The Model of Fuzzy Logic in IoT System as Decision Support System for Determining Flood Disaster Status

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Abstract. Flood is the most frequent disaster in the world. The impact of floods is very large, like human and animal death, the villages vanished and other environments damaged. In disaster preparedness, it is very necessary to divide the stages of the disaster status level. Therefore the public can prepare themselves according to these stages. The stage of disaster preparedness status is also beneficial for the government and related institutions to act according to the status stage of the disaster. This paper will propose the early warning system for flood disaster based on fuzzy logic in IoT system. This algorithm was built 8 rules. The inputs are the rainfall and height of water. The output is the status of flood disaster. The types of disaster status are normal, moderate 1, moderate 2, emergency 1, and emergency 2. From the simulation result, it is concluded that this fuzzy logic model can to determine the status of flood disaster very well.

1. Introduction
Flood is a disaster that often occurs in many countries. For example at Indonesia, floods occur more than a thousand times every year. The data of natural disasters in the last 10 are shown in Figure 1. Figure 1 shows that floods are the most frequent disasters at Indonesia. The floods occur as a result of urbanization, conversion of forests into agricultural land and settlements as well as climate change. The impact of flood disasters varies, depending on the size of the flood, the plain of the environment around the river, and the readiness of residents to face flooding. In [1] also give information that the effects of flood disaster at Indonesia are highest than other disaster. The effects include death, disappeared, refugees, and broken public facility and home.
Citizens' readiness in facing floods is supported by several things, including: disaster mitigation education for residents and the existence of flood disaster early warning facilities. The risk of floods can be reduced if the residents have time to save themselves, their families and their assets. EWS flood disaster is needed so that there is readiness of citizens to face the floods so that the risk of flood disaster can be reduced. Flood forecasting must be made as quickly and accurately as possible so it needs to be calibrated with past events[2].

Yussof et.al reviewed the flood disaster management from Malaysian perspective [3]. There are four phases of flood disaster management. Figure 2 shows the flood disaster mitigation phase in Malaysia are prevention/mitigation, preparedness, response and recovery. Flood disaster preparedness is a system to provide early warning of flood disasters, through providing relevant information to the public so that there is a growing awareness of the risk of flood disasters and knowing how to respond or react to facing floods so that the risk of flood disasters decreases [4].

In order to be more effective in handling flood disasters, related institutions or agencies must have some capability and knowledge. First, the ability to cope with the possibility of flood, secondly, the ability to identify parties who will be affected by floods, and thirdly, the ability to disseminate information to communities that may be affected efficiently and accurately. Besides that, also giving advice or instruction on what action should be taken by the community[5]. In preparedness, it is very necessary to divide the stages of the disaster status level. So the public can prepare themselves
according to these stages. The stage of disaster preparedness status is also beneficial for the
government and related institutions to act according to the status stage of the disaster.
This paper proposes the fuzzy model in IoT system for determining the flood disaster status as
early warning to public. The organization of the paper is as follows: Related works will be presented
in Section 2, methodology is described in Section 3, results and discussion is in Section 4, and
conclusion of this study is summarized in Section 5.

2. Related Works
Many researchers examine the flood disaster early warning for flood disaster preparedness. In the
study, most researchers propose algorithms to predict flood disasters and the accuracy of predictions,
without any stage of preparedness status from early warning. The following will be presented a review
of several papers related to flood prediction.

Monitoring and prediction of flooding using IoT and artificial neural networks (ANN) can be found
in [6]. In this research, an IoT system was built with a Wi-Fi-based communication infrastructure,
cloud server, and algorithm to help predict flood situations. The study uses temperature, humidity, air
pressure, and rainfall as parameters used to determine flood predictions. The accuracy of the proposed
method is 88%. ANN method was also used for decision support systems for early warning of flash
flood disasters real time[7].

Other study used the NNARX Model to predict flooding[8]. NNARX is Neural Network
Autoregressive with Exogenous Inputs. The predicted NNARX model for predicting flood water
levels 3, 4 and 5 hours in advance based at Kuala Lumpur-Malaysia is using real-time data. The
performance of this algorithm is able to predict with a 4 hour prediction time well and with a RMSE
prediction of 0.0792 m. Ruslan et.al used the Multiple-Input Single-Output (MISO) Autoregressive
with Exogenous Input (ARX) and MISO Autoregressive Moving Average with Exogenous Input
(ARMAX) structure for flood prediction. ARX is Autoregressive with Exogenous input. The
identification method uses the least squares that are able to solve linear equations and unique
solutions. ARMAX is an Autoregressive Moving Average with Exogenous Input. The ARMAX model
includes stochastic dynamics. The ARMAX model has good flexibility in dealing with
disturbances[9].

Tun and Sein used the Markov Chain model for the flood prediction system at Magway region-
Myanmar [10]. This system is for monitoring weather conditions and water levels in dams and
supports early warning. The public can access weather and water level information using a mobile
phone.

Zaji et.al examined the right and accurate way to predict air discharge using satellite
information[11]. This paper successfully introduced a new statistical index, HE (Horizontal Error). To
predict future river satellite signals, one of the most economical options is to create a combination
index of HE and VE (Horizontal Error) to achieve an accurate model[11].

Flood prediction using an empirical model of hydrograph and RRM (Rainfall-Runoff) has been
carried out by Jun et.al[2]. The object of research is in Kasipillay-Kuala Lumpur. Empirical model of
hydrograph is data of past rainfall, water level and discharge. From 15 flood events, prediction errors
are 2.06% to 5.82%.

Flood prediction using multi-layer ANN with input rainfall, water level, and soil moisture has been
done by Cruz et.al [12]. The infrastructure used in this study was tipping bucket rain gauge, an
ultrasonic sensor, a soil moisture sensor and a web server. The performance of this system was
measured by RMSD. The RMSD between prediction and actual is 2.2648.

Determining the direction of flood distribution is an important parameter for disaster mitigation.
Prasetya et.al used Cellular automata algorithms to determine the direction of flood distribution[13].
Cellular automata is the process of modelling physical systems into mathematical models based on
space and time as discrete quantities. In the context of flood spread prediction, automata cells are the
input parameters that affect flood spreading. The inputs are evaluation data, soil type, river mapping,
river volume, and rainfall. In this study, the prediction accuracy was 64%[13].
Corani and Guariso combined fuzzy algorithms with artificial neural networks for flood forecasting. With input is the saturation of the basin [14]. The performance of this algorithm combined exceeds that of conventional ANN[14].

Hafiz et al. used The Integrated Flood Analysis System (IFAS) model to convert rainfall into river basin runoff. Simulation using rainfall data on earth and satellite [15]. The result is water discharge in the river, so that flooding can be predicted.

A decision support system framework for flood disaster early warning was developed by Mirfenderesk et al. [16]. This framework integrated hydrologic, rain hydrodynamic modelling and web-based controlled. This system is able to predict and flood levels in real time.

Boni et al. proposed a flood mapping algorithm real time in the Po River by developing CSK image classifications and modifying S-1 data[17]. They claimed that flood predictions were reliable and accurate, but for agriculture areas ambiguous signatures were found.

Determination of disaster status is very important for community preparedness in facing disasters. In this paper, the status of a disaster is divided into five levels: Normal, Moderate 1, moderate 2, emergency 1, and emergency 2. The community will prepare themselves for disasters in accordance with the status of disaster warnings. For example, during the emergency phase 2, the community must save themselves and their assets or property by evacuating to a safe place. This paper will present the DSS to determine disaster status using fuzzy systems.

3. Methodology
The Block diagram fuzzy model in IoT system for determining flood disaster is presented in Figure 3. Fuzzy model get two inputs, i.e. water high/level and rain intensity. The output of fuzzy system is disaster status. This status will send to public via internet. In this research, we focus on the fuzzy algorithm as soft tool to support determining disaster status.

![Figure 3](Image)

**Figure 3.** The Block diagram fuzzy model in IoT system for determining flood disaster

The stages of disaster status in this paper are Normal (in Indonesian : Normal), Moderate (in Indonesian : Waspada and Siaga), and Emergency (in Indonesian: awas) [18]. These terms refer to the term that usually use by the Indonesian Government for eruption disaster status. The normal status shows the save condition. Moderate status indicates an increase in status above normal conditions, in this status the community should increase preparedness. While emergency status indicates a significant increase in threats and risks, all resources can be immediately mobilized to rescue and evacuate communities and secure assets.

The design phase of fuzzy algorithm is as follow:

a. Defining the characteristics of the model in a functional and operational manner.

This phase examines the variables associated with flood disaster status. In addition, there is also a
logical connection between the variables and the external status of the flood disaster.

b. Decomposing model variables into fuzzy sets At this stage, the fuzzy set of input and output variables are arranged. The selection of this membership function considers the model or trend data variable used. In this study, we used two inputs, namely the height of water and the intensity of rainfall. Input data of water high and rainfall intensity using trapezoidal and triangular combination models. Output is the status of disaster using discrete rectangle model. Determining of the member function based on the parameters like high of river, maximum of rainfall intensity, and number of disaster status. In this study, We use the data from river with high is 300 cm (3m), and maximum of rainfall intensity is 100 mm/day. The number of disaster status is five statuses. They are Normal, Moderate 1, Moderate 2, Emergency 1, and emergency 2.

The model of member functions of input and output as below. Member function of height of water (Input 1):

- **Low**
  \[ \mu(x) = 1, \text{ untuk } x \leq 50 \]
  \[ (100-x)/50 \text{ untuk } 50<x \leq 100 \]
  \[ 0, \text{ untuk } x>100 \]

- **Middle**
  \[ \mu(x) = 0, \text{ untuk } x \leq 50 \text{ atau } x \geq 250 \]
  \[ (x-50)/100 \text{ untuk } 50<x \leq 150 \]
  \[ (250-x)/100, \text{ untuk } 150<x \leq 250 \]

- **High**
  \[ \mu(x) = 0, \text{ untuk } x \leq 200 \]
  \[ (x-200)/75 \text{ untuk } 200<x \leq 275 \]
  \[ 1, \text{ untuk } x \geq 275 \]

**Figure 4** shows the member function of water high/level

**Member function of rain intensity (Input 2):**

- **Low**
  \[ \mu(x) = 1, \text{ untuk } x \leq 10 \]
  \[ (30-x)/20 \text{ untuk } 10<x \leq 30 \]
  \[ 0, \text{ untuk } x>30 \]

- **Middle**
  \[ \mu(x) = 0, \text{ untuk } x \leq 10 \text{ atau } x \geq 80 \]
  \[ (x-10)/40 \text{ untuk } 10<x \leq 50 \]
  \[ (80-x)/30, \text{ untuk } 50<x \leq 80 \]

- **High**
  \[ \mu(x) = 0, \text{ untuk } x \leq 60 \]
  \[ (x-60)/25 \text{ untuk } 60<x \leq 85 \]
  \[ 1, \text{ untuk } x \geq 85 \]

**Figure 5** shows the member function of input 2 (rainfall intensity).
Figure 5. Member function of input 2 (rainfall intensity) Member function of disaster status (Output):

Status “Normal” \(0 \leq x \leq 200\) Status “Moderate 1” \(200 < x \leq 400\)  
Status “Moderate 2” \(400 < x \leq 600\)  
Status “Emergency 1” \(600 < x \leq 900\)  
Status “Emergency 2” \(x \geq 900\)  
Figure 4 shows the member function of the output.

Figure 6. Member function of output (disaster status)

c. Creating a fuzzy rule

The next step is to design fuzzy rules. These rules are based on the rationale of the relationship between the disaster status and the input of an influential parameter. Table 1 shows the rules of fuzzy set.

| No | Input (Height of water) | Input (Rain Intensity) | Output (Disaster Status) |
|----|-------------------------|------------------------|--------------------------|
| 1  | Low                     | Low                    | Normal                   |
| 2  | Middle                  | Low                    | Normal                   |
| 3  | Low                     | Middle                 | Moderate1                |
| 4  | Middle                  | Middle                 | Moderate2                |
| 5  | High                    | Low                    | Moderate2                |
| 6  | High                    | Middle                 | Emergency1               |
| 7  | Middle                  | High                   | Emergency1               |
| 8  | High                    | High                   | Emergency2               |
d. Defuzzification method for each solution variable

Defuzzification is the opposite process of fuzzification. In this research, we used the centroid method. This defuzzification result will determine the status of flood disaster.

4. Results and Discussion

In this section, we will discuss the results of DSS for flood disaster status system using fuzzy logic. In each sub-section will present one by one the status of flood disaster.

4.1 Disaster Status “Normal”

Figure 7(a) and Figure 7(b) show the normal status. Figure 7(a) is based on rule 1 (height of water is low and rainfall intensity is low). Figure 7(b) is based on rule 2 (height of water is middle and rainfall intensity is low). In this case, the value of status is 100 and 165, it has meaning that status is “normal”.

Figure 7a. Disaster status “Normal” from rule 1
4.2 **Disaster Status “Moderate 1”**

Figure 8 shows the Moderate 1 status. Based on the rule 3, it state that if height of water is low and the rainfall is middle then status is “Moderate 1”. The example is height of water in low is 37 cm and the rainfall intensity in middle is 50 mm. These values produce the value 305. Therefore, based on the member function of output, this value is **Moderate 1**.

![Figure 8](image-url)

**Figure 8.** Disaster status “Moderate 1” from rule 3

4.3 **Disaster Status “Moderate 2”**

Figure 9(a) and 9(b) show the status “Moderate 2”. This status is supported by rule 4 and rule 5. Based on the rule 4, it state that if height of water is middle and the rainfall intensity is middle then status is “Moderate 2”. While the rule 5 state that if height of water is high and the rainfall is low then status is “Moderate 2”. Figure 9(a) is supported by rule 4, while figure 9(b) is supported by rule 5.

![Figure 9(a)](image-url)

**Figure 9(a).** Disaster status “Moderate 2” from rule 4
4.4 Disaster Status “Emergency 1”

Figure 10(a) and Figure 10(b) show the status “Moderate 1”. This status is supported by rule 6 and rule 7. Based on the rule 6, it states that if height of water is high and the rainfall intensity is middle then status is “Emergency 1”. While the rule 7 states that if height of water is middle and the rainfall is high then status is “Emergency 1”.

Figure 10(a). Disaster status “Emergency 1” from rule 6
4.5 Disaster Status “Emergency 2”

Figure 11 shows the Emergency 2 status. Based on the rule 8, it state that if height of water is high and the rainfall intensity is high then status is “Emergency 2”. In Figure 11, the example of height of water in high is 260 cm and the rainfall intensity in high is 88.6 mm. These values produce the value 955. So based on the member function of output, this value is Emergency 2.

5. Conclusion

In the disaster preparedness, it is very necessary to divide the stages of the disaster status level. So the public can prepare themselves according to these stages. The stage of disaster preparedness status is also beneficial for the government and related institutions to act according to the status. The fuzzy model for the determination of flood disaster status has been discussed. In the model it uses 2 inputs, 1 output, and 8 rules. Two input variables are height of water and rainfall intensity, while output is a flood disaster status. From the testing of several samples representing each status, this model is able to determine the status of flood disaster according to the specified rule. Further research is the
implementation and measurement the accuracy of this model in real condition.

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