Forecast of Tropical Cyclone Occurrences based on Fuzzy Logic Algorithm

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Abstract. Most studies of the tropical cyclone (TC) forecasting are focused on the track and the wind radius forecasting, even though a tropical cyclone formation alerts also developed. This paper takes a different approach and explores and forecast the TC occurrences. This study presents the development of fuzzy logic (FL) models for predicting the occurrence of TC from five primary TC genesis parameters. These parameters are low-level relative vorticity (θ), horizontal wind of upper troposphere (u), sea surface temperature (SST), equivalent potential temperature (θe), and specific humidity (q). The FL model was developed by employing the trapezoidal and triangular fuzzy membership functions for the input and output variables. The fuzzy rules were inferred from the TC genesis parameters data, with a daily calculation period from 1989 to 2018. The amount of TC genesis parameters when the cyclone occurred of the lowest, middle, and upper tercile reconstruction was used as a threshold to build FL model. The model satisfactorily simulated the occurrence of TC with comparable error measures. The result exhibits the accuracy at 0.75 (range: 0 to 1, perfect score: 1). The evidence shows that the result provides insights into the adequacy of FL methods for forecasting the TC occurrences.

Keywords : tropical cyclone, fuzzy logic, relative vorticity.

1. Introduction
TC is the generic term for a non-frontal synoptic scale low-pressure system originating over tropical or subtropical waters with organized convection and definite cyclonic surface wind circulation. Tropical cyclones with maximum sustained surface winds of less than 17 ms⁻¹ are generally called "tropical depressions (TD)." Once a tropical cyclone achieves surface wind strengths of at least 17 m/s, it is typically called a "tropical storm" or "tropical cyclone" and assigned a name [1]. In the northern hemisphere, TC occurs between June and November peaking in September; moreover, in the southern hemisphere, the season lasts from November to April. More than one TC can occur in the same ocean and region at once. Among cyclones that occur in the Southern Hemisphere, almost half are formed above the Northern coast of Australia, a quarter appear above the South Pacific Ocean, and others occur above the ocean of South Indonesia [2]. Tropical cyclones are perhaps the most devastating of natural disasters both because of the loss of human life they cause and the large economic losses they induce [3-7].

One of the most challenging subjects in term of ocean-atmosphere interaction is that of understanding the tropical cyclone (TC) occurrences. Many opinions stated that the environmental conditions and the physical mechanisms which bring about tropical cyclone formation is important to understand why and how TC form. Among scientists who have studied this phenomenon there lies a wide variety of opinion. For instance, Neiburger, Edinger, and Bonner [2] observed that TC possibly form when sea surface
temperatures (SST) depicts the magnitude more than 27°C and do not form between the 4°N and 4°S (tropical areas) of the equator. Based on this TC form requirements, TC will be less likely to pass through Indonesia due to a tropical characteristic of Indonesia region. However, the effects of TC that occur around Indonesia could affect bad weather and meteorological disaster in various places in Indonesia. Vulnerability to tropical cyclones is becoming more pronounced because the fastest population growth is in tropical coastal regions. In Indonesia, for example, TC Cempaka that occurred on 28 October 2017 generated extreme weather has caused floods, landslides, and tornadoes in 21 regencies/cities in Java and Bali. Temporary data collected by National Agency for Disaster and Management (BNPB) post, the disaster occurred in the large area of Java such as Semarang, Kulon, Progo, Ponogoro, Bantul, and Kudus [8]

In this research, fuzzy logic (FL) algorithm was used to forecast both TC and TD occurrences. This method has some advantage, i.e. (i) it mimics the human thinking and reasoning, (ii) it can detect the uncertainties of dynamic system behaviors, (iii) it is based on training and experiences rather than of the theory. This new approach is necessary since it could have some implications for the TC and TD forecast.

2. Data and Method

2.1 Study Site

To assess TC forecasting related to the main parameters in the formation of TCs such as wind—pressure relationship, finding a suitable study site is important [9]. Tropical cyclones generally occur in the tropics with low latitudes between 10° and 20° N / S from the equator [10]. In addition, the most active TC growth area for the Southern Hemisphere is Australia's northern coast which experienced 124 incidents within 100 years [11]. As explained by the Australian Bureau of Meteorology (BOM), this region reaches an average of 10 times of TC occurrences per year. From this literature, Australia's northern coast is an area that has higher TC occurrences more than many places in the world. In the Southern Hemisphere, almost TC occurrences are formed above the northern Australia ocean, South Indonesia and South Pacific Ocean [2]. Therefore, in this study, the Southern Ocean of East Nusa Tenggara (15°-10°S and 115°-130° E), Indonesia, is employed as the study site. This area is an example of a populated TC occurrence that is highly vulnerable to the storm which is mainly caused by TC.

As illustrated in figure 1, the layer of the study domain shows an ocean between East Nusa Tenggara and Australia North coast. Based on the archive of tropical cyclones [12], there were 56 occurrences of tropical cyclones in the research grid during the period 1989-2018 in winter and spring periods.
2.2 Input Selection

Gray [13] explained that the frequency of tropical cyclones could be directly related to a combination of several physical parameters called the main parameters in the formation of tropical cyclones. These parameters are:

1. The amount of vorticity in the lower troposphere. Tropical cyclones only form in large areas of vorticity in the lower troposphere.
2. The zonal wind vertical shear role. According to Gray [13], the requirements of tropical cyclones are a weak zonal wind shear approximately at 0-1 m/s.
3. The role of ocean thermal energy. Tropical cyclones have a large influence on sea surface temperature, when the sea surface temperature changes, it changes the cyclone characteristics. Tropical cyclones can have a profound influence on the temperature of the ocean over which they travel. The altered ocean temperature, in turn, can feedback and alter the character of the cyclone.
4. The influence of the surface to the equivalent potential temperature in the middle troposphere. Cyclone formation is related to moist buoyancy potential or the extent of the layer boundary of the atmosphere to the middle troposphere. Representative Buoyancy to study TC characteristics is the difference between the surface (1000 mb) and 600 mb layer.
5. The role of moisture in the middle troposphere. Moisture parameters vary from 0 to 1. The development of cyclones does not occur if the humidity in the layer 500-700 mb is less than 40%. This factor increases linearly by 1 in the humidity between layers 700-500 mb reaching 100%, or humidity parameter is between 40% and 70%. So tropical cyclones only form in regions with relatively high humidity (RH) or specific humidity (q) in the middle troposphere.

Therefore, the input parameters used in this study are the main parameters in the formation of tropical cyclones, i.e., low-level relative vorticity ($\Theta$), the horizontal wind of upper troposphere (u), sea surface temperature (SST), equivalent potential temperature ($\theta_e$), and specific humidity (q). The input variables are selected during the rainy season in Indonesia on December, January, February (DJF) and March, April, May (MAM). These periods were selected due to the highest frequency of TC occurrences in the south of Indonesia started from October to May with a peak in December to March [14].

All of the input parameters are obtained from the Japan Meteorological Agency (JMA), Tokyo, Japan [15]. Furthermore, this study employed the input parameter data with a daily calculation period from 1989 to 2010 as a training data and 2011 to 2018 as a validation data.

2.3 Fuzzy Logic (FL) Reconstruction

Bellman and Zadeh [16] suggested that fuzzy is a different aspect of uncertainty with randomness. Then they proposed a mathematical form to see how obscurity can be expressed in a human language whose approach is called "fuzzy logic (FL)”. In fuzzy it is known that membership degrees have intervals $[0,1]$. With fuzzy logic, we can express the same information (less specific), then manipulate it, and conclude from that information. FL is used in this study because it can handle the determination of event predictions based on input data.

Many scientists have employed the FL algorithm to meteorology and hydrology problems [17-20]. The method of FL algorithm is to consider the system depicts in the form of subsets or fuzzy approaches, each of which is stated with words such as “low”, “medium”, “high”, etc. An FL algorithm consists of parameters that have varying membership degrees in the set. This idea is in contrast with classical algorithm theory because for crisp sets an element either is a member of that set or is not. FL rule-based on systems can be used as useful representations of either simple or complex physical problems. A small number of fuzzy sets leads to unrepresentative forecasts whereas a large number leads to many calculations. In this research, we set 3 number of fuzzy and labeled with, low, medium, and high. This study depicts the following steps to construct an FL algorithm. These are:

(i) Fuzzification of the input and output parameters by considering convenient linguistic subsets, i.e., low, medium, high

(ii) Fuzzy rules construction based on IF-THEN rules to simulate the model. The rules relate the combined linguistic subsets of input parameters to the output fuzzy sets. The input subsets within
the premise part are combined interchangeably with the logical “and” or “or” conjunction whereas the rules of this study used a logical “and” conjunction based on the formation of tropical cyclones, (iii) The implication part of a fuzzy system is defined as the shaping of the consequent based on the premise (antecedent) part, and finally (iv) The result is a fuzzy set, and therefore, requires defuzzification to arrive at a crisp value, which is required to simulate the model.

In the applications of the FL algorithm in control and forecasting, there are mainly two approaches: the first one is the Mamdani method, and the other is Takagi-Sugeno. For the Mamdani method, they use clear procedures, i.e., fuzzification, logic decision, and defuzzification procedure. For Takagi-Sugeno algorithm [21], however, does not have a clear defuzzification method. For the Mamdani approach, the outcome of each IF-THEN rule will be a fuzzy set for the output variable so that the step of defuzzification is indispensable to obtain the crisp value of the output variable. Therefore, this study utilising Mamdani procedure to construct FL rules.

2.4 Tropical Cyclone (TC) Forecasting Model

Before determining the threshold of the fuzzy membership function, this paper aims at examining the lagged input data to predict TC and TD occurrences. We used the cross-correlation method to evaluate the relationship between the lag time of each input variable and both TC and TD occurrences. The lag time with best biseria correlation with TC and TD occurrences were chosen as predictors.

Furthermore, we categorized the predictor threshold based on 33th percentile of TC and TD occurrences for 1991-2010 periods and divided into three classes (low, moderate & high). After the fuzzy rule base is identified and a defuzzification algorithm is selected, forecast accuracy is tested using a different set of the historical data set (training data) from the one used to obtain the rule base. If it is unsatisfactory, then the number of fuzzy membership functions and/or shape of the fuzzy membership functions can be changed, and a new FL rule base is obtained. The iterative process of designing the rule base, choosing a defuzzification algorithm, and testing the system performance may be repeated several times with a different number of fuzzy membership functions and/or different shapes of fuzzy memberships. The FL rule base that provides the minimum error measure for the test set is selected for real-time forecasting.

This study used trapezoidal and triangular membership function in term of the main characteristics of five TC and TD input parameters. The results of the model will be verified using 'categorical statistics' from the 'contingency table'. Contingency table or also called cross-tabulation table or crosstab is a table arranged based on data tabulation according to 2 or more categories that are displayed because an element with other elements is in conformity or relationship. Each column of the matrix is an example in the prediction class, while each row represents an example in the actual class. Dimensions or sizes of various contingency tables, the simplest are dimension 2, like the example below:

| Forecast | Observed | Total |
|----------|----------|-------|
|          | Yes      | No    |       |
| Yes      | Hits     | False alarms | Forecast yes |
| No       | Misses   | Correct negatives | Forecast no |
| Total    | Observed yes | Observed no | Total |

The four combinations of forecasts (yes or no) and observations (yes or no), called the joint distribution, are hits (event forecast to occur, and did occur), misses (event forecast not to occur, but did occur), false alarm (event forecast to occur, but did not occur) and correct negative (event forecast not to occur, and did not occur).
According to Provost and Fawcett [22], performance measurement algorithms that can be measured include Accuracy (AC) which is the correctness of the whole model and is calculated as the sum of the correct classifications divided by the total number of classifications. This skill was calculated based on the proportion of the correct number of predictions and is determined using the equation of the contingency table above.

\[
Accuracy (AC) = \frac{\text{Hits} + \text{Correct negatives}}{\text{Total}} \quad (1)
\]

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3. Results and Discussion

3.1 Time Lag Analysis and Fuzzy Rules Construction

Figure 2 shows the relationship between the lag time of each model input with the occurrence of TC and TD. All of the inputs exhibit the highest correlation in lag 1, and those relationships decrease with an increase of lag time.

![Figure 2. Biserial correlation between input parameters and TC and TD occurrences](image)

Among input parameters, negative relationships were found in low-level relative vorticity (\( \Theta \)), the horizontal wind of upper troposphere (\( U \)), sea surface temperature (SST), and equivalent potential temperature (\( \theta_e \)).

In contrast, specific humidity (q) employed positive correlation with TC and TD occurrences in the south of East Nusa Tenggara. Based on the above time lag analysis, we used input variables based on the highest correlation with TC and TD occurrences. Furthermore, we construct FL rules regarding the input parameters that were chosen. The class of FL rules was a construct based on 33th percentile of TC occurrences data. Table 2 exhibits the threshold value of each input parameter in each class.

| Term      | \( \Theta \) (10^6, S^(-1)) | \( U \) (ms^(-1)) | SST (°C)       | \( \theta_e \) (°C) | Q (10^4, gkg^(-1)) |
|-----------|------------------------------|-------------------|----------------|-------------------|-------------------|
| Low       | [−31 to −8]                  | [−18.75 to −8.64] | [26.78 to 28.18] | [7.39 to 12.20]   | [8.57 to 41.56]   |
| Moderate  | [−8.1 to 0]                  | [−8.65 to −3.55]  | [28.19 to 29.09] | [12.21 to 14.10]  | [41.57 to 49.55]  |
| High      | >0                           | [−3.56 to 14.56]  | >29.09         | >14.10           | >49.55           |

After the FL rule base is identified and a defuzzification algorithm is selected, forecast accuracy is tested using a different set of the historical data set (training data) from the one used to obtain the rule base. FL rules were obtained and changed based on the best accuracy of training data. From Table 2, we build 243 rules for the occurrence of TC and TD. We set the rules regarding the highest accuracy of
training data from 1991 to 2010. It should be noted that the FL approach will work reasonably as the degree of fuzziness is suitable with the variables and the natural behavior of the system. Furthermore, FL rules are constructed between input parameters in IF-THEN format regarding the variables and expert decision. Lastly, results are defuzzified to a specific number as an output thought to the best represent fuzzy (figure 3).

Figure 3. The instance of FL model reconstruction (rule 1) by using centroid method for $\theta = -9.5 \, S^{-1}$, $u = -16 \, m/s$, SST $= 29.5^\circ C$, $\theta_e = 15^\circ C$, and $q = 39.5 \, g/kg$. In this study, we build and simulate 243 FL rules that depict the complexity of the model.

Many scientists used centroid as defuzzification method to model FL algorithm [23]. Therefore, in this study, we continue to use the centroid method to compute FL algorithm of TC and TD occurrences based on the expert decision. Figure 3 was made to facilitate understanding of the relationship between the input parameter and both TC and TD occurrences. It depicts the rule relationships between all input parameters and both TC and TD occurrences. TC and TD will occur when they employ value from 0.51 to 1. For instance, Figure 3 exhibits FL computation by using centroid method for $\theta = -9.5 \, S^{-1}$, $u = -16 \, m/s$, SST $= 29.5^\circ C$, $\theta_e = 15^\circ C$, and $q = 39.5 \, g/kg$. With those values, the rules depict the probability of either TC or TD occurs with a degree of membership approximately at 0.3. The rule illustrated in Figure 3 exhibits the condition of TC and TD to appear is fulfilled. However, this study builds fuzzy rule up to 243 rules that make the computation run complexly.

3.2 The System of Tropical Cyclone (TC) Forecast Design
The Matlab® commercial FL Toolbox was used to design the Graphical User Interface (GUI) of TC occurrences forecast. This structure is stored inside a GUI tool. All the information for a given fuzzy
inference system is contained in the GUI design, including variable names, input parameter definitions, and so on. This system can itself be thought of as supervised learning to predict the occurrences of both TC and TD.

![TC Forecast GUI](image)

**Figure 4.** The GUI main screen of the TC occurrences forecast.

The implementation of the GUI of the TC occurrences forecast is analogous to the GUI used for Type-1 FL in the Matlab® Fuzzy Logic Toolbox, thus permitting the experienced user to adapt easily to the use of this GUI. This GUI was built through the process of an algorithm learning from the training dataset that can be thought of as a teacher supervising the learning process based on the FL rule that we constructed. The supervised learning problem in this study was classified into two groups, i.e., ‘OCCUR, and NO OCCUR’. OCCUR is indicate that all the input variables are possible to make TC appeared, while NO OCCUR is the contrast condition. Figure 4 exhibited the example of all input variables that enable to make TC occurred in the study area.

3.3 The accuracy of the Forecast

The accuracy of the forecast was calculated from the total numbers of observed and forecast occurrences and non-occurrences which are given on the lower and right sides of the contingency table. The validation of the forecast was calculated based on daily data from 2011 to 2017 in DJF and MAM periods.

| Forecast | Observed | Total |
|----------|----------|-------|
|          | Yes      | No    |       |
| Yes      | 10       | 329   | 339   |
| No       | 4        | 1022  | 1026  |
| Total    | 14       | 1351  | 1365  |

In Table 3, a yes/no forecast of TC occurrences for 21 months are presented, and the high values of hit and correct negatives indicate that the model may be considered as practically accurate. Interestingly,
the results reveal that the model predictions are in good agreement with the observed TC and TD events. Table 3 depicts that this system can predict 1032 event that matched with TC observation and only 333 events that miss predicted during 2011 to 2017 periods. During these periods, 10 TC occurrences can be predicted accurately from 14 number of TC events. From table 3, the accuracy of the forecast can be calculated based on the correct number of predictions. The model satisfactorily simulated the occurrence of TC with comparable error measures. The result exhibits the accuracy at 0.75 (range: 0 to 1, perfect score: 1).

3.4 Comparing of FL model with previous studies in term of TC and TD forecasting

Most studies of the tropical cyclone (TC) forecasting are focused on the track and the wind radius forecasting, even though a tropical cyclone formation alerts also developed. For instance, Vitart, Leroy and Wheeler [24] compared the accuracy of the European Centre for Medium-Range Weather Forecasts (ECMWF) forecast system to predict the genesis of tropical cyclones (TCs) over the Southern Hemisphere during intraseasonal (10-60 days) periods have been investigated and compared to the skill of a statistical approach. Other studies have been developed to investigate the potential link between TCs and its impacts both at a regional and global scale in worldwide [25-29]. For instance, in terms of extremes, Khouakhi, Villarini and Vecchi [29] employing annual maximum (AM) and peak-over-threshold (POT) methods, the highest impact of tropical cyclone to rainfall are found in East Asia, followed by Australia and North and Central America, with fractional contributions generally decreasing farther inland from the coast. He found that the relationship between extreme rainfall induced by TC and ENSO exhibits that extreme rainfall caused by TC tends to occur more frequently in Australia and along the East Coast of the U.S. during La Niña and in East Asia and the northwest Pacific islands during El Niño.

For the forecast of TC formation, Li, Fu, Ge, Wang and Peng [30] used QuikSCAT satellite products and the Tropical Rainfall Measurement Mission Microwave Image data to document temporal and spatial structures of Rossby wave to investigate cyclogenesis formation in the western North Pacific. However, there is still a lack of studies to predict the genesis of TC occurrences. Therefore, this paper takes a different approach and explores and forecast the TC occurrences based on unsupervised machine learning (self-organized) system. This study presents the development of fuzzy logic (FL) models as an unsupervised machine learning approach [31] for predicting the occurrence of TC from five primary TC genesis parameters. This machine learning approach is a family of statistical methods with origins in the area of artificial intelligence. This method is developed as holding great breakthrough for the improvement of understanding and prediction about the earth-science system. This modeling approach is quite flexible to resolve complex problems with various interacting parameters and typically outcompete traditional methods (e.g., generalized linear models), performing them ideal for modeling atmospheric environment [32]. In this study, for the results, the skill of the model exhibits good agreement with the observed TC and TD events.

3.5 Limitations

There are some limitations for this study to develop FL model. A small number of fuzzy sets leads to unrepresentative forecasts whereas a large number leads to many calculations. In previous studies, many numbers of fuzzy sets are selected initially from 3 to 6 [33, 34]. Therefore, it is difficult to determine the length of interval for FL approaches. In this study, we set 3 number of fuzzy and labeled with, low, medium, and high based on the highest accuracy of the training dataset. In addition, we used 3 number of fuzzy sets to save computational resources. In FL systems, membership functions play a very important role in representing problems [35]. The membership function that is used in this study is a trapezoidal and triangular membership function. We used the trapezoidal and triangular membership function regarding the behavior of TC that visually matched with its pattern criteria. This TC behavior can come from expert knowledge and training data. In this study, we construct TC behavior based on the training data in a daily calculation period from 1989 to 2010. The longer periods that potentially be used in future research may result in different membership function.

Furthermore, the selection of training data can also be a difficulty, because the data used must represent the actual data. The selection of training data will determine the knowledge and accuracy of
the generated fuzzy logic. Ultimately, in this study, the accuracy of fuzzy logic depends on the expert or training data. In this method, it is also possible to combined FL approach with another method such as adaptive neuro-fuzzy inference system (ANFIS) to get the better skill of TCs prediction.

From the results, the forecasting of TC occurrences using FL algorithm is generally accurate based on the accuracy score at 0.75. However, this model only can be used in this study area (15°S–10° S and 115°E–130°E). It is a need either to do a cluster analysis or to explore other TC occurrences at potential areas such as North Atlantic, West Pacific or the South China Sea before making a forecast. Different locations are possible to produce different rules of FL algorithm. For further research, it also possible to employ another input variable to increase the forecast accuracy of TC occurrences.

4. Conclusion
This contribution explored the new forecasting of TC occurrences method utilizing FL algorithm as an unsupervised machine learning approach. We built-up FL rules and identified a defuzzification algorithm based on 33rd percentile of TC and TD historical data set from 1991-2010. Forecast accuracy is tested using a different set of training data from the one used to obtain the rule base. The model satisfactorily simulated the occurrence of TC with comparable error measures in the study area. The result exhibits the accuracy at 0.75 (range: 0 to 1, perfect score: 1) showing a good agreement with the observed TC and TD events. In addition, we employed The Matlab® commercial FL Toolbox to design the Graphical User Interface (GUI) of TC genesis (occurrences) forecast. The evidence shows that the result provides insights into the adequacy of FL methods for forecasting the TC occurrences.

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