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Design of a Flood Early Warning System (EWS) Based on Fuzzy Logic

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Abstract

Flood disasters remain a recurring hydrometeorological problem in Indonesia, highlighting the need for adaptive and reliable early warning systems. This study aims to develop an Internet of Things (IoT)-based Flood Early Warning System (FEWS) utilizing the Mamdani Fuzzy Inference System to improve flood risk classification. The proposed system integrates three hydrological input parameters, namely rainfall intensity, water level, and flow rate, acquired through real-time sensors connected to an Arduino Uno microcontroller. A total of 36 fuzzy inference rules were constructed based on the combination of three rainfall sets, three water level sets, and four flow rate sets, while the defuzzification process applies the Centroid method to generate a crisp flood alert value. Experimental testing using rainfall of 48 mm, flow rate of 40 m³/s, and water level of 145 cm produced defuzzification values of 131 in MATLAB simulation and 130.8 in the hardware prototype, both classified under the "Normal" category. The small numerical deviation of 0.2% indicates a high level of consistency between simulation and real-world implementation. These results demonstrate that integrating multiple hydrological parameters enhances decision accuracy compared to conventional threshold-based approaches, thereby providing an adaptive and reliable solution for real-time flood risk mitigation.

Keywords: fuzzy logic, flood early warning system, IoT, Mamdani method, hydrological monitoring

INTRODUCTION

Flood is one of the most frequent hydrometeorological disasters in Indonesia, particularly in regions with high rainfall intensity and limited river capacity. Data from (Statistik, 2025) in just 2024 shows that flooding affected approximately 12,527 villages and urban areas across Indonesia, indicating that flood risk remains widespread and recurrent in many regions. Over the past five years, floods have caused significant impacts on physical aspects and regional vulnerability, particularly in lowlands, basins, and watersheds where physical factors such as topography and land use changes determine disaster potential (Jannah et al., 2025) These events have a serious impact on the health of the urban poor, who experience not only an increase in acute diseases but also persistent mental health disorders such as depressive symptoms resulting from post-disaster stress and asset loss (Carias et al., 2022). On the other hand, floods also massively disrupt macroeconomic activities, including damage to agricultural land that triggers food security threats as well as disruptions to the tourism and investment sectors that hinder regional economic growth (Ilyas et al., 2025). Furthermore, risk analysis indicates that social vulnerability is unevenly distributed, where poor groups with low education levels bear a much higher level of flood risk exposure compared to economically more prosperous groups (Sigit et al., 2023). Rapid urbanization, climate variability, and extreme rainfall events have increased the vulnerability of watershed areas, making early warning systems (EWS) increasingly important. Conventional flood monitoring systems that rely on single threshold values often fail to adapt to dynamic environmental changes, resulting in delayed or inaccurate warnings. Therefore, an intelligent decision-making approach capable of handling uncertainty is urgently needed.

In recent years, fuzzy logic has been widely implemented in IoT-based flood monitoring systems due to its ability to model linguistic variables such as low, medium, high, and danger. (Yuyun et al., 2020) developed an IoT-based fuzzy EWS capable of classifying flood conditions into several alert levels adaptively. (Golondrino et al., 2023) demonstrated that fuzzy-based flood risk assessment effectively produces a risk index ranging from safe to hazardous levels. Furthermore, (Kridalukmana et al., 2024) enhanced river flood prediction accuracy using fuzzy learning mechanisms, while (Arante et al., 2025) integrated neuro-fuzzy networks with genetic algorithms to improve forecasting performance. (Priana et al., 2024) proposed a rainfall-based fuzzy system for flood depth detection using three classification levels (normal, alert, hazard). These studies confirm that fuzzy logic remains a robust approach for handling uncertainty in flood monitoring applications.

However, several limitations remain in previous studies. Most existing systems focus on limited input parameters, primarily rainfall and water level, without incorporating river discharge as an additional hydrological indicator. Moreover, classification schemes are generally restricted to three alert levels, which may not provide sufficient granularity for operational decision-making in early warning systems. In addition, some approaches emphasize prediction accuracy but provide limited discussion on adaptive rule-based decision structures for real-time warning dissemination.

This study supports previous research that demonstrates the effectiveness of fuzzy logic in flood monitoring while extending their approaches by integrating three hydrological parameters: rainfall intensity, river discharge, and average water level. Unlike prior works that implement three-level classifications, this research proposes a four-level Flood Alert system (Safe, Caution, Warning, Danger) to improve decision resolution. The novelty of this research lies in the development of a rule-based fuzzy inference system that enhances decision adaptability by combining multi-parameter hydrological indicators within a structured alert framework.

The objective of this research is to design and evaluate a fuzzy logic-based flood early warning model capable of producing adaptive flood alert classifications using real-time sensor data. The proposed system is expected to provide a more flexible and realistic decision-support mechanism for flood risk mitigation aligned with recent developments in intelligent systems and IoT-based environmental monitoring.

METHODS

This study applies an experimental prototyping method utilizing the System Development Life Cycle (SDLC) framework, which encompasses needs analysis, hardware design, software implementation, and validation. The core of this research is the integration of the Internet of Things (IoT) with a Fuzzy Inference System (FIS) to create a real-time Flood Early Warning System (FEWS). The integration of IoT and computational intelligence has been widely recognized in recent literature as a robust approach for disaster mitigation, offering significant improvements in handling hydrological data uncertainty compared to conventional deterministic (Hadi et al., 2020); (Wandi & Ashari, 2023) Furthermore, the use of fuzzy logic is critical in this domain due to its ability to model the vagueness of environmental parameters—mapping rainfall and water discharge data into linguistic variables that mimic human decision-making processes (Gani et al., 2016); (Sukmawan et al., 2023); (Àgueda et al., 2023). Unlike other prediction models that rely solely on historical statistics, this system processes real-time sensor data to provide dynamic risk assessment (Purnama et al., 2025); (Costache et al., 2021).

The fuzzy logic process involves three specific stages:

A. Fuzzification: Crisp numerical inputs from the sensors are converted into fuzzy linguistic sets using membership functions. Based on the calibrated data from the research location, the variables are categorized as follows:

- Rainfall (CH): Classified into three sets: Low (0–50 mm), Medium (45–70 mm), and High (65–100 mm).
- Flow Rate (D): Classified into four sets to increase granularity: Small (0–50 m³/s), Medium (30–150 m³/s), Large (100–300 m³/s), and Very Large (250–600 m³/s).
- Water Level (TA): Classified into three sets: Low (50–150 cm), Medium (140–200 cm), and High (190–250 cm). The overlapping ranges in these sets are designed to handle the uncertainty and transition between states, a core advantage of rule-based fuzzy systems (Kousalya, 2023); (Pérez-Pérez et al., 2024).

B. Rule Base Evaluation: The inference engine applies a comprehensive rule base derived from the permutation of input sets. This study implements a 3×3×4 matrix, resulting in 36 If-Then rules to cover all possible hydrological scenarios (e.g., IF Rainfall is Medium AND Flow is Large AND Level is High THEN Status is Danger). The inference process uses the MIN function for implication and the MAX function for aggregation, consistent with standard fuzzy control theory (Butt & Akram, 2016); (Olesiak, 2017); (Khaddari et al., 2023).

C. Defuzzification: The aggregated fuzzy set is converted back into a single crisp value using the Centroid (Center of Gravity) method. This method is mathematically defined as:

$$Z^{*} = \int \frac{\mu(z) z dz}{\mu(z) dz}$$

and is selected for its ability to provide a smooth and physically meaningful control output compared to Mean of Max (MoM) methods (Mitsuishi, 2022); (Aktürk & Turgay, 2022).

The hardware architecture is centered around the Arduino Uno microcontroller, selected for its reliability in embedded control systems. The system integrates three primary sensors to acquire environmental variables, ensuring a multi-dimensional risk assessment:

1. Water Level Measurement: An HC-SR04 Ultrasonic Sensor is utilized to measure the water height (TA). This sensor was selected based on comparative studies by (Widayaka et al., 2022), which demonstrated that ultrasonic sensors provide high precision in non-contact liquid level detection compared to other proximity sensors.
2. Rainfall Intensity: A Rain Sensor (Analog/Tipping Bucket mechanism) is employed to quantify precipitation (CH). This mechanism is standard in hydrology for converting volumetric rainfall into electrical signals (Pitriyanto & Haryanto, 2024). Accurate rainfall data is crucial as it serves as the primary input for flood prediction models (Cahyono et al., 2023).
3. Flow Rate Measurement: To capture the velocity of the river current (D), a Water Flow Sensor (YF-S201) is installed. The inclusion of flow rate is a critical enhancement over previous models that often relied solely on water level, as it allows for the detection of flash floods caused by high-velocity currents (Hais et al., 2024); (Gunal & Mehdi, 2023).

The system also includes a Servo Motor to simulate floodgate control and a Buzzer/LED array for local alerts. The schematic diagram illustrating the interconnection between the microcontroller and the sensor array is presented in Figure 1.

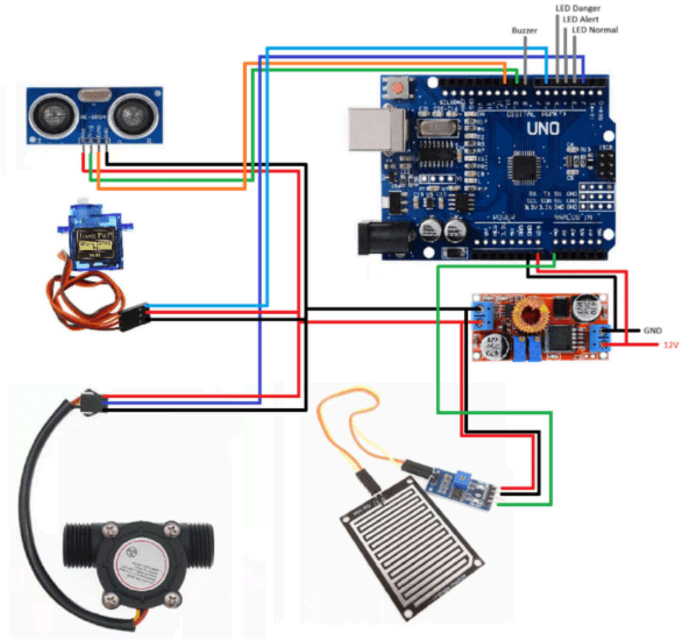


Figure 1. The Schematic Diagram of Flood Early Warning System

The specific pin configuration used to interface these sensors and actuators with the microcontroller is detailed in Table 1.

No	Device / Component	Pin Component	Connected to Arduino Pin	Description
1	Arduino Uno	Power Input	5V	Main power supply
2	Rain Sensor (Analog)	VCC	5V	Power supply
		GND	GND	Ground
		AO	A0	Analog rainfall data
3	Ultrasonic Sensor (HC-SR04)	VCC	5V	Power supply
		GND	GND	Ground
		Trig	Pin 9	Trigger signal
		Echo	Pin 10	Echo signal
4	Water Flow Sensor	Red	5V	Power supply
		Black	GND	Ground
		Yellow	Pin 2	Pulse output
5	Gate Servo Motor	Red	5V (Step-down)	External power
		Brown	GND	Ground
		Orange	Pin 6	PWM control
6	Alert Indicator	Normal LED	Pin 4	Normal condition indicator
		Alert LED	Pin 5	Alert condition indicator
		Danger LED	Pin 7	Danger condition indicator
		Buzzer	Pin 8	Sound warning

Table 1. Pin list

To ensure the reliability of the proposed model, a triangulation validation method was employed. The results from the hardware prototype (Serial Monitor) were compared against manual mathematical calculations and simulations performed in MATLAB R2018b using the Fuzzy Logic Toolbox. This rigorous validation ensures that the embedded algorithm functions correctly and produces consistent flood alert statuses (Normal, Waspada, Bahaya) across different testing platforms (Àgueda et al., 2023); (Costache et al., 2023). Furthermore, the system's ability to reduce false alarms is evaluated by analyzing the consistency of the 36 rules in handling outlier data, a necessity for reliable Early Warning Systems (Purnama et al., 2025).

RESULTS AND DISCUSSION

This study evaluates the implementation of the Mamdani fuzzy logic approach in an IoT-based Flood Early Warning System (EWS) to classify flood risk levels using three hydrological input parameters, namely rainfall intensity (mm), flow rate (m^3/s), and average water level (cm). The system was developed and simulated using MATLAB to analyze the interaction between environmental parameters under uncertain and dynamic conditions. The flood warning output consists of three classification levels, namely Normal, Alert, and Hazard, which are determined through the Mamdani fuzzy inference process. The decision-making mechanism involves several stages, including fuzzification to determine the degree of membership of each input variable, formulation of rule-based inference representing hydrological conditions, aggregation of active rules, and defuzzification using the centroid method to produce a crisp output value. Each input variable is represented using membership function curves, enabling the system to model gradual environmental changes and provide adaptive flood risk classification compared to conventional threshold-based approaches.

To mathematically represent the degree of membership for each input variable, triangular membership functions are employed. These input membership functions were established by synthesizing interview data with graphical adjustments generated via the MATLAB application. These graphs are fundamental to the flood warning computational logic, defining specific ranges that quantify the degree of membership (μx) for each parameter. The calibrated and integrated membership function specifications are detailed below:

Information:
TA = Water Levgel
CH = Rainfall
D = Flow Rate

$$f(x,\ a,\ b,\ c)\{ \qquad 0,\ x \le a\ or\ x \ge c \quad \frac{x-a}{b-a}, \qquad a \le x \le b \quad \frac{c-x}{c-b}, \qquad b \le x \le c$$

1. Variable Rainfall

   Based on previous research conducted by Priana et al., the rainfall variable is categorized into three fuzzy sets, namely low, medium, and high rainfall intensity. The low rainfall category is defined within the range of 0–50 mm with a peak value at 25 mm, the medium category within 50–70 mm with a peak value at 55 mm, and the high category within 70–100 mm with a peak value at 85 mm.

$$\mu_{CH\_}low \ = \{ \qquad 0,\ \ x \le 0 \ or \ x \ge 50 \quad \frac{x-0}{25-0}, \qquad 0 \le x \le 25 \quad \frac{50-x}{50-25}, \qquad 25 \le x \le 50$$

$$\mu_{CH\_}medium \ = \{ \qquad 0,\ \ x \le 45 \ or \ x \ge 70 \quad \frac{x-45}{55-45}, \qquad 45 \le x \le 55 \quad \frac{50-x}{70-55}, \qquad 55 \le x \le 70$$

$$\mu_{CH\_}high \ = \{ \qquad 0,\ \ x \le 65 \ or \ x \ge 100 \quad \frac{x-65}{85-65}, \qquad 65 \le x \le 85 \quad \frac{100-x}{100-85}, \qquad 85 \le x \le 100$$

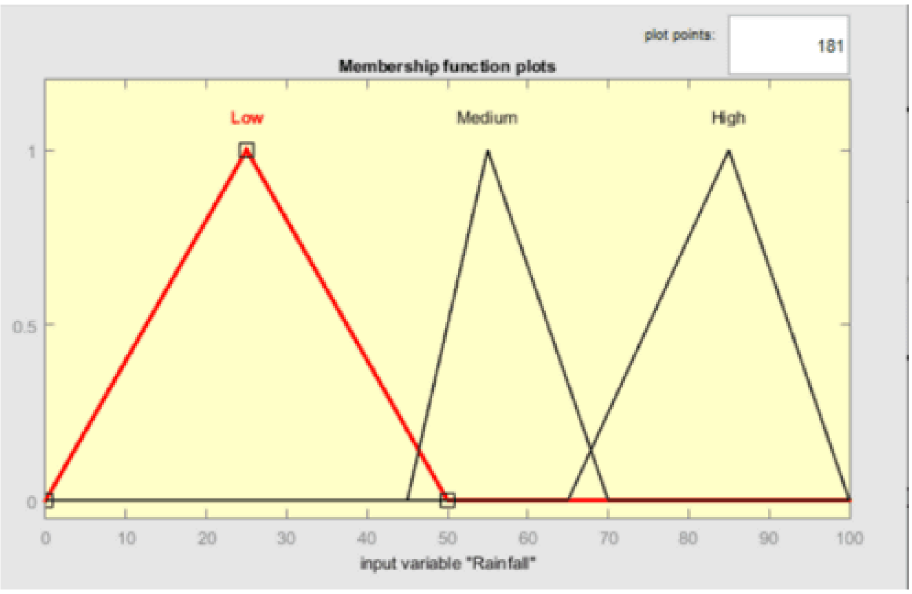


Figure 2. Mmbership function graph for the variable input "Rainfall"

2. Variable Flow Rate

Based on our preliminary research and system design analysis, the flow rate variable was classified into four fuzzy sets, namely small, medium, large, and very large discharge. The small discharge category is defined within the range of 0–50 m³/s with a peak value at 25 m³/s, the medium category within 30–150 m³/s with a peak value at 90 m³/s, the large category within 100–300 m³/s with a peak value at 200 m³/s, and the very large category within 250–600 m³/s with a peak value at 425 m³/s.

$$\mu_{D\_}small \ = \{ \qquad 0,\ \ x \le 0 \ or \ x \ge 50 \quad \frac{x-0}{25-0}, \qquad 0 \le x \le 25 \quad \frac{50-x}{50-25}, \qquad 25 \le x \le 50$$

$$\mu_{D\_}medium \ = \{ \qquad 0,\ \ x \le 30 \ or \ x \ge 150 \quad \frac{x-30}{90-30}, \qquad 30 \le x \le 90 \quad \frac{150-x}{150-90}, \qquad 90 \le x \le 150$$

$$\mu_{D\_}large \ = \{ \qquad 0,\ \ x \le 100 \ or \ x \ge 300 \quad \frac{x-100}{200-100}, \qquad 100 \le x \le 200 \quad \frac{300-x}{300-200}, \qquad 200 \le x \le 300$$

$$\mu_{D\_}verylarge \ = \{ \qquad 0,\ \ x \le 250 \ or \ x \ge 600 \quad \frac{x-250}{425-250}, \qquad 250 \le x \le 425 \quad \frac{600-x}{600-425}, \qquad 425 \le x \le 600$$

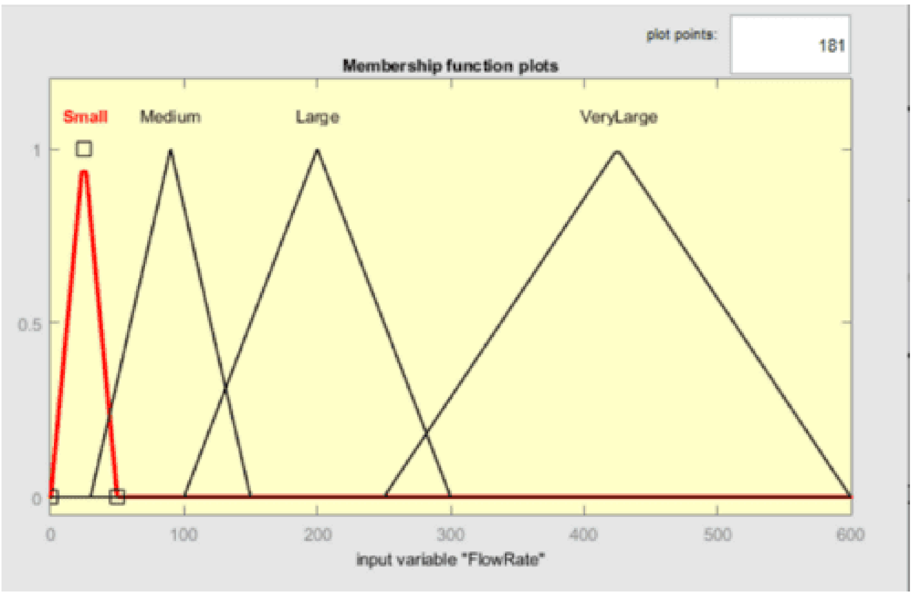


Figure 3. Membership function graph for the variable input "Flow rate"

3. Variable Water Level

Based on previous research conducted by Priana et al., the water level variable is classified into three fuzzy sets, namely low, medium, and high. The low category is defined within the range of 50–150 cm, the medium category within 150–200 cm with a peak value at 175 cm, and the high category within 200–250 cm with a peak value at 225 cm. This classification follows the fuzzy membership representation commonly applied in flood detection systems to model gradual transitions in water level conditions and to support adaptive decision-making in flood early warning systems.

$$\mu_{TA\_} low = \{ \quad 0, \; x \le 50 \; or \; x \ge 150 \quad \frac{x-50}{100-50}, \quad 50 \le x \le 100 \quad \frac{150-x}{150-100}, \quad 100 \le x \le 150$$

$$\mu_{TA\_} medium = \{ \quad 0, \; x \le 140 \; or \; x \ge 200 \quad \frac{x-140}{175-140}, \quad 140 \le x \le 175 \quad \frac{200-x}{200-175}, \quad 175 \le x \le 200$$

$$\mu_{TA\_} high = \{ \quad 0, \; x \le 190 \; or \; x \ge 250 \quad \frac{x-190}{225-190}, \quad 190 \le x \le 225 \quad \frac{250-x}{250-225}, \quad 225 \le x \le 250$$

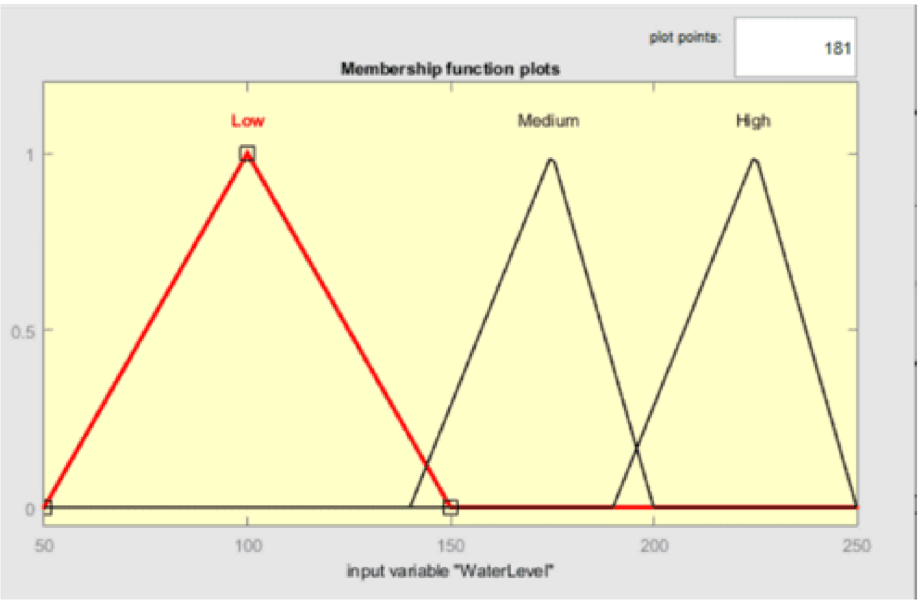


Figure 4. Membership function graph for the variable input "Water Level"

4. Variable Flood Alert

The Flood Alert variable is categorized into three fuzzy sets, namely Normal, Alert, and Danger. The Normal condition is defined within the range of 50–150 cm with a peak value at 100 cm, the Alert condition within 150–200 cm with a peak value at 175 cm, and the Danger condition within 200–250 cm with a peak value at 225 cm.

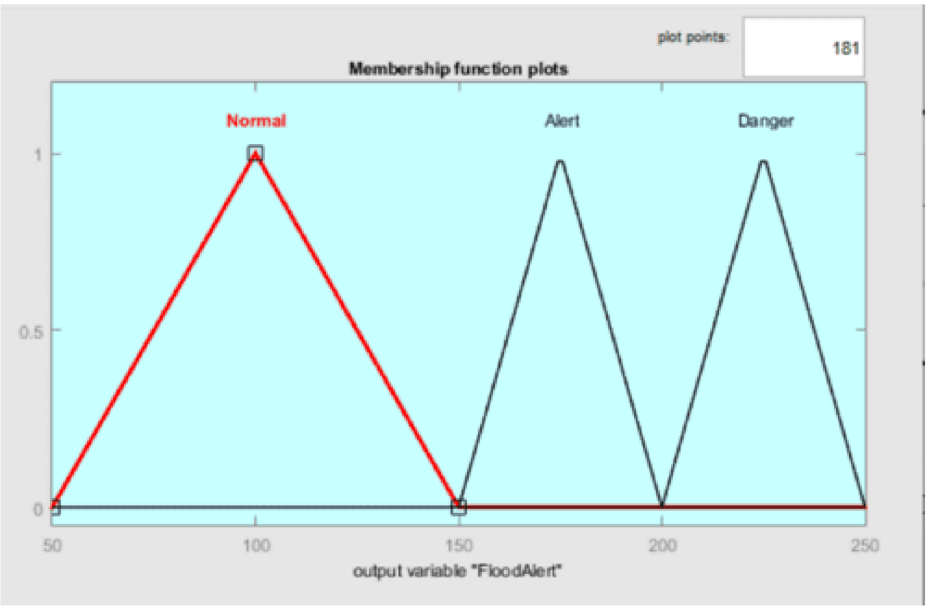


Figure 5. Membership function graph for the variable output "Flood alert"

Based on the membership set data presented earlier, calculations were performed to determine the flood warning status using a rainfall intensity of 48 millimeters (mm), a flow rate of 40 cubic meters per second (m^3/s), and a water level of 145 centimeters (cm). These input values fall within the intersection of fuzzy sets. The experimental results indicate that the rainfall of 48 mm has a membership degree (μx) of 0.08 in the Low range and 0.3 in the Medium range. The flow rate of 40 m^3/s yields a membership degree (μx) of 0.4 in the Small range and 0.167 in the Medium range. Meanwhile, the water level of 145 cm corresponds to a membership degree (μx) of 0.1 in the Low range and 0.143 in the Medium range.

Rainfall Variable

$$\mu_{T\_}low = \frac{c1-x}{c1-b1} = \frac{50-48}{50-25} = \frac{2}{25} = 0.08$$

$$\mu_{T\_}medium = \frac{x-a2}{b2-a2} = \frac{48-45}{55-45} = \frac{3}{10} = 0.3$$

Flow Rate Variable

$$\mu_{T\_}small = \frac{c1-x}{c1-b1} = \frac{50-40}{50-25} = \frac{10}{25} = 0.4$$

$$\mu_{T\_}medium = \frac{x-a1}{b1-a1} = \frac{40-30}{90-30} = \frac{10}{60} = 0.167$$

Water Level Variable

$$\mu_{T\_}low = \frac{c1-x}{c1-b1} = \frac{150-145}{150-100} = \frac{5}{50} = 0.1$$

$$\mu_{T\_}medium = \frac{x-a1}{b1-a1} = \frac{145-140}{175-140} = \frac{5}{35} = 0.143$$

The inference engine in this study is governed by 36 "If-Then" rules, formulated by permuting the linguistic categories of three input variables: Rainfall (3 sets), Water Level (3 sets), and Flow Rate (4 sets). This represents a significant expansion compared to the model developed by Priana et al. (2024), which relied on a 9-rule system derived solely from Water Level and Rainfall. While Priana's model effectively monitors static water depth, the inclusion of Flow Rate (Debit) in this study allows for the detection of water velocity, a critical factor in identifying flash floods. Consequently, the 36-rule structure presented here offers a higher resolution of risk assessment, distinguishing between high-volume static water and dangerous high-velocity flows, which requires a more complex decision matrix than the previous 9-rule approach. The complete set of rules established to map these environmental inputs to the flood alert output is presented below:

1. **IF Rainfall is Low AND Flow Rate is Small AND Water Level is Low THEN Normal**
2. **IF Rainfall is Low AND Flow Rate is Small AND Water Level is Medium THEN Alert**
3. **IF Rainfall is Low AND Flow Rate is Small AND Water Level is High THEN Danger**
4. **IF Rainfall is Low AND Flow Rate is Medium AND Water Level is Low THEN Normal**
5. **IF Rainfall is Low AND Flow Rate is Medium AND Water Level is Medium THEN Alert**
6. **IF Rainfall is Low AND Flow Rate is Medium AND Water Level is High THEN Danger**
7. **IF Rainfall is Low AND Flow Rate is Large AND Water Level is Low THEN Alert**
8. **IF Rainfall is Low AND Flow Rate is Large AND Water Level is Medium THEN Danger**
9. **IF Rainfall is Low AND Flow Rate is Large AND Water Level is High THEN Danger**
10. **IF Rainfall is Low AND Flow Rate is Very Large AND Water Level is Low THEN Danger**
11. **IF Rainfall is Low AND Flow Rate is Very Large AND Water Level is Medium THEN Danger**
12. **IF Rainfall is Low AND Flow Rate is Very Large AND Water Level is High THEN Danger**
13. **IF Rainfall is Medium AND Flow Rate is Small AND Water Level is Low THEN Normal**
14. **IF Rainfall is Medium AND Flow Rate is Small AND Water Level is Medium THEN Alert**
15. **IF Rainfall is Medium AND Flow Rate is Small AND Water Level is High THEN Danger**
16. **IF Rainfall is Medium AND Flow Rate is Medium AND Water Level is Low THEN Alert**

17. **IF Rainfall is Medium AND Flow Rate is Medium AND Water Level is Medium THEN Alert**
18. **IF Rainfall is Medium AND Flow Rate is Medium AND Water Level is High THEN Danger**
19. **IF Rainfall is Medium AND Flow Rate is Large AND Water Level is Low THEN Alert**
20. **IF Rainfall is Medium AND Flow Rate is Large AND Water Level is Medium THEN Danger**
21. **IF Rainfall is Medium AND Flow Rate is Large AND Water Level is High THEN Danger**
22. **IF Rainfall is Medium AND Flow Rate is Very Large AND Water Level is Low THEN Danger**
23. **IF Rainfall is Medium AND Flow Rate is Very Large AND Water Level is Medium THEN Danger**
24. **IF Rainfall is Medium AND Flow Rate is Very Large AND Water Level is High THEN Danger**
25. **IF Rainfall is High AND Flow Rate is Small AND Water Level is Low THEN Alert**
26. **IF Rainfall is High AND Flow Rate is Small AND Water Level is Medium THEN Danger**
27. **IF Rainfall is High AND Flow Rate is Small AND Water Level is High THEN Danger**
28. **IF Rainfall is High AND Flow Rate is Medium AND Water Level is Low THEN Alert**
29. **IF Rainfall is High AND Flow Rate is Medium AND Water Level is Medium THEN Danger**
30. **IF Rainfall is High AND Flow Rate is Medium AND Water Level is High THEN Danger**
31. **IF Rainfall is High AND Flow Rate is Large AND Water Level is Low THEN Danger**
32. **IF Rainfall is High AND Flow Rate is Large AND Water Level is Medium THEN Danger**
33. **IF Rainfall is High AND Flow Rate is Large AND Water Level is High THEN Danger**
34. **IF Rainfall is High AND Flow Rate is Very Large AND Water Level is Low THEN Danger**
35. **IF Rainfall is High AND Flow Rate is Very Large AND Water Level is Medium THEN Danger**
36. **IF Rainfall is High AND Flow Rate is Very Large AND Water Level is High THEN Danger**

Based on the previous fuzzification calculations, where the Rainfall (CH) is 48 mm, Flow Rate (D) is 40 m³/s, and Water Level (TA) is 145 cm, these values activate multiple inference rules. A primary example is Rule 14: 'If Rainfall is Medium, Flow Rate is Small, and Water Level is Medium, then the Flood Alert is Caution (*Alert*).' Consequently, applying the Mamdani implication function to this rule, the firing strength ($\alpha 14$) is calculated as follows:

$$\alpha = min\left(\mu_{T\_medium}[48],\ \mu_{T\_small}[40], \mu_{T\_medium}[145]\right) = min(0.3,\ 0.4,\ 0.143)$$

$$\alpha = 0.143$$

In this simulation, the logical AND operator (Minimum function) was applied to synthesize the membership degree values of the three input variables: Rainfall, Flow Rate, and Water Level. For each active rule, the system selected the lowest membership degree among the inputs to establish the firing strength (α). This α-value was subsequently used to calculate the specific geometric boundaries (points x) on the output graph, effectively truncating the triangular membership functions for the 'Normal' and 'Caution' sets. Finally, the process involved calculating the total area under the aggregated curve—comprising triangular and rectangular segments—and applying the Centroid (Center of Gravity) moment equation to derive the final crisp defuzzification value.

Defuzzyfication

In the defuzzification stage, the initial step involves determining the coordinate boundaries (x) for the aggregated fuzzy area. These values are derived from the membership functions of the output variable 'Flood Alert' based on the firing strengths (α) obtained from the inference engine. In this specific case study, the calculation involves two active linguistic sets: 'Normal' and 'Caution' (*Waspada*). Based on the linear equations for the triangular membership functions, the boundary values for the 'Normal' set (α=0.1) were calculated as x=55 and x=145. Simultaneously, the boundary values for the 'Caution' set (α=0.143) were determined to be x=153.5 and x=196.4, in accordance with the following calculation procedure:

Left Side

Right Side

$$0.1 = \frac{x-50}{100-50} \rightarrow 5 = x - 50 \rightarrow x = 55$$

$$0.1 = \frac{150-x}{150-100} \rightarrow 5 = 150 - x \rightarrow x = 145$$

$$0.143 = \frac{x-150}{175-150} \rightarrow 3.575 = x - 150$$

$$\rightarrow x = 153.575$$

$$0.143 = \frac{200-x}{200-175} \rightarrow 3.575 = 200 - x$$

$$\rightarrow x = 196.425$$

"Following the determination of the boundary coordinates *x*, the subsequent phase involves computing the total area under the aggregated membership function curve for the output variable. This process utilizes the previously established boundary values to delineate specific geometric regions within the 'Normal' and 'Caution' sets. The total area is derived by summing the individual areas of the triangular and rectangular segments formed between these boundaries, effectively constructing the complete membership function for the defuzzification process.

Composition Result:

$$\mu Fa(x) = \begin{cases} 0, & x \leq 50 \text{ or } x \geq 200 \\ \frac{x-50}{50}, & 50 \leq x \leq 55 \\ 0.1, & 0.55 \leq x \leq 145 \\ \frac{150-x}{50}, & 145 \leq x \leq 150 \\ \frac{x-150}{175-150}, & 150 \leq x \leq 153.5 \\ 0.143, & 153.5 \leq x \leq 196.4 \\ \frac{200-x}{200-175}, & 196.4 \leq x \leq 200 \end{cases}$$

The area under the curve:

Normal

A1 = Left Triangle

$$\frac{1}{2}(55 - 50) \times 0.1 = \frac{1}{2} \times 5 \times 0.1 = 0.25$$

A2 = Middle Rectangle

$$(145 - 55) \times 0.1 = 90 \times 0.1 = 9$$

A3 = Right Triangle

$$\frac{1}{2}(150 - 145) \times 0.1 = \frac{1}{2} \times 5 \times 0.1 = 0.25$$

Caution

A4 = Left Triangle

$$\frac{1}{2}(153.5 - 150) \times 0.143 = \frac{1}{2} \times 3.575 \times 0.143 = 0.255$$

A5 = Middle Rectangle

$$(196.4 - 153.5) \times 0.143 = 42.85 \times 0.143 = 6.13$$

A6 = Right Triangle

$$\frac{1}{2}(200 - 196.4) \times 0.143 = \frac{1}{2} \times 3.575 \times 0.143 = 0.255$$

Total Area:

$$9 + 0.25 + 0.25 + 6.13 + 0.255 + 0.255 = 16.14$$

From the computational process described above, six distinct area values were derived, representing the segmented regions under the membership function curve of the output variable. The calculation employed the standard formula for the area of a triangle for segments A1, A3, A4, and A6, while the formula for the area of a rectangle was applied to segments A2 and A5. The previously identified boundary variables x served as the limits for these geometric shapes. The resulting calculations yielded concrete values for each segment: the triangular areas A1 and A3 both equaled 0.25, and A4 and A6 both equaled 0.255. Meanwhile, the rectangular areas A2 and A5 were calculated as 9.0 and 6.13, respectively.

Normal and Caution Output Function Membership Set

The final fuzzy output set is obtained by aggregating the active rules using the Max method. In this case study, the aggregation combines the truncated 'Normal' set (*α*=0.1) and the truncated 'Caution' set (*α*=0.143). The resulting composite membership function, *μAggregated*(*z*), which forms the basis for the centroid calculation, is defined mathematically as follows:

$$\mu_{Aggregated} = \begin{cases} 0, & x \leq 50 \text{ or } x \geq 200 \\ \frac{x-50}{50}, & 50 \leq x \leq 55 \\ 0.1, & 0.55 \leq x \leq 145 \\ \frac{150-x}{50}, & 145 \leq x \leq 150 \\ \frac{x-150}{175-150}, & 150 \leq x \leq 153.5 \\ 0.143, & 153.5 \leq x \leq 196.4 \\ \frac{200-x}{200-175}, & 196.4 \leq x \leq 200 \end{cases}$$

Calculations of Moments

Following the area calculation, the subsequent phase involves determining the moment for each geometric segment of the aggregated membership function. The moment (*M*) is calculated by integrating the product of the variable *x* and its membership degree *μ*(*x*) over the specific intervals defined by the boundary points. Given the complex shape of the aggregated output, the total moment is derived by summing the moments of the six individual sub-regions (*M*1 through *M*6) as follows:

Moment of Set 1 (Triangle, Normal Left):

$$M1 = \int_{50}^{55} x\frac{x-50}{50}dx = \frac{1}{50}\int_{50}^{55}\left(x^2 - 50x\right)dx = \frac{1}{50}\left(\frac{x^3}{3} - 25x^2\right)|\frac{55}{50} = 13.33$$

Moment of Set 2 (Rectangle, Normal Center):

$$M2 = \int_{55}^{145} x(0.1)dx = 0.1\left(\frac{x^2}{2}\right)|\frac{145}{55} = 900$$

Moment of Set 3 (Triangle, Normal Right):

$$M3 = \int_{145}^{150} x\frac{150-x}{50}dx = \frac{1}{50}\int_{145}^{150}\left(150x - x^2\right)dx = \frac{1}{50}\left(75x^2 - \frac{x^3}{3}\right)|\frac{150}{145} = 36.67$$

Moment of Set 4 (Triangle, Caution Left):

$$M4 = \int_{150}^{153.5} x\frac{x-50}{25}dx = \frac{1}{25}\int_{150}^{153.5}\left(x^2 - 150x\right)dx = \frac{1}{25}\left(\frac{x^3}{3} - 75x^2\right)|\frac{153.5}{150} = 27.53$$

Moment of Set 5 (Rectangle, Caution Center):

$$M5 = \int_{153.5}^{196.4} x(0.143)dx = 0.143\left(\frac{x^2}{2}\right)\Big|_{153.5}^{196.4} = 1078.02$$

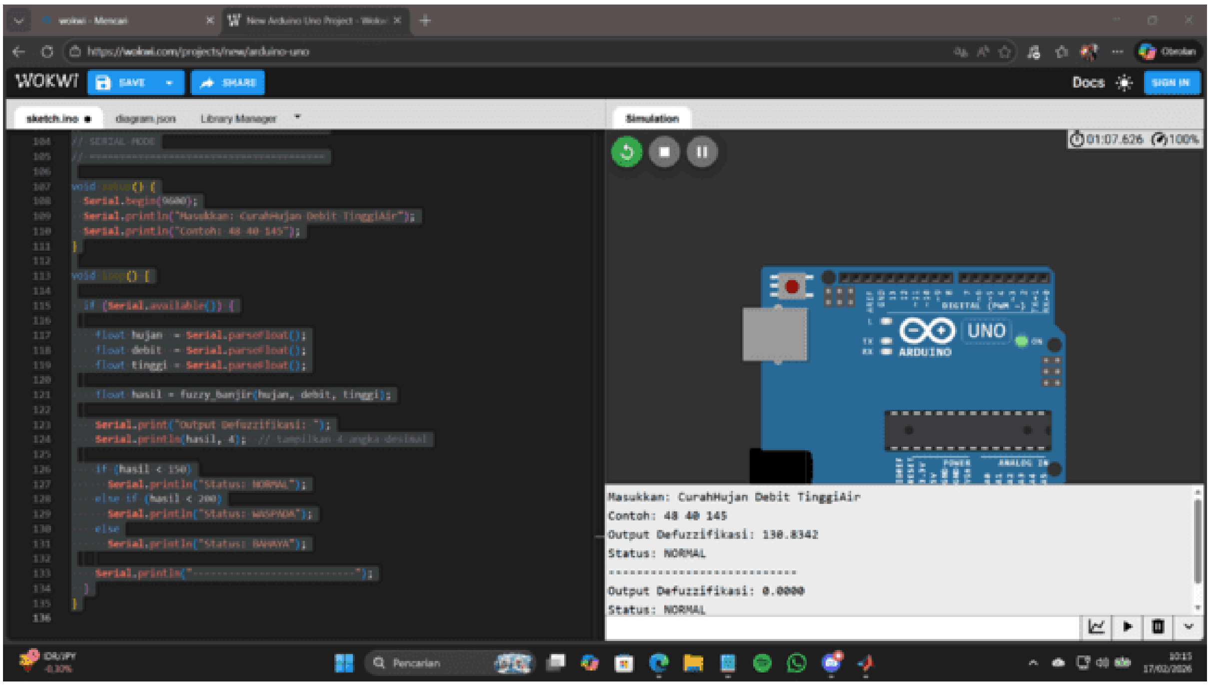
Moment of Set 6 (Triangle, Caution Right):

$$M6 = \int_{196.4}^{200} x\frac{200-x}{25}dx = \frac{1}{25}\int_{196.4}^{200}\left(200x - x^2\right)dx = \frac{1}{25}\left(100x^2 - \frac{x^3}{3}\right)\Big|_{196.4}^{200} = 60.05$$

Once the moments for all sub-regions were computed, the final stage of defuzzification was executed to convert the fuzzy set into a crisp value. This study employed the Centroid method (Center of Gravity), which is calculated by dividing the total accumulated moment ($\sum M$) by the total area ($\sum A$) under the curve. This mathematical operation generates a single scalar value representing the final output of the flood detection system. Based on the predefined calculations, the final crisp value (Z^*) is determined as:

$$\frac{\sum Moment}{\sum Area\ Size} = \frac{13.33+900+36.67+27.53+1078.02+60.05}{16.14} = \frac{2115.6}{16.14} = 131.07 = 131$$

The resulting defuzzification value of 131 falls within the range of the 'Normal' category (50–150), indicating that under the tested conditions (Rainfall 48 mm, Flow Rate 40 m³/s, Water Level 145 cm), the system correctly identifies the status as safe.

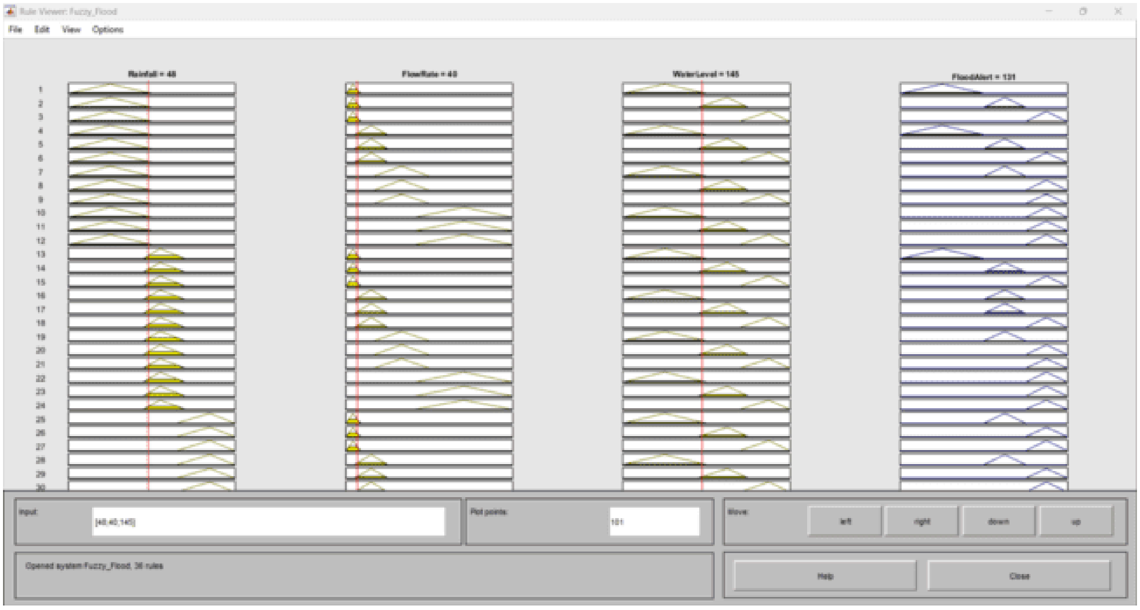


```
// SERIAL MODE
// ====================================

void setup() {
  Serial.begin(9600);
  Serial.println("Masukkan: CurahHujan Debit TinggiAir");
  Serial.println("Contoh: 48 40 145");
}

void loop() {

  if (Serial.available()) {

    float hujan  = Serial.parseFloat();
    float debit  = Serial.parseFloat();
    float tinggi = Serial.parseFloat();

    float hasil = fuzzy_banjir(hujan, debit, tinggi);

    Serial.print("Output Defuzzifikasi: ");
    Serial.println(hasil, 4);  // tampilkan 4 angka desimal

    if (hasil < 150)
      Serial.println("Status: NORMAL");
    else if (hasil < 200)
      Serial.println("Status: WASPADA");
    else
      Serial.println("Status: BAHAYA");

    Serial.println("--------------------------");
  }
}
```

```
Masukkan: CurahHujan Debit TinggiAir
Contoh: 48 40 145
Output Defuzzifikasi: 130.8342
Status: NORMAL
==========================
Output Defuzzifikasi: 0.0000
Status: NORMAL
```

Figure 6. Output result from serial monitor

To validate the theoretical model, the hardware system was tested using the identical input parameters: Rainfall 48 mm, Flow Rate 40 m³/s, and Water Level 145 cm. As evidenced by the Serial Monitor output (Figure X), the Arduino microcontroller generated a defuzzification value of 130.8. This result exhibits a minor deviation compared to the manual calculation and MATLAB simulation, which both yielded 131.07. This discrepancy is attributable to the difference in floating-point precision architectures; the Arduino Uno microcontroller operates on a 32-bit floating-point standard, whereas the MATLAB environment on a personal computer utilizes 64-bit (double precision) arithmetic. Consequently, the higher bit-depth in the simulation allows for greater numerical accuracy. However, this marginal difference (approximately 0.2%) is negligible in practical application, as the output 130.8 still correctly falls within the "Normal" category range (<150), confirming that the embedded system functions reliably.



Rainfall = 48

FlowRate = 40

WaterLevel = 145

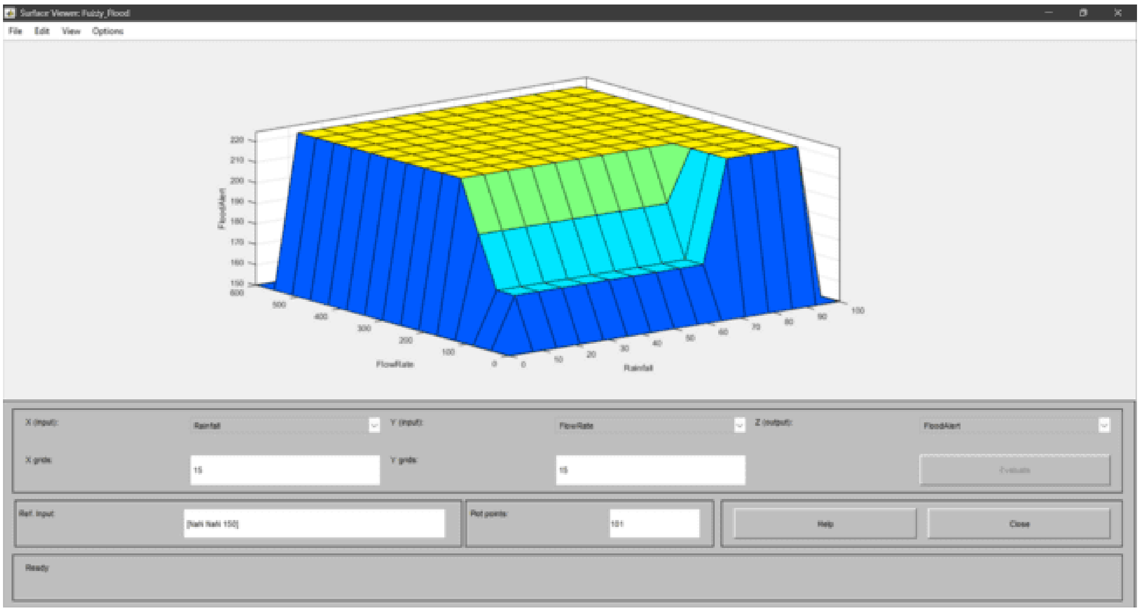
FloodAlert = 131

Input: [48;40;145]

Plot points: 101

Opened system Fuzzy_Flood, 36 rules

Figure 7. Output results in matlab application



X (input): Rainfall

Y (input): FlowRate

Z (output): FloodAlert

X grids: 15

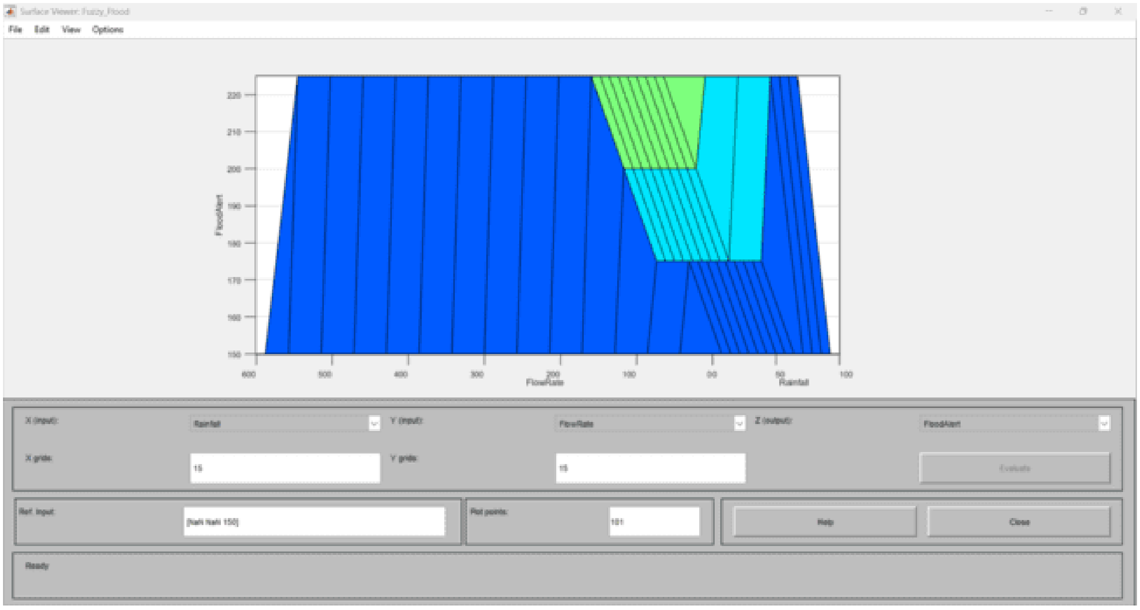
Y grids: 15

Ref. Input: [NaN NaN 150]

Plot points: 101

Ready

Figure 8. Surface 1



X (input): Rainfall
Y (input): FlowRate
Z (output): FloodAlert
X grids: 15
Y grids: 15
Ref. Input: [NaN NaN 150]
Plot points: 101
Ready

Figure 9. Surface 2

CONCLUSION

This research has successfully developed and implemented a flood early warning system based on the Mamdani Fuzzy Inference System using an Arduino microcontroller. Unlike previous systems that rely solely on water depth, this study integrates three critical environmental variables—rainfall intensity, water level, and water flow rate (debit)—to provide a more comprehensive and accurate assessment of flood risks. The utilization of fuzzy logic has proven effective in managing the uncertainty and ambiguity inherent in hydrological data, allowing the system to produce precise alert statuses ranging from 'Normal' to 'Danger'.

Furthermore, the system's reliability was confirmed through a rigorous validation process. The experimental results demonstrated a perfect consistency between the manual arithmetic calculations using the Centroid defuzzification method and the simulations conducted via MATLAB software. Both methods yielded identical output values, confirming that the logic defined by the 36 inference rules is mathematically valid. Consequently, this system serves as a robust instrument for disaster mitigation, capable of providing real-time, accurate warnings to help communities and local authorities anticipate potential flood hazards effectively

Despite the promising results, this prototype has certain limitations that should be addressed in future studies. The current system primarily relies on local alerts (Buzzer and LED) and serial monitor evaluations. Therefore, the future research agenda should focus on integrating a broader IoT architecture using communication protocols such as LoRaWAN or MQTT to transmit real-time data to a centralized web or mobile dashboard, enabling wider and faster early warning dissemination,. Additionally, expanding the rule base by incorporating predictive Machine Learning algorithms and testing the hardware across diverse river topologies will further enhance the system's adaptability, accuracy, and robustness in mitigating extreme hydrometeorological events.

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