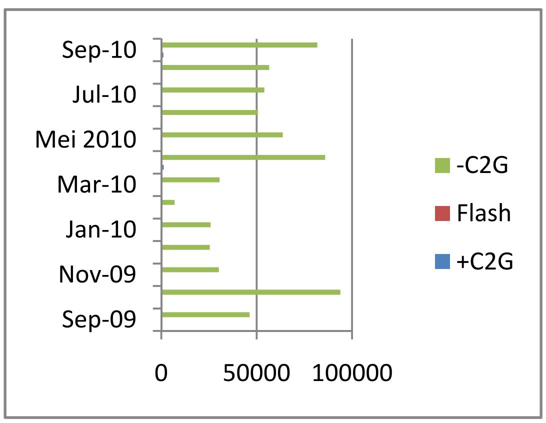

Figure 9: Graph number of lightning incidence corresponds to the types of lightning

From the results, 90% of the lightning incidence occurred are negative lightning. Meanwhile, there are no flash occurred. This is because flash occurred between the clouds and do not strike the ground as shown in Figure 9.
The number of lightning incidence occurred in each month are analyzed corresponds to their region. Table 5 show the sampled of classified data for lightning strike for each month. From the analysis results, October 2009 has the highest number of lightning incident with 94628 strikes followed by April 2010 with 87459 strikes. The least number of lightning occurred in February 2009 with 7056 strikes. In October 2009, the lightning strike the most in Region Central (C) with 15919 strikes, followed by Region South (S) with 15764 strikes. The state which included in these regions are Wilayah Persekutuan Kuala Lumpur, Melaka, Selangor, Johor, Negeri Sembilan, Perak and Pahang. A high level of lightning current which occurred in locations such as Kuala Lumpur and Selangor have the possibilities to cause a flash flood. This is due to the locations which is situated in the center of city.

Table 5: Samples of classified data

Latitude	Longitude	Current (A)	Level of Current	Types of Lightning	Region
3.9039866	99.8766398	-24500	Low	-C2G	W
3.4932748	100.8141976	-32800	Low	-C2G	C
4.448587	99.4433357	-94100	Medium	-C2G	W
3.314881	100.9970393	-33000	Low	-C2G	C
4.4359484	99.449027	-78800	Medium	-C2G	W
6.7442604	99.4652051	-41100	Low	-C2G	NW
6.6765929	99.3709131	-13800	Low	-C2G	NW
3.4340879	100.744215	-20200	Low	-C2G	C
3.2193951	100.8315325	-23700	Low	-C2G	C
1.8678969	102.1172289	-48700	Low	-C2G	S
3.99088	99.9881279	-33700	Low	-C2G	W
2.1323426	101.7601432	18700	Low	+C2G	S
2.1273015	101.7917015	-16200	Low	-C2G	S
3.2061696	100.8866052	-180000	High	-C2G	C
3.2396767	100.8903621	-41800	Low	-C2G	C

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The obtained results are then mapped into the Malaysian map using Google Earth as shown in Figure 10. This figure shows the locations where the lightning strike and Figure 11 shows the mapping of lightning characteristics for one month data. The light blue, purple and red icons indicate low, medium and high level of current respectively. By clicking the icon, a dialog box as shown in figure below appeared. It tells user the lightning current value, level of current and also the region its corresponds to. Based on the mapping, most of the lightning occurred at the west coast of Peninsular Malaysia. Most of the states in the west coast of Peninsular Malaysia are catogarized as a developed states. Thus, a high population density and plenty of industrial location attract the lightning strike.

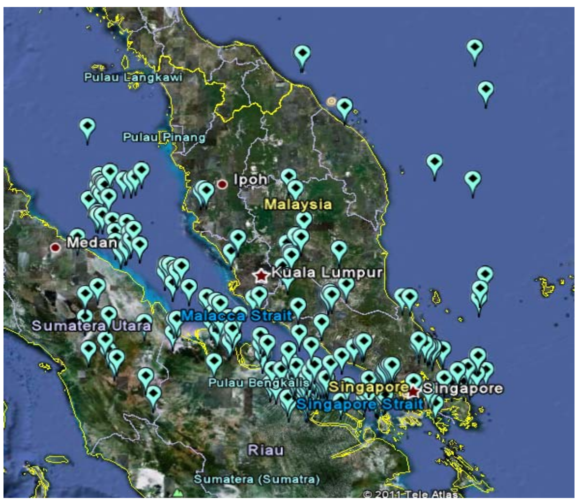

Figure 10: Mapping of the lightning strike locations

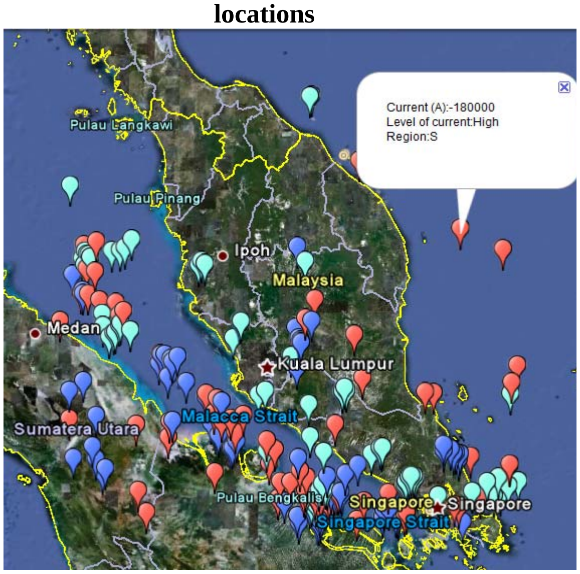

Figure 11: Mapping of the lightning characteristics

The developed classifier program are able to classify the lightning parameters according to the desired characteristics. Based on the statistical analysis, 90 % percent of lightning incidence are negative lightning. Meanwhile, the majority of the levels of lightning current are Low level. Areas that are situated in the west coast of Peninsular Malaysia have a higher number of lightning incidence compared to the east coast. There are some limitations found in mapping the lightning characteristics using Google Earth.

3.2 Neural Network Analysis

The data is classified into nine regions as follows;

- Southern Regions:
  - S1-latitude $=1^0$ to 2.5^0 & longitude = 99^0 to 100.5^0
  - S2-latitude $=1^0$ to 2.5^0 & longitude = 100.5^0 to 103.5^0
  - S3-latitude $=1^0$ to 2.5^0 & longitude = 103.5^0 to 105^0
- Center Regions:
  - C1-latitude $=2.5^0$ to 5.5^0 & longitude = 99^0 to 100.5^0
  - C2-latitude $=2.5^0$ to 5.5^0 & longitude = 100.5^0 to 103.5^0
  - C3-latitude $=2.5^0$ to 5.5^0 & longitude = 103.5^0 to 105^0
- Northern Regions:
  - N1-latitude $=5.5^0$ to 7^0 & longitude = 99^0 to 100.5^0
  - N2-latitude $=5.5^0$ to 7^0 & longitude = 100.5^0 to 103.5^0
  - N3-latitude $=5.5^0$ to 7^0 & longitude = 103.5^0 to 105^0

The system stops at 250 epochs with MSE of 0.0462 as shown in Figure 12.

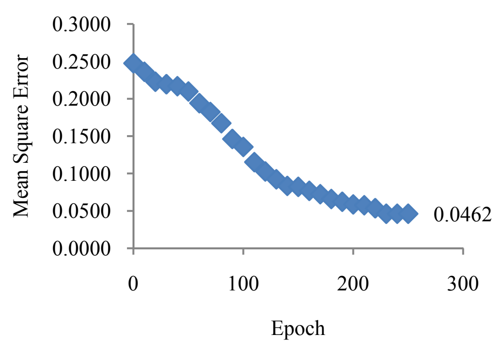

Figure 12: The Mean Square Error change with the change in epoch value

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From initial analysis of the data, the average lightning strikes for peninsular Malaysia are 19 strikes per hour. This number will give about 456 strikes per day. The frequency of the strikes shown that the Peninsular of Malaysia really need a system that give an information about the classified lightning strikes distribution in order to create and design a suitable protection system that can handle the lightning strikes without giving interruption to the system and equipment in the utility area. The lightning strikes at all nine regions are low February because it can be considered as pacific monsoon which does not hit the peninsula area.

Figure 13, describes the lightning characteristic according to the level of current for all months. It shows that the MEDIUM level almost manipulates or be the most common strike for all month. The LOW and HIGH level basically just happen for several times in a month. So this show that the common strikes happen in our country in peninsular area is a MEDIUM lightning strike.

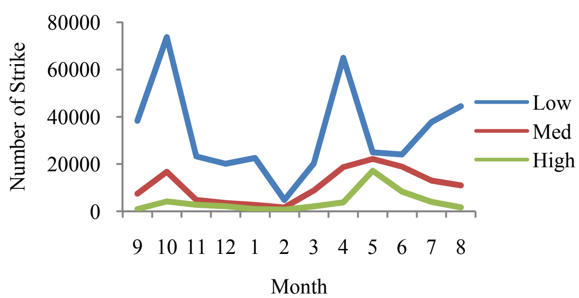

Figure 13: The strike level for Oct 2009-Sept 2010

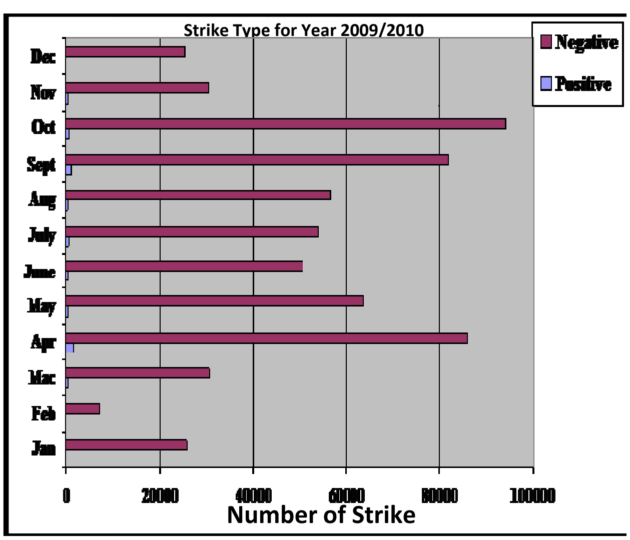

Figure 14: The lightning strike's type from Oct 2009-Sept 2010

Figure 14 shows the lightning strike of cloud to ground (-CG) is the highest type of strike that occurred in Peninsular area. This shows that most of the strike is made of negative charges that travel from the cloud to the ground when it is initiated by the positive charge on the earth surfaces.

3.3 Neuro-fuzzy Analysis

The neuro-fuzzy results is divided into two sections, (i) Training result, (ii) Data Analysis

(i) Training Result

Figure 15 and Table 6 represent the neuro-fuzzy classifier system. The graph as illustrated in Figure 15 is the training error of neuro-fuzzy classifier after 250 epoch training. At epoch 230 the weight changed in small values, which cause the constant training error for the last 20 epoch. Thus, the learning was terminated at epoch 230 with result of Mean Squared Error (MSE) of 0.0462. The learning rate and momentum rate is selected as 0.02 and 0.3 accordingly as recommended by Kamiyama [15].

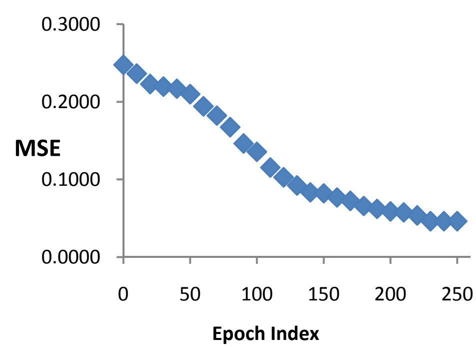

Figure 15: Training Error of neuro-fuzzy classifier

Table 6: Neuro-fuzzy classifier training result

Data Set	Training	
Data Entry	4449 data (Random pick from all month database)	
MSE	0.0462	
Area Analysis	NorthWest: 2.45% North: 2.00% North East: 3.34% West: 2.45% Central: 53.01%	East: 5.57% South West: 0.22% South: 6.46% South East: 7.13%
Training Setting	Learning rate: 0.02	
	Momentum rate: 0.3	
	Accuracy: 73.5 %	

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(ii) Data Analysis

From the analysis, lightning were mainly strikes at the Central region with an average of 5172 strikes during September 2009 to October 2010. The Southern region was identified the second largest lightning strikes area with an average of 4096.5 strikes per year. Meanwhile, the lowest area was identified at Northern East region with average of 435.7 strikes per year. However, the lightning strikes were very minimal during November to March 2010.

The level of lightning strike has shown that Peninsular Malaysia has received a relatively low strike with average of 17380.8 strikes per month. May 2010 was considered a good month because it has a well balance of lightning strike level distribution. The Low strike recorded at 38.86%, Medium at 34.51% and High at 26.63%. The medium and high Strike was very minimal during November 2009 until February 2010. However, the high Strikes were extended until April 2010.

4. CONCLUSION

Fuzzy logic has been successfully applied in order to characterize the location into eight regions to identify the location where the lightning strikes. Moreover, Basic 'IF rule' has been successfully implemented to characterize the other two characteristics which are type of lightning and level of lightning current. The fuzzy logic and 'IF rule' are successfully implemented and mapped into Malaysian map using Google Earth. The paper successfully designs the proposed back propagation neural networks that combine with properties of IF THEN Rules that performs as the classifier. They are trained and tested to classify lightning characteristics. It also included the design of a software tool suitable for the training and testing NN for dataset. The results have shown considerable degree of confidence of 97% of accuracy in classification by referring to the graph of MSE. It was evident that as the number of epoch increased, the MSE will reduces with certain parameter been initialize first. The proposed neuro-fuzzy system has achieved 73.5% accuracy. The proposed neuro-fuzzy is able to classify the data. Thus further study to increase the accuracy could be done to enlighten prospective of lightning classification with artificial intelligence method.

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