Lightning Prediction Using Fuzzy Logic Technique

Lemuel Chung Chen Nyap
School of Engineering
Asia Pacific University of Technology and Innovation
Kuala Lumpur, Malaysia
TP038024@mail.apu.edu.my

Waddah Waheeb
School of Computing
Asia Pacific University of Technology and Innovation
Kuala Lumpur, Malaysia
waddah.waheeb@staffemail.apu.edu.my

Jacqueline Luokse
School of Engineering
Asia Pacific University of Technology and Innovation
Kuala Lumpur, Malaysia
jacqueline.lukose@staffemail.apu.edu.my

Abstract— **Lightning is an event where electrical charges are released from the clouds. A lightning prediction system is used to estimate the probability of a lightning strike according to the changes in the environment. By the identification process, the safety of life and structures could be protected from lightning strikes. This paper is to develop an algorithm for lightning prediction using the fuzzy logic technique. A few tests have been conducted to evaluate the performance of the system. For the validity test, the system gives a positive result of more than 90% accuracy for being able to predict the imminence of lightning. The consistency test shows that the system was able to predict lightning repetitively at least 1 hour before lightning activity happens. The sensitivity test proves that lightning prediction relies heavily on the humidity and that 70% is the threshold to change between not imminent to imminent. The linearity test once again proves that humidity has a direct relationship that could affect the prediction of lightning. The stability test shows that the system will be stable after predicting the 6th to 7th hour data. Finally, it could be concluded that the accuracy of this system in lightning prediction is more than 95% after being tested with real data from the meteorological department.**

Keywords— Lightning*, *Lightning prediction, Fuzzy Logic

I. Introduction

Lightning is an event where electrical charges are released from the clouds. This happens when there is friction between positively charged and negatively charged areas of the cloud. This event happens to equalize the amount of charges found in the clouds, and lightning could be released either from cloud-to-cloud, cloud-to-ground, or cloud-to-air [1]. A lightning prediction system is used to estimate the probability of a lightning strike according to the changes in the environment. By the identification process, the safety of life and structures could be protected from lightning strikes. However, most of the methodologies used were based on computational methods such as regression techniques and sampling methods.

As the calculation process is tedious when more data or samples are taken into consideration, the machine learning techniques could act as a replacement for the calculations. Machine learning is a system where a processor learns from the given data. From the given data, the "machine" will process the data, and generate a certain outcome.

Fuzzy logic technique could be implemented in the prediction of lightning as it is one of the commonly used machine learning techniques. The reason is that fuzzy logic can classify arbitrary parameters that could not be defined by exact values. For example, humidity. A given environment could not be described to have high humidity at one time and changes to low humidity at the next second. It takes some time for vapor to be reduced at the environment before turning to a low humid state. By using sets, transitional parameters could be classified better to obtain a more realistic result. Thus, the aim of this research is to design and develop a lightning prediction system using fuzzy logic technique and that users could be notified when lightning is imminent.

The remainder of this study is organized as follows. In Section II, the related works was presented. In Section III, we present the proposed methodology. Section IV presents results and discussion. The conclusion and ideas for future works are given in Section V.

II. Related works

A. Lightning prediction systems

Studies related to lightning prediction system has been conducted in recent years and it could be observed that different researchers have different proposed methodologies in dealing with lightning prediction. The selection of input parameters differs as well and thus, it will be noted differently. Raindrops were used as the input parameter in one of the patents [2]. It was used to obtain the reflectivity data for the prediction of future weather conditions. Reflectivity data is the distance of reflection of raindrops from the sensor. With the reflectivity data collected, the system could analyze the possibility of sparks being discharged from the clouds. However, as the raindrops are carried away by the wind, the accuracy of the device in lightning prediction might be affected as the distance between the raindrops and the sensor has been manipulated.

From another patent, radar data and temperature data were used [3]. In a selected enclosed area of a location, radar data, which is information about the location, and the temperature data is collected to allow the predictor components to work effectively. The predictor sets an acceptable range to be considered that lightning is not imminent for the collected data and when the present data has exceeded the higher limit, the system notifies the users that lightning is imminent. Since the temperature is always rising due to global warming, the incidence might affect the judgement of the predictor as the range, indicating that lightning is imminent, will always change according to the temperature. The credibility of the system could be questioned as the standards set for indicating that lightning is imminent is unreliable due to the mentioned changes.

Electromagnetic field and acoustic signals were considered as the input parameter in another patent and yet again, the temperature is involved, integrating with Global Positioning Satellite (GPS) [4]. The GPS was used to assist in mapping the location, electromagnetic field parameter was considered to detect the electromagnetic field of the lightning, and acoustic signals were detected with a microphone to capture the acoustic characteristic of lightning. Both electromagnetic fields and acoustic signals could be easily disturbed by other parameters. The electromagnetic field could change when there are surrounding current or magnetic changes, and the acoustic signals could be easily mixed up with surrounding noises.

Radio frequency was taken as a parameter for the lightning prediction that is applied on an airplane [5]. The signal was being compared with the amplified version of the signal as well as the non-filtered version of the signal. The difference between the three signals produces a static difference and that would determine the imminence of lightning. The risk of using radio frequencies is that interference of signal might happen. When other applications are using the same frequency range, the detector might receive the interfered signal, resulting in a false alarm. The common method between the patents for lightning prediction is through devices that could process input parameters to determine the imminence of lightning as presented by the reviewed patents. Generally, parameters will be read by the device and processing will be done towards the parameters to determine the imminence of lightning. Then, the system will either provide the users with information about the future lightning event or a certain reaction could be a response to the input data.

There were studies conducted that use simulation and modeling to create a lightning prediction system. One of the studies was conducted in Australia at different locations from January 2004 till most February 2013. The climatology and weather of Australia are quite unpredictable across all cities. That is due to different weather humidity, causing different lightning count and sat in different cities [6]. As such, data obtained from different places in Australia were analyzed with six classification techniques. A validation technique was used to compare the performance of the classification techniques and it was discovered that the logistic regression method was the best. This method has a setback due to the varying parameter that was caused by different climate in different areas. The study uses the same atmospheric data collected for different areas. As such, the results collected might not be accurate as a different area might have different atmospheric data [7].

Another study aims to analyze a lightning prediction system located in Europe [8]. Across Europe, it could be divided into three areas with different climate profiles. However, the researchers focused their research at the Central-South of Europe, and a numerical simulation model was built based on Weather Research and Forecasting (WRF). Data were obtained from ZEUS, a network that detects lightning operated by the National Observatory of Athens. The data collected were parameterized with multiple parameterization methods. The system was evaluated with a simple decision-making procedure, showing the imminence of lightning. However, the overall system was proven to perform better on the sea than land. As such, the prediction conducted on land might not be reliable as the parameters for both sea and land are different.

In addition to WRF simulations, a study was conducted to build a system that could understand the convective nature near the clouds as convection occurrence contributes towards the formation of lightning [9]. Rainfall and thunderstorms are considered as complementary reactions that come together with lightning. Thus, a system was built based on microphysics parameter that includes rainwater, cloud water, cloud ice, snow, graupel, hail, concentration number for rainwater, concentration number for cloud water, concentration number for cloud ice, concentration number for snow, concentration number for graupel, concentration number for hail, cloud condensation nuclei concentration number, and graupel volume to understand the convection process. Furthermore, a Lightning Potential Index (LPI) was produced to have a better understanding of the V-shape back-building Mesoscale Convective Systems, an event of heavy and routine thunderstorms. It could be a torrential rainfall event that happens at a short duration of time in a small area and is equal to the time of concentration of catchment that happened in the Liguria region. As the interest lies in the predictive ability of the system, the spatial distribution, LPI maps, and observed flashes were used to validate the system. As each microphysics parameters were obtained from different researchers and is adopted into the lightning prediction system, results indicate that the WRF single-moment six-class scheme (WSM6) has the highest cumulated values of LPI that matches the spatial pattern with the observed lightning activities. The limitation of the system lies in the microphysics parameter selection as not all places experience snow and hail events and so, the system might not work properly in regions where places do not experience ice-related events.

In [10], a study was conducted to evaluate the performance of the Lightning Potential Index and POTential difference (POT). Both systems are similar in the sense that they accept the same type of parameter, which is a microphysical parameter. To study the performance of the system, ten years' worth of data at Tehran area was used to be studied. Four thundercloud cases were used as a case study and to understand the relationship of the physical properties, WRF-ELEC model fed with ERA-Interim data were used to conduct simulations. LPI and POT were obtained from the cases. As a result of all the case studies, it was concluded that LPI is more beneficial to be used as the lightning prediction system, considering that requires lesser computational costs and is generally favorable. However, since the system relies on microphysical parameters which relate to snow, hail, and graupel, it might not be suitable for all places as some of the places do not experience ice-related events.

Another research introduces a dynamic lightning forecast scheme with lightning assimilation (ASML) and without lightning assimilation (CNTL) [11]. This system converts energy that is time and space-dependent into lightning. The main parameters were obtained from WRF as well. Water vapor content was monitored as it was added at a constant temperature to observe the convective response. Both ASML and CNTL were compared to observed lightning. Case studies were done with this system to simulate the different convective conditions. This study was concluded that lightning prediction is improved when the system is integrated with lightning assimilation. The limitation of this system is once again, due to the acceptance of the microphysics parameter into the system, it is therefore not suitable or applicable to all places.

Other lightning prediction methods include calculations as well. A study was conducted towards the famous "Catatumbo Lightning" that happens at the area located in North-Western Venezuela [12]. The name was given due to the consistency of the phenomenon happening every night. Potential lightning predictors were determined with Canonical Correlation Analysis through data collected from various sensors. These data include lightning data from NASA's Global Hydrology Resource Center, atmospheric fields such as wind field, Convective Available Potential Energy (CAPE), specific humidity and temperature, and lastly, sea-surface temperature. The analysis was conducted to show the relativity of the parameters and estimated outputs. A comparison was done between the performance of local drivers and large-scale drivers. These drivers are used to detect the parameters that contribute to the heavy lightning rate in that area. Local drivers detect more on atmospheric parameters such as wind and wave radiations. Large-scale drivers detect potential and kinetic energies. The results have shown that large-scale drivers are more efficient for long-term lightning prediction compared to local drivers. As the lightning predictor was built upon a high lightning density environment, it might not be versatile enough to detect smaller lightning events. As the analysis was done to map parameters to estimated lightning happenings, the parameters considered are always related to high lightning density events and thus, the predictor would most probably be suitable only for predicting lightning imminence at high lightning density environments.

In [13], a methodology of lightning prediction by clustering tall buildings, specifically windmills was presented. The prediction of lightning was done by using an equation that includes the lightning data collected from external sources. It could be observed that as the number of windmills increase, the lightning count increases as well. The predictor might be effective for tall buildings as that is the focus of the research. However, the possibility of lightning striking lower buildings could not be neglected as it might happen as well.

A study was conducted towards the European Eastern Alps [14]. The data was obtained from the Austrian Lightning Detection & Information System and it was used to build a data regression model in determining the imminence of lightning. The mechanism to calculate the imminence of lightning is the usage of Bernoulli distribution. Alongside, Markov chain Monte Carlo sampling method was used to give reliable support for the lightning prediction. It could be seen that this method is more suitable for places that have complex features on the land, such as mountains and hills, compared to places with lesser features. The reason behind this is that mountainous areas experience events like orographic lifting, thermally affected circulations, and lee effects, which happens when the flow of wind is disrupted by obstacles like mountain causing internal gravity waves. Hence, this method is more suitable for mountainous areas.

An alternative methodology that was presented in a study was to develop a numerical weather prediction (NWP) model-based statistical lightning prediction scheme that has the ability to predict the events of cloud-to-ground lightning near southern Africa during the summer period [15]. The selection of the most proper predictors from the Unified Model (UM) to be involved in the lighting scheme will be done by using logistic regression techniques. The United Kingdom Meteorological Office has created an NWP model which is known as UM. Equations were developed to predict the probability of at least one lightning stroke per grid box by using a rare-event logistic regression technique. Data from summer days of 2011/12 and 2012/13 were used for predictors selections and equations development. The system was validated with independent summer days data from 2013/14. Lightning threat index (LTI) is the name used to represent the statistical scheme. The parameters that were involved include potential temperature, precipitable water, relative humidity, lifted index, lapse rates of equivalent potential temperature, and air temperature. There were 25 predictors for lightning prediction and the most-performing predictors were selected to be used to develop LTI. There is a setback for the system where it is not dependable from September to October as over-forecasting is significant during that period. The system is only dependable from December to February as the over-forecasting is not as significant. Thus, the reliability of the system is considered seasonal as it could function better at a specific duration of time.

A work using an artificial neural network (ANN) for lightning prediction was presented in [16]. The research was conducted near Amazon. There were a few parameters that were chosen to be the deciding factor of lightning imminence in this system. One of the parameters accepted by the system is atmospheric sounding, which is the information obtained from the earth's atmosphere. That includes the temperature, humidity, dew point temperature, and several other parameters. These data were obtained with sensors and information from the satellite. From the obtained data, a few indices were developed to set the range of lightning imminence and severity. Another parameter that was included in the system is the electromagnetic signals captured by sensors. Multiple components were set to train ANN for versatility in detecting changes. The data that was made into components were normalized to reduce the difference between data. ANN was supplied with two types of input parameters, the temperature data and related parameters like humidity and dew point temperature, and historical data of lightning events. ANN was programmed and trained to recognize patterns and to predict the imminence of lightning. ANN requires a large database of data to create an effective lightning predictor and thus, it would take a longer time to train the system for more data as well as more space is needed to store the possible combination of data for a versatile lightning prediction system.

Another study integrated ANN with the general regression technique [17]. It was claimed to have nonlinear estimation ability, good non-interfered performance, fast convergence speed, and independent learning. The system uses past lightning data of lightning location system (LLS) as well as past lightning outage data in power systems. The two parameters could relate to each other to form a prediction that lightning is imminent. The fundamental of the system executes the general regressions technique, which is a nonlinearity calculation process. As it is an ANN system, the samples were collected and the whole system was trained. After the data collection process, the samples will be processed with a general regression technique. Predictions will be made based on the inputs, which is the historical data from LLS and lightning outage data in power systems. The system was compared with other ANN systems such as backpropagation ANN and radial basis function ANN. It was concluded that the performance of the general regression neural network has a lower false alarm rate and higher accuracy. The limitation of this system is that the system is unable to classify all the samples and that the initial lightning outage could not be predicted as the system requires an accumulation of data to predict accurately.

In [18], the authors used proximity sounding and lightning data in order to evaluate the utility of thermodynamic and kinematic parameters for lightning forecasting. Forecasts of the total membership function for lightning were derived from the combination of membership functions of selected thermodynamic and kinematic parameters with each objective weight using a fuzzy logic algorithm. Based on the obtained result, it was found that the proposed method can be applied to lightning forecasting using radio observations after calculation and adjustment of the weights for each parameter.

B. *Fuzzy Logic for Lightning Prediction*

Fuzzy Logic [19] can be implemented for lightning prediction system applications as it is able to simulate realistic conditions for lightning to happen. This system is considered as a rational system that works with the ‘if-then’ concept. This concept reflects that there is a cause and consequence for each case. For each consequence to happen, there must be a certain order or rules that should be applied towards the causes, allowing the consequence to behave in such a manner [20]. This system is best used for conditions where the significance of information is known rather than specific, precise, and accurate details of that information. For example, if the water in a kettle was being boiled, the only thing that could be inferred about the kettle is that it is hot. However, the details of the temperature are unknown and the definition of “hot” could differ from people to people. Thus, the system only works when the needed adjectives used to describe the parameters were properly defined first. After identifying the type of parameters used, functions were set to define the possible trend of changes for all the parameters. For example, temperature, generally, will not change drastically. From 40°C will not drop to a drastic 10°C in one second for normal conditions. Thus, a smooth curve could be applied for this parameter.

III. METHODOLGY

A. *Data*

Temperature, humidity, and dew point were considered as the input of the proposed system. As temperature decreases in the cloud area, more precipitates will be formed in the clouds. When precipitates increase, the chances of the precipitates colliding each other will increase as well, charging the cloud area with more electrons. Humidity is considered as one of the parameters as it shows the amount of water content in the clouds. Having high humidity signifies that the water content in the clouds is high and the formation of ice could easily happen alongside low temperature. The ice that was formed will collide with other precipitates, forming electrons in the cloud area. Dew point temperature is the point where the water vapor could not hold in the water anymore. Thus, gaseous state changes into a liquid state. The process will be almost similar to the reason on the humidity parameter, where the water will be turned to ice. The data for respective parameters were all extracted from the Malaysian Meteorological Department, specifically at Subang area, in the duration of June 2018 and November 2018.

The lightning data was important as it is a source of validation for the system. This data was obtained from ‘www.timeandate.com’. This is a website that provides weather conditions and keeps a record of it. Thus, the weather condition data of June 2018 and November 2018 could be validated from this website.

B. *Data Normalization*

The ground temperature, which obtained from the dataset, was subtracted from a constant of 6.5 multiplied by the distance of the clouds from the earth’s surface, 6.5km was used in this research. This to calculate the temperature at clouds. Then, the temperature at clouds was normalized by the mean of temperature at clouds for 24 hours. This is to ensure that the temperature is normalized according to the Malaysian weather and the deviation pattern will be fixed as temperature will not face drastic fluctuations in Malaysia.

For humidity, the data was normalized by dividing it by 100 to obtain the actual humidity directly into 0 to 1 scale. The dew point temperature was obtained by identifying the minimum value from the the ground temperature for 24 hours. Then, dew point temperature was normalized by dividing itself as it will always be lowest temperature from the whole set of data.

C. *Fuzzy Logic system*

After data normalization, each parameter will be checked whether it exceeds the threshold that was set in the system to be considered as high or low. For temperature, exceeding the range of 1.3 to 1.4 will be considered high and if the value is below the range, the temperature is considered low. Humidity will be considered high when it exceeds 0.7, and low when it is below the threshold. Dew point temperature will always be kept to 1. This is because dew point temperature is considered as equivalent with the minimum temperature in a set of temperature.

The boundary is set to indicate the significance of each parameter in causing lightning to happen. The range of the output was also defined where lightning is imminent and not imminent. The output of the system is determined by the rules set towards the input parameters, through the 'if-then' approach. Each parameter has its own threshold to mark its significance towards lightning occurrence. Lightning is not imminent when the parameters are below the threshold that was set. Inversely, lightning is imminent when the parameters meet the threshold. Some of the examples of conditions set in the system are that when the temperature is low, humidity is high and dew point temperature is low, lightning is imminent, or when the temperature is high, humidity is low, and dew point temperature is high, lightning is not imminent. Thus, the fuzzy logic system is suitable for the implementation of the lightning prediction system as there are a lot of uncertainties on the presence of the parameters as well as the amount of it at a certain point in time.

In MATLAB, all parameters were defined by entering to the toolbox of each parameter, including the output. Adjectives were set to describe the condition of the parameter. Taking temperature as an example, it could be "low", and "high". The clouds temperature for lightning to occur is at around -15°C to -25°C, the threshold is set to 37°C. The normalized value is set according to the range of data obtained from the Meteorological Department. Each of these adjectives was given a function type. However, the assignation of the function type is the same for all of the adjectives. For lower boundary conditions, a "zmf" function type is used to simulate the lower open-end of the parameters that do not cause significant changes to the output. It is a function that decreases to 0 as the slope movers from left to right. A transition between lower boundary and upper boundary will be present to show that the input is entering a significant stage where, as it increases, the input will contribute even more to the possibility of lightning occurrences. Upper boundary cases use "smf" function type to simulate the upper open-end of the parameter, to indicate that as the value continues to increase, the significance of the parameter in contributing towards the lightning prediction increases as well. This function is selected and suitable as it could indicate the gradual growth of the parameter. It is a function that experiences few stages of growth, gradually at first, rapid growth in the middle, and slow growth at last. Fig 1 shows the configuration of the temperature parameter. Fig. 2 shows the configuration of the output, indicating whether lightning is "Not imminent", and "Imminent".

After the parameters have been defined, the conditions were set. For this application, the Mamdani-type of fuzzy inference was selected. Mamdani-type treats the output as a fuzzy set and that the output requires defuzzification. Defuzzification is a process where a range of values becomes a single value through processing. The centroid method was chosen to identify the area under the parameters. This is to signify the intensity of each parameter in contributing to lightning prediction. The conditions use simple logical operators like "AND" and "OR" to decide the significance of each parameter in determining the imminence of lightning. In the case of the lightning prediction system, it shows how temperature, relative humidity, and dew point temperature could affect the judgement of the fuzzy logic system in determining the imminence of lightning. The amount or intensity of each parameter could lead to a different judgment for the fuzzy logic system.

A set of rules were set to guide the Fuzzy Logic in determining whether lightning is imminent. The conditions are as follows:

1. If *temperature* is low, and the *humidity* is high, and the *dew point temperature* is high, then *lightning* is imminent.
2. If *temperature* is low, and the *humidity* is low, and the *dew point temperature* is high, then *lightning* is not imminent.
3. If *temperature* is high, and the *humidity* is low, and the *dew point temperature* is high, then *lightning* is not imminent.
4. If *temperature* is high, and the *humidity* is high, and the *dew point temperature* is high, then *lightning* is not imminent.

With the set of conditions above, the parameters will be accepted into the fuzzy logic system and prediction will be made according to the conditions set. From the input combinations, if the value exceeds 0.5, lightning will be predicted as imminent and a notification will appear in the graphical user interface, whereas if the value is below 0.5, lightning will be predicted as not imminent. The whole process repeats and continues to predict.

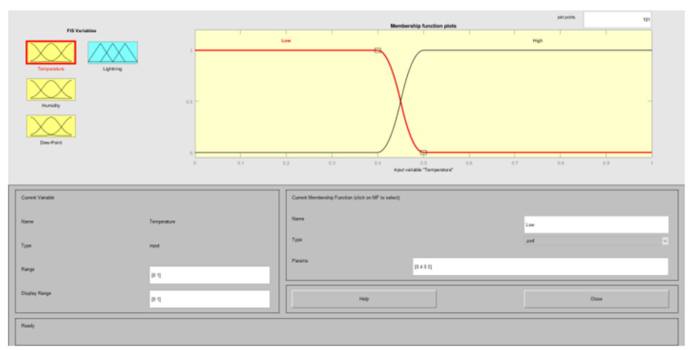

Fig. 1. Configuration of Temperature Parameter

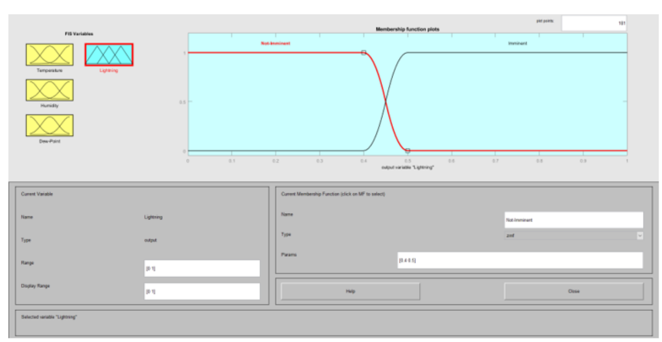

Fig. 2. Configuration of Output Parameter

IV. Results and discussions

The system was tested to understand its performance. Explanation of each test was made in terms of the purpose of the test being conducted, setting up procedures, and results. The following are the conducted tests :

- Validity test
- Consistency test
- Sensitivity test
- Linearity test
- Stability test

A. *Validation Test*

This test was conducted to verify that the output of the system is similar or close to the actual data that was recorded from 'www.timeanddate.com'. For the first case, data of 1st June 2018 was treated as input to the system. The output prediction of the system was matched with the recorded data from the website. Table I shows the results collected from the simulation and the weather conditions from the website.

From Table I, it could be observed that the results that were simulated is considered valid. From the 1st hour to the 10th hour, the prediction that lightning is imminent is considered appropriate as the temperature is lower in the morning and humidity is higher. This could be verified with the cloud condition of "Partly Cloudy". Understanding heaving more clouds show that the formation of precipitation is significant. When there are lots of precipitation, chances of collision are higher and thus, forming lightning. Thus, the prediction is considered valid. As the day moves on, the temperature starts to increase, and humidity starts to drop. Lightning is not imminent from 11th hour to 18th hour. The weather condition was described as "Partly Sunny". Contrary to the first few hours, there are lesser clouds and that chances of collision are lesser. Thus, the prediction is considered valid again. 19th hour to 24th hour sees the change where lightning is predicted to be imminent. Since the temperature at night is lower than daytime, and that humidity is high, there is a possibility that lightning is imminent. In a few hours, the condition of "Partly Sunny" becomes cloudy and rain eventually occurs. Since this is a prediction system, it is considered as a system that takes precautionary measures to protect lives and structures from lightning, it is important for the system to be able to discern the imminence of lightning in a few hours duration. This could allow humans to take safety measures earlier.

The second case study accepts input data from 28th November 2018. From Table II, a similar discussion could be drawn from the first case. A noticeable case that could be discussed happens in the 15th hour. The trend of temperature and humidity before the 15th hour makes sense as it is near the noontime, which generally has a higher temperature and lower humidity. The 15th hour sees quite a steep drop in temperature and a steep rise of humidity. With this occasion, the lightning prediction system has predicted that lightning will be imminent. At the 16th hour, thunderstorms happened. This validates that the system is not just versatile in detecting changes, but also indicates that this system does not need the training to be able to perform lightning prediction.

B. *Consistency Test*

This test was conducted to ensure that the system is consistent in predicting the imminence of lightning for at least one hour ahead before the lightning activity occurs. For this test, cases of 1st June 2018 and 28th November 2018 was studied again to observe the consistency of the system. From Table I, the prediction was made in the 19th hour and there was rain on the 23rd hour. Rainy weather conditions could be treated as lightning events as the precipitation and rainwater have a high probability of collision, causing the formation of lightning. Thus, for the first case study, it could be claimed that lightning was successfully predicted 4 hours before the lightning event happened. In the second case, referring to Table II, lightning was predicted to be imminent since the 1st hour of the day and thunderstorm happened at the 7th hour. This indicates that lightning was predicted to be imminent 6 hours before the actual lightning happened. The case on the 15th hour predicts lightning will happen in the next hour. Surely enough, thunderstorms happened in the next hour. It could be said that this system is consistent in providing lightning prediction at least an hour ahead.

TABLE I. Comparison of Simulated Results and Past Data for 1st June 2018

Hour	Temperature (°C)	Humidity (%)	Dew Point Temperature (°C)	Lightning Imminence	Weather Conditions
1	25.2	92	24.6	Yes	Partly Cloudy
2	24.9	92	24.6	Yes	Partly Cloudy
3	24.9	91	24.6	Yes	Partly Cloudy
4	25	90	24.6	Yes	Partly Cloudy
5	24.9	91	24.6	Yes	Partly Cloudy
6	24.8	90	24.6	Yes	Partly Cloudy
7	24.6	92	24.6	Yes	Partly Cloudy
8	24.9	90	24.6	Yes	Partly Cloudy
9	26.3	83	24.6	Yes	Partly Cloudy
10	27.9	76	24.6	Yes	Partly Sunny
11	29.3	68	24.6	No	Partly Sunny
12	30.4	64	24.6	No	Partly Sunny
13	31.2	63	24.6	No	Partly Sunny

14	31.7	56	24.6	No	Partly Sunny
15	31.8	56	24.6	No	Partly Sunny
16	31.7	55	24.6	No	Partly Sunny
17	31.4	57	24.6	No	Partly Sunny
18	30.8	61	24.6	No	Partly Sunny
19	29.2	74	24.6	Yes	Broken Clouds
20	28.8	77	24.6	Yes	Partly Sunny
21	28.3	80	24.6	Yes	Partly Sunny
22	28.2	83	24.6	Yes	Passing Clouds
23	27.7	86	24.6	Yes	Light rain. Partly Cloudy
24	27.4	88	24.6	Yes	Light rain. Overcast

TABLE II. COMPARISON OF SIMULATED RESULTS AND PAST DATA FOR 28TH NOVEMBER 2018

Hour	Temperature (°C)	Humidity (%)	Dew Point Temperature (°C)	Lightning Imminence	Weather Conditions
1	27.2	90	26.2	Yes	Partly Cloudy
2	27	91	26.2	Yes	Partly Cloudy
3	26.6	93	26.2	Yes	Partly Cloudy
4	26.8	91	26.2	Yes	Partly Cloudy
5	26.7	91	26.2	Yes	Partly Cloudy
6	26.4	93	26.2	Yes	Partly Cloudy
7	26.2	94	26.2	Yes	Thunderstorms. Partly Cloudy
8	26.7	91	26.2	Yes	Fog
9	28.3	83	26.2	Yes	Partly Cloudy
10	29.9	75	26.2	Yes	Broken Clouds
11	31.2	68	26.2	No	Broken Clouds
12	33	60	26.2	No	Broken Clouds
13	33.1	61	26.2	No	Broken Clouds
14	31.4	69	26.2	No	Broken Clouds
15	27.2	94	26.2	Yes	Broken Clouds
16	26.3	93	26.2	Yes	Thunderstorms. Broken Clouds
17	27	92	26.2	Yes	Light rain. Broken Clouds
18	27.5	91	26.2	Yes	Thunderstorms. Broken Clouds
19	27	88	26.2	Yes	Light rain. Partly Sunny
20	26.6	91	26.2	Yes	Partly Sunny
21	26.6	94	26.2	Yes	Light rain. Passing Clouds
22	26.6	94	26.2	Yes	Partly Cloudy
23	26.3	94	26.2	Yes	Partly Cloudy
24	26.2	95	26.2	Yes	Partly Cloudy

C. Sensitivity Test

This test is to understand the effects of the slightest change towards the system. As the whole system is fully dependent on the combination of input, the point of change will be identified by manipulating both temperature and humidity. From the data of 1st June 2018, the sensitivity test could be conducted by attempting to change the temperature and humidity at the 19th hour. The temperature will be changed until a point where lightning becomes not imminent. Table III shows the attempts and the results of the tweaking.

From Table III, it could be noticed that humidity plays a huge role in the sensitivity test. The change in humidity to below 70% has caused the prediction of lightning to be not imminent. Regardless of the temperature, whether it is 32°C or lower, as long as the humidity does not pass 70%, lightning will still be predicted as not imminent. The reason for the temperature to be unable to have huge effects on the system is due to the fact that the average value keeps changing and that data normalization is based on the average temperature. Hence, the dynamic nature of temperature data causes the temperature to be a secondary factor for the system to predict lightning. Thus, the sensitivity for the whole system lies in the humidity, where a 1% change in humidity will cause the system to predict lightning is imminent or not.

TABLE III. SENSITIVITY TEST RESULTS

Temperature (°C)	Humidity (%)	Dew Point Temperature (°C)	Lightning Imminence
29.2	74	24.6	Yes
32	65	24.6	No
32	70	24.6	Yes
32	69	24.6	No
22	69	24.6	No

D. Linearity Test

This test is to understand the effects of each parameter on the output of the system. This test has three cases, which is to tweak the temperature and humidity to 0 respectively, and to observe the relationship between a single input and the output. It will not be possible for dew point temperature to be 0 as it takes the value of the lowest temperature and divides itself. For this test, data from the 23rd hour and 24th hour will be taken for tweaking. Table IV shows the results of the tests.

TABLE IV. RESULTS FOR LINEARITY TEST

Temperature (°C)	Humidity (%)	Dew Point Temperature (°C)	Lightning Imminence
27.7	86	24.6	Yes
0	86	24.6	Yes
27.7	0	24.6	No
27.4	88	24.6	Yes
0	88	24.6	Yes

From Table IV, it could be observed that a similar inference to the sensitivity test could be made. Since humidity plays a huge role in affecting the prediction of lightning. Thus, when the humidity was changed to 0, lightning was predicted to be not imminent. However, the temperature does not have a significant effect that affects the prediction of lightning.

E. Stability Test

This test was conducted to find out the processing capability of the system and to identify the stable period of the system in predicting lightning. With the same set of data, the system was executed twice. To analyze the stability of the system better, a graph is plotted to show the performance of the system from the 1st hour to the 24th hour.

In Fig. 3, the blue line indicates the first attempt, followed by orange, green, and purple. It could be seen that the system is considered to be more stable after approximately the 8th hour of prediction. The common fluctuation point of the system stability lies around the 5th to 7th hour prediction. The performance of the system depends heavily on the processing speed of the machine.

F. Possible Sources of Error and Troubleshooting Methods Employed

For this system, a possible source of error will be on the fuzzy logic inferencing system. As the system tries to discern the combination of the inputs, there is a possibility that the system might provide the wrong output. From the input combination and the rules that were added into the system, it is important for all parameters to be defined properly to clearly classify whether the parameters could be described as "High" or "Low". To ensure that the system works for Malaysian weather, fine-tuning was done to ensure that the threshold set for each parameter will be as close to the actual setting in the real world.

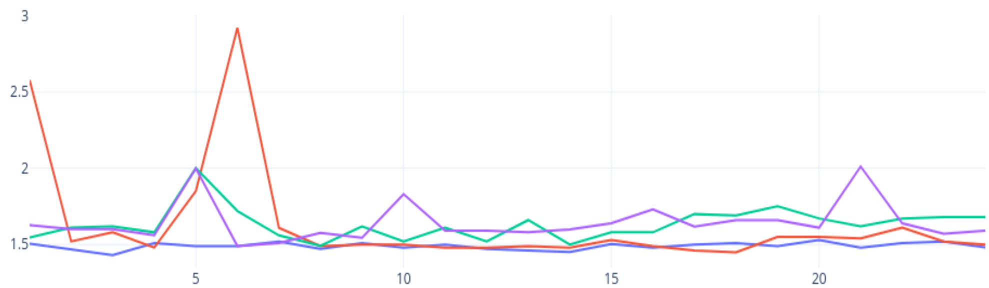

Fig.3 Graph of Stability of the System

V. CONCLUSIONS

This paper developed an algorithm for lightning prediction using the fuzzy logic technique. The system can predict lightning when temperature, humidity, and dew point temperature reaches a certain threshold and with that, the implementation of fuzzy logic into a lightning prediction system is considered successful. Some of the parameters that were used in previous research include reflections of raindrops, radio frequencies, electromagnetic field, and different climate conditions. However, this proposed system proves that using the three main parameters, namely temperature, humidity, and dew point temperature could have achieved the purpose of lightning prediction.

Different tests were conducted to examine the performance of the system working at different conditions. For the validity test, the system gives a positive result of more than 90% accuracy for being able to predict the imminence of lightning. The consistency test shows that the system was able to predict lightning repetitively at least 1 hour before lightning activity happens. The sensitivity test proves that lightning prediction relies heavily on the humidity and that 70% is the threshold to

change between not imminent to imminent. The linearity test once again proves that humidity has a direct relationship that could affect the prediction of lightning. The stability test shows that the system will be stable after predicting the 6th to 7th hour data. Finally, it could be concluded that the accuracy of this system in lightning prediction is more than 95% after being tested with real data from the meteorological department.

The system that was implemented has some untested areas as well as limitations. The system is untested with parameters from other places that have different weather profiles with Malaysia. As this system is built upon the weather conditions of Malaysia, specifically at the Subang area, the system is not guaranteed to work at places that experience drastic fluctuations of temperature, different humidity levels, and different dew point temperatures, for example, places that experience four seasons or even desert locations. Thus, it might not be able to predict properly at different places.

In hopes of improving the system, it is recommended for research to be done on ways to implement this lightning prediction system using fuzzy logic automation elements. As lightning prediction is considered as the precautionary step for the protection of structures and lives, it will be beneficial for this system to implement elements that could automate circuit breakers or protective equipment to be prepared for lightning strikes. It is also suggested to integrate this system with sensors that sense the temperature, humidity, dew point temperature. In this way, the system will be able to obtain real-time data to predict lightning. Lastly, it is advised to test the system for different weather conditions. This is to ensure that the system is versatile to be used at different locations that might experience drastic changes in temperature, humidity, and dew point temperature.

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