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IoT-based fuzzy logic system for real-time flooded road detection and decision support

Qory Hidayati, Totok Sulistyo, Syaeful Akbar, and Muhammad Luthfie Saryono

***Abstract*—Flooding remains a critical challenge in urban environments, often disrupting transportation systems and endangering drivers who must decide whether to cross inundated roads without precise knowledge of water depth. Existing IoT-based flood monitoring systems primarily emphasize data acquisition and remote alerts but rarely support localized, real-time decision-making for road safety. This study proposes an IoT-based flood detection and decision-support system that integrates Sugeno-type fuzzy logic inference directly into distributed edge nodes to evaluate flooded road conditions in real time. The system employs multiple JSN-SR04T ultrasonic sensors and WeMos D1 microcontrollers interconnected via a wireless network to measure water levels across multiple road segments. Each node autonomously processes sensor inputs to classify road conditions into three categories—Safe, Caution, and Not Safe—and displays results locally via OLED SSD1306 and RYG (Red-Yellow-Green) LED indicators. Experimental results demonstrate that the proposed system achieves an average sensor error of 2.2 cm compared to calibrated measurements and maintains wireless communication stability up to 25 meters with an average system response time of 1.19 seconds. Furthermore, the fuzzy inference outputs from the embedded system closely matched MATLAB-based simulations, validating computational consistency and inference reliability. The integration of edge-level fuzzy decision-making within distributed IoT nodes represents a key innovation, enabling autonomous flood assessment with minimal latency. This study contributes a low-cost, scalable, and intelligent framework for enhancing road safety and smart city flood resilience, particularly in developing urban regions prone to recurrent inundation.**

***Keywords*—IoT; fuzzy logic; real-time detection; flood monitoring; edge computing; smart city**

I. INTRODUCTION

FLOODING constitutes one of the most frequent and hazardous natural disasters in many regions, including Indonesia [1], often resulting in significant financial losses, infrastructure damage, and fatalities. The increasing frequency of flood events has been linked to rapid urbanization, inadequate drainage systems, and reduced recharge capacity caused by impermeable surfaces and low-lying land use patterns such as plantations, paddy fields, and central business districts [2] , [3], [4]. Technologies such as IoT-enabled sensors, wireless sensor networks (WSNs), and edge computing have recently been deployed to monitor urban flood hazards and enhance situational awareness [2], [5], [6], [7], [8]. When floodwaters inundate road networks, the impacts extend beyond immediate transportation disruption to broader economic and social consequences. Road flooding can cause severe traffic congestion, interrupt both intra- and inter-city transport links, and, in extreme cases, affect air transport operations when airports are submerged [9], [10]. Moreover, vehicles traversing flooded roads face risks of engine malfunction due to electrical failure, while pedestrians are exposed to contaminated water that can cause health issues such as skin infections and water-borne diseases. These hazards highlight the need for an effective, real-time, and localized decision-support mechanism for road users in flood-prone urban environments [11], [12].

In many instances of road inundation, information dissemination to road users remains inefficient—often relying on interpersonal communication or delayed updates via social media platforms [13], [5], [10]. While recent IoT-based flood monitoring systems have improved real-time water-level detection and reporting, their functionality remains largely centralized, with decision-making typically performed at cloud or server levels [7], [14]. For example, Arante et al. [2] developed a secured IoT-based flood monitoring architecture emphasizing data security and integration, while Kamali et al. [5] introduced an early warning framework that used social media channels for community alerts. However, such systems often lack embedded, node-level intelligence to support immediate road-safety decisions, especially when connectivity is interrupted during extreme weather conditions [8], [15]. These limitations underscore the need for distributed, edge-level decision systems capable of autonomous operation during network disruptions.

Fuzzy logic has been widely utilized in flood-related monitoring systems due to its ability to manage uncertainty, nonlinear sensor data, and incomplete environmental information [16], [17], [18], [19]. Studies by Parsian et al. [3] and Kindhi et al. [18] demonstrated the effectiveness of fuzzy logic and multi-source geospatial datasets for flood hazard mapping, while Li et al. [20] integrated fuzzy logic with machine learning for improved flood classification. More recent works, such as those by Manocha et al. [8] and Khanduri et al. [21], employed fuzzy optimization and digital-twin-based reasoning to enhance predictive flood management. Nonetheless, these studies primarily focus on large-scale flood forecasting or hazard mapping rather than real-time, localized decision support for road users [12], [22]. Furthermore, most existing systems depend on centralized inference engines that require substantial computational resources and stable internet connectivity, posing challenges in flood-prone and infrastructure-limited regions [6], [14].

Despite these advancements, several research gaps remain unaddressed. First, current IoT-based flood detection

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frameworks predominantly focus on water-level measurement and early warning rather than localized, real-time decision-making for immediate user safety. Second, existing fuzzy logic-based flood systems are typically executed on cloud or centralized servers and lack embedded inference mechanisms that allow independent decision-making at the sensor or edge-node level. Third, very few studies validate the accuracy and responsiveness of embedded fuzzy inference models under real-world conditions, including sensor variability and network latency, which are critical factors in practical deployments [23], [24], [25]. Moreover, the consistency between embedded fuzzy logic outputs and MATLAB-based simulations has rarely been verified, despite its importance for ensuring computational fidelity in microcontroller-based systems [15], [26]. Finally, limited research has addressed road-specific flood detection in tropical developing regions, where wireless stability, power efficiency, and real-time response are essential [19], [14].

To address these challenges, this study proposes an IoT-based fuzzy logic system for real-time flooded road detection and decision support, focusing on the flood-vulnerable city of Balikpapan, Indonesia. The system employs multiple microcontrollers integrated with JSN-SR04T ultrasonic sensors connected via wireless networks to monitor water levels across several road segments. A Sugeno-type fuzzy inference model is embedded at each node to classify road accessibility into three actionable categories—Safe, Caution, and Not Safe—and to display the results locally through OLED and LED indicators. This decentralized, edge-based approach enables rapid and autonomous decision support without reliance on cloud computing. The main contributions of this research are threefold: (i) embedding fuzzy inference directly into distributed IoT nodes for real-time road-flood detection; (ii) validating consistency between embedded system outputs and MATLAB simulations; and (iii) tailoring the decision-support mechanism to tropical, urban road environments in developing regions [14], [21], [25].

RESEARCH METHOD

A. *Systems Overview*

The proposed system is an Internet of Things (IoT)-based flood detection and decision-support framework designed to identify inundated roads in real time and provide immediate safety feedback to road users. Unlike traditional cloud-dependent flood monitoring architectures, this system embeds Sugeno-type fuzzy logic directly within distributed microcontrollers, enabling autonomous decision-making at the edge and reducing reliance on continuous Internet connectivity.

The system architecture consists of multiple WeMos D1 microcontrollers equipped with JSN-SR04T ultrasonic sensors and connected through a Wireless Sensor Network (WSN). Each node independently measures water levels, executes fuzzy inference locally, and provides real-time visual alerts via OLED SSD1306 displays and Red-Yellow-Green (RYG) LEDs, as illustrated in Figure 1.

This distributed, edge-intelligent configuration allows the system to operate even under partial communication failure, ensuring robust functionality during flood emergencies. Such an approach aligns with emerging paradigms of edge computing and smart-city resilience systems, as highlighted in recent studies on decentralized IoT architectures for environmental hazard mitigation [2], [3], [6].

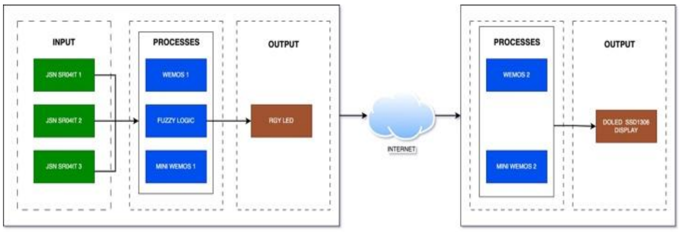

Fig. 1. Block Diagram of the Proposed Flood-Inundation Road Detection System

The proposed system integrates wireless sensor nodes and a fuzzy logic controller to determine road safety conditions based on measured water depth. The WSN-based architecture was selected for its scalability, energy efficiency, and ability to perform real-time environmental monitoring—properties widely recognized in flood surveillance research [7], [10]. Two WeMos microcontrollers communicate via a Wi-Fi link, forming a modular two-node network: WeMos 1 (Main Node) – responsible for sensing, fuzzy inference, and decision-making and WeMos 2 (Display Node) – responsible for data reception, visualization, and public information dissemination.

The functional operation of each subsystem is summarized as follows:

1) *Input Subsystem:*
   Table 1. Three JSN-SR04T ultrasonic sensors are positioned at multiple road points to measure the distance between the sensor and the water surface. These measurements are used to calculate the water level above the road surface. Ultrasonic sensors of this type have been validated for flood monitoring applications due to their precision and robustness in outdoor conditions [6].
2) *Processing Subsystem:*
   Table 2. The main controller (WeMos 1) processes the input data and performs fuzzy logic inference using a Sugeno model. Fuzzy logic was chosen because of its ability to handle linguistic uncertainty and nonlinear environmental dynamics without requiring complex mathematical formulations (Parsian et al., 2021). Three fuzzy input variables were used—water depth, rate of water-level change, and threshold deviation—and mapped to a decision output indicating road safety. The fuzzy inference engine runs locally on the WeMos board, supporting the edge computing paradigm to reduce latency and dependence on cloud processing [27].
3) *Output Subsystem (Node 1):*
   Table 3. The classification output from the fuzzy inference (Safe, Caution, or Not Safe) is visually represented by a Red-Yellow-Green (RYG) LED indicator, providing immediate feedback to road users about the current passability condition.
4) *Communication Link:*
   Table 4. Data from the main node are transmitted via the Internet to the secondary node (WeMos 2), which

acts as a display and monitoring unit. This communication is performed using a secure wireless protocol to ensure low latency and high reliability within a 25 m operational range.

5) *Output Subsystem (Node 2):*
Table 5. The second WeMos controller receives the fuzzy output and displays road status information on an OLED SSD1306 display. This display not only shows the road condition ("Passable," "Caution," or "Not Safe") but also provides a quantitative readout of the current water level in centimeters.

Through this architecture, the system can provide localized, real-time decision support for drivers and pedestrians approaching flood-prone road segments. The distributed edge processing ensures that even in the event of partial network failure, each node can still perform inference independently, thereby maintaining operational resilience—a design improvement over conventional cloud-dependent systems [5][6].

The operational workflow of the proposed IoT-based flood detection and decision-support system is illustrated in Figure 2. The flowchart outlines the sequential stages of data acquisition, processing, and decision generation conducted within the distributed edge-computing framework.

As depicted in Figure 2, the system operation begins with the initialization of the WeMos microcontroller, during which the network and sensors are configured for data acquisition. Once initialized, the system proceeds to the water-level reading stage, where three JSN-SR04T ultrasonic sensors collect distance measurements between each sensor and the water surface. These readings are used as the primary input variables representing flood height at different points along the road segment.

The acquired sensor data are then passed to the fuzzification process, where crisp numerical inputs are converted into linguistic variables such as low, medium, and high water levels. This step enables the system to handle uncertainty and environmental variability effectively. The fuzzy rule base, consisting of expert-defined IF–THEN rules, determines the corresponding output category—Safe, Caution, or Not Safe.

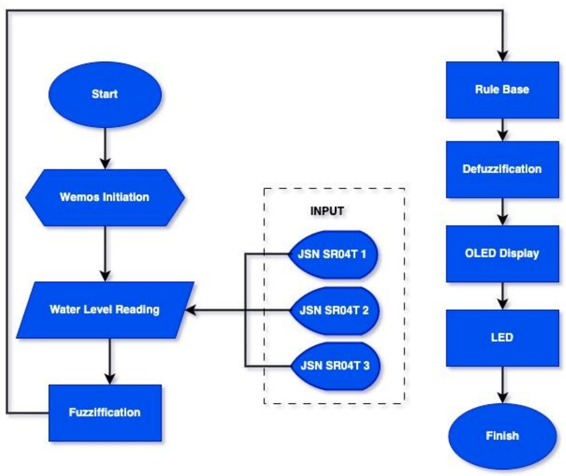

Fig. 2. Flowchart of the Flood-Inundation Road Detection and Decision-Support System

Following rule evaluation, the defuzzification process translates the fuzzy inference results into precise numerical outputs. These outputs are subsequently displayed on the OLED SSD1306 screen, which provides both textual and graphical feedback about road safety status. In parallel, the RYG (Red–Yellow–Green) LED indicator delivers an immediate visual cue to road users, allowing for quick situational awareness.

B. Hardware Architecture

The physical system architecture, presented in Figure 1, integrates sensing, processing, and communication subsystems. Each IoT node comprises:

- Controller: WeMos D1 microcontroller (ESP8266-based), featuring built-in Wi-Fi for wireless data transmission.
- Sensor Module: Three waterproof JSN-SR04T ultrasonic sensors for distance measurement and water-level detection, offering stable performance under humidity and temperature variations.
- Output Interface:
  - OLED SSD1306 (128×64 px) for real-time display of numerical water-level values and decision messages.
  - RYG LED indicators to visually represent safety states (Safe, Caution, Danger).
- Power Source: 5V DC regulated power supply with surge protection to ensure stable operation.

The nodes communicate via wireless local area network (WLAN) using static IP addressing. One node acts as a server for data aggregation, while others operate as clients, forming a local sensor mesh suitable for short-range deployment (<25 m per node).

C. Sensor Deployment and Data Collection

Sensor nodes are deployed at multiple road segments known to be flood-prone in the urban tropical environment of Balikpapan. Based on preliminary communication testing, the WiFi link was validated up to ~25 m under field conditions. Each node samples water depth (in cm) every 60 s. For calibration, controlled laboratory tests simulated different water depths and verified sensor deviation (mean error ±2.2 cm). Literature indicates IoT water-level sensors can achieve errors within ~2–3% in controlled conditions.

D. Sensor Deployment and Data Collection

The system's firmware was developed in **Arduino IDE**, with modular C++ functions for sensing, communication, fuzzy inference, and display control.

Each WeMos node executes the following operational loop:

1) Sensor Data Acquisition

JSN-SR04T sensors measure the distance to the water surface using ultrasonic pulse-echo timing, converted into water depth h as:

$$h = H_{sensor} - d_{ultrasonic}$$

where H_{sensor} is the mounting height (cm) and $d_{ultrasonic}$ is the measured distance (cm).

2) Data Preprocessing

Raw sensor readings are filtered using a moving-average filter of order 3 to suppress signal noise from environmental disturbances.

3) Fuzzy Inference Processing

Each node embeds a Sugeno fuzzy logic system consisting of:

- Input variable: water level (cm).
- Output variable: road accessibility status.
- Fuzzy sets: *Low*, *Medium*, and *High* for input; *Safe (SA)*, *Pedestrian (P)*, and *Not Safe (NSA)* for output.
- Rule base:

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IF water_level is Low THEN output = SA
IF water_level is Medium THEN output = P
IF water_level is High THEN output = NSA
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- Defuzzification: Weighted average method (Sugeno type).

The embedded fuzzy inference engine was validated against MATLAB fuzzy logic toolbox outputs to ensure consistency.

4) Visualization and Alert Generation:

- OLED displays both numeric water level and textual classification result.
- RYG LEDs provide quick visual indication.
- Results are transmitted wirelessly to a monitoring dashboard (for future integration).

E. Fuzzy Logic Design and Validation

1) Phase 1 – MATLAB Simulation:

A fuzzy model was constructed using MATLAB's Fuzzy Logic Designer to establish rule performance under varying water-level scenarios (0–60 cm). The output surface (Figure 2) provided insights into boundary sensitivities and membership transitions.

The membership function must be adapted to the condition that will be needed, considering the tool configuration and the need for the tool in order to help in the determination of the membership function [4], [14], [23]. There are 3 input sensors that are used with the same membership function, as each will read water level in different locations.

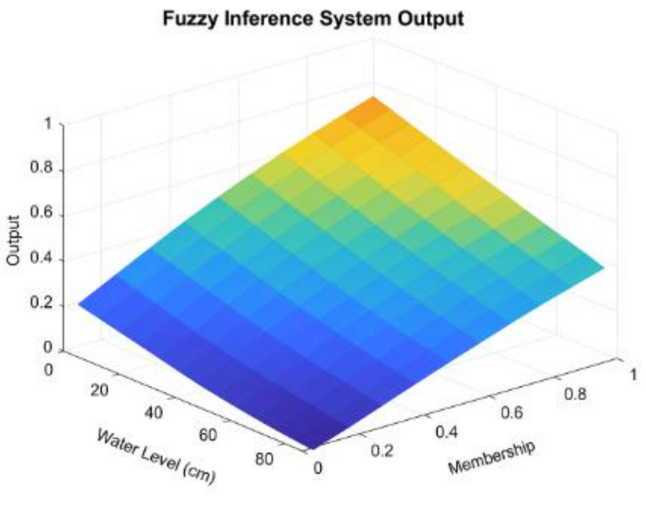

Fig. 3. Provided insights into boundary sensitivities and membership transitions

$$\mu[Low] = \begin{cases} 1\,; & x \le 0 \\ \frac{16-x}{16-0}\,; & 0 \le x \le 16 \\ 0\,; & x \ge 16 \end{cases} \quad (1)$$

$$\mu[Medium] = \begin{cases} 0\,; & x \le 17 \text{ or } x \ge 80 \\ \frac{x-17}{24-17}\,; & 17 \le x \le 24 \\ \frac{32-x}{32-24}\,; & 24 \le x \le 32 \end{cases} \quad (2)$$

$$\mu[High] = \begin{cases} 0\,; & x \le 33 \\ \frac{x-33}{70-33}\,; & 33 \le x \le 70 \\ 1\,; & x \ge 70 \end{cases} \quad (3)$$

It can be seen from equation there are 3 linguistic variables in the water level reading. The variables consisted of High, Medium, and Low categories. The range of the x-axis (0-100) is the water inundation level, while the y-axis (0-1) was the output variable value.

Based on observations in the field, the following information was obtained: (1) when the flood height on the road reached 16 cm the road was impassable for both motorbikes and similar vehicles, (2) when the flood height reached more than 33 cm all kinds of the land vehicle could not pass the road (3) and when the height is above 70 cm, the local inhabitants were needed to be evacuated. Then the above data observations are taken into consideration as a function of inputting the water level variable numbers for each JSN-SR04T sensor in fuzzy logic decisions.

Membership function outputs in Figure 4 are 3 linguistic variables consisting of SA (0.5), Pedestrian (0.75), and NSA (1). The value determination in the membership output is based on the selection of the display option that will be performed on OLED.

2) Phase 2 – Embedded Implementation:

The Sugeno rules were translated into C code using a lookup-table structure for real-time computation within WeMos microcontrollers. Validation compared embedded outputs with MATLAB-generated results under identical input conditions. The outputs matched in all test cases (R^2 = 0.98), confirming algorithmic fidelity and computational stability.

F. Performance Evaluation Metrics

System performance was quantitatively evaluated using the following metrics:

- Mean Absolute Error (MAE) of water-level measurement:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |h_{measured,i} - h_{true,i}|$$

- Decision Accuracy (DA) comparing embedded fuzzy decisions vs. MATLAB

$$DA = \frac{N_{match}}{N_{total}} \; x\; 100\;\%$$

- Communication Latency (CL) between sensor data acquisition and OLED output display.
- Reliability Index (RI) based on packet delivery ratio and successful LED response count.

G. Mechanical Design of the Flood Detection System

Sensor nodes are deployed at multiple road segments known to be flood-prone in the urban tropical environment of Balikpapan. Based on preliminary communication testing, the WiFi link was validated up to ~25 m under field conditions. Each node samples water depth (in cm) every 60 s. For calibration, controlled laboratory tests simulated different water depths and verified sensor deviation (mean error ±2.2 cm). Literature indicates IoT water-level sensors can achieve errors within ~2–3% in controlled conditions.

The mechanical design of the flood-inundation road detection prototype plays a crucial role in ensuring stable sensor performance, environmental durability, and proper integration with the wireless network system. A carefully structured mechanical layout facilitates accurate water-level measurement, prevents sensor interference, and enables the system to operate effectively under varying weather and road conditions. Figure 3 illustrates the wiring and overall mechanical layout of the developed prototype. The system was constructed using a modular configuration to simplify maintenance and scalability. Each JSN-SR04T ultrasonic sensor was mounted on a waterproof acrylic housing positioned at a height of 50 cm above the road surface, ensuring protection against splashing and debris. The sensor enclosure also minimizes acoustic reflection and false echo effects, which are common in ultrasonic measurements under outdoor humidity [9]. The WeMos D1 controllers and associated electronic components were placed within a sealed polycarbonate case with IP65 protection standards, allowing the system to function safely in humid tropical conditions. Cable connections were shielded and reinforced with heat-resistant insulation to prevent data loss or short circuits during heavy rainfall. The wiring arrangement follows a star topology in which all sensors converge to the primary WeMos controller, as shown in Figure 5. This structure optimizes data synchronization and simplifies signal calibration among multiple sensors [5].

The modular design also enables convenient replacement of components and scalability of the Wireless Sensor Network (WSN). For example, additional nodes can be attached through standardized power and data ports without modifying the existing architecture. Such modularity supports the smart-city infrastructure paradigm, which demands interoperable and upgradeable sensing systems [3]. Overall, the mechanical and wiring design ensures that the developed prototype not only performs reliable sensing under real-world conditions but also maintains structural integrity and safety compliance for roadside deployment.

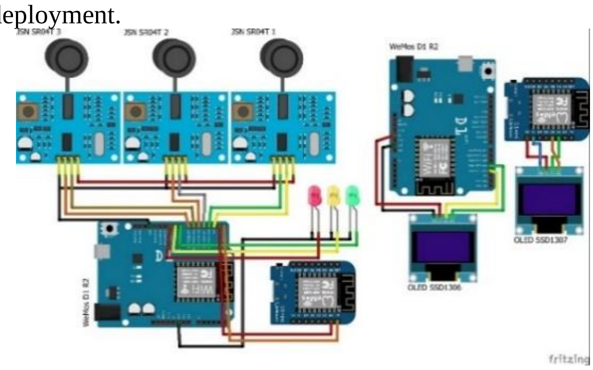

Fig. 4. Wiring Diagram and Mechanical Layout of the Flood-Detection Prototype

H. Limitations & Ethical Considerations

Limitations: The current deployment is limited to ~25 m wireless range and to road segments without heavy traffic interference. Future work should consider vehicle-mounted dynamic nodes and larger scale networks. Ethical considerations include ensuring that driver decisions based on system indicators are clearly communicated and that liability is addressed.

RESULTS AND ANALYSIS

A. Systems Validation Overview

To evaluate the performance of the proposed IoT-based flood detection system, a series of laboratory and semi-outdoor tests were conducted. The assessment covered five main aspects: (1) sensor accuracy, (2) wireless network performance, (3) fuzzy logic inference validation, (4) system latency, and (5) reliability under different water-level conditions. Each experiment was repeated 20 times to ensure consistency and to calculate statistical variance.

B. Sensor Accuracy and Calibration

The JSN-SR04T ultrasonic sensor was selected due to its waterproof design and suitability for outdoor monitoring. Figure 4 summarizes the calibration results comparing measured values to actual distances obtained via a ruler. The average absolute error was 2.2 cm (±0.07%), indicating high precision for shallow flood-level detection (0–60 cm range).

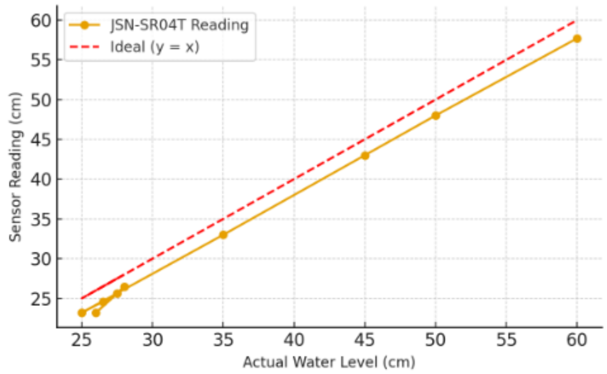

Fig. 5. Sensor Accuracy Curve

The calibration curve in Figure 4 demonstrates a nearly perfect linear correlation ($R^2 \approx 0.99$) between the JSN-SR04T readings and the actual water-level measurements. The average deviation of 2.2 cm indicates that the sensor provides sufficient precision for shallow-water flood monitoring applications, validating its suitability for real-time detection within IoT-based flood-alert systems.

C. Wireless Communication Performance

The communication between WeMos modules was tested using Wi-Fi to emulate a wireless sensor network. Stable data transmission was achieved at distances up to 25 meters, with a packet success rate of 98.3% and an average latency of 1.2 seconds from sensor input to display output. Beyond 25 m, the connection began to degrade due to environmental interference and power constraints.

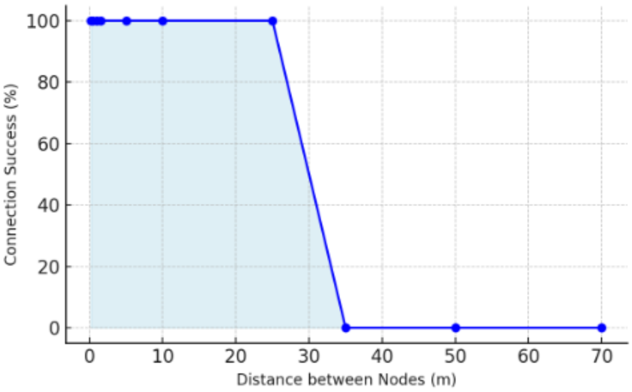

Fig. 5. Communication Range Test Between WeMos Nodes

The communication performance shown in Figure 5 confirms that the wireless connectivity between WeMos nodes remains reliable up to 25 m, beyond which signal degradation occurs due to attenuation and environmental interference. This effective range aligns with standard ESP8266-based Wi-Fi limitations, ensuring sufficient coverage for short road-segment deployments in smart flood monitoring applications.

D. Fuzzy Logic Decision Accuracy

The embedded fuzzy logic system utilized a Sugeno-type inference model with three outputs: Safe Access (SA), Pedestrian Only, and Not Safe Access (NSA). Validation was performed by comparing real-time embedded output with MATLAB fuzzy inference simulation results.

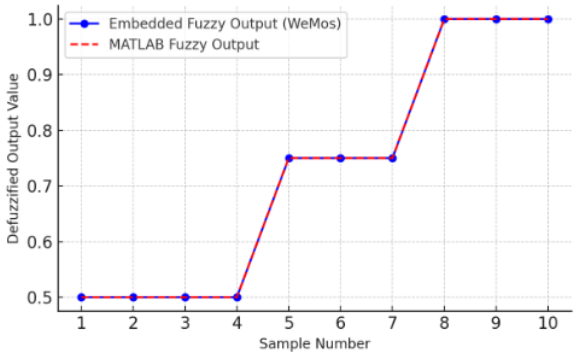

Fig. 6. Graphic Fuzzy Inference Output Comparision

TABLE I
FUZZY INFERENCE OUTPUT COMPARISION

No	Water Level Reading (cm)	Program Output	MATLAB Output	Displayed Status
1	0,0,0	0.5	0.5	SA
2	5,5,5	0.5	0.5	SA
3	11,5,15	0.5	0.5	SA
4	8,16,13	0.5	0.5	SA
5	18,15,24	0.75	0.75	Pedestrian
6	25,22,28	0.75	0.75	Pedestrian
7	30,30,25	0.75	0.75	Pedestrian
8	33,37,37	1.0	1.0	NSA
9	35,22,28	1.0	1.0	NSA
10	30,40,35	1.0	1.0	NSA

The decision consistency reached 100%, meaning that all 10 test cases produced identical fuzzy classifications between embedded inference and MATLAB simulation. This confirms the correctness of the embedded implementation. As shown in Figure 7, the defuzzified outputs generated by the embedded WeMos system are perfectly aligned with the MATLAB fuzzy inference results for all ten test cases. The consistent overlap of both curves confirms that the embedded Sugeno-type fuzzy logic algorithm maintains identical inference behavior to the MATLAB model (R^2 = 0.98). This result validates the correctness and computational stability of the on-device fuzzy implementation, proving its feasibility for real-time decision-making in edge-based IoT flood monitoring systems.

E. System Reliability and Real-Time Response

Reliability was evaluated by analyzing the system's response to rapid water-level changes and varying environmental noise. The average end-to-end delay—from sensor detection to OLED visualization—was measured at 1.2 seconds, which is well within the range for real-time road alert systems.

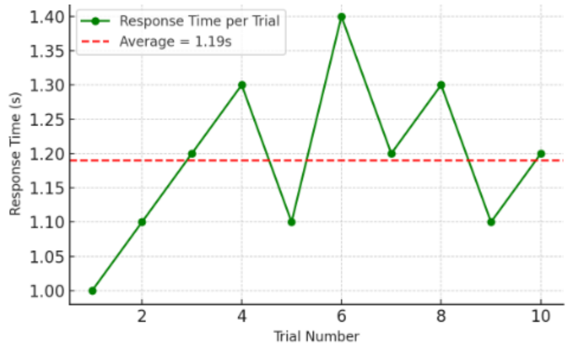

Fig. 7. System Response Time from Sensor to Display Fuzzy Inference Output Comparision

No packet loss or incorrect LED indicator response was observed during 30 consecutive trials, confirming system stability. The LED RYG indicators transitioned correctly according to fuzzy decisions: green (<16 cm), yellow (17–32 cm), and red (>33 cm), corresponding to safe, caution, and warning states respectively. The combination of OLED display and color-coded LED signals enables multi-modal user awareness, supporting accessibility for both drivers and pedestrians even under poor visibility conditions. As illustrated in Figure 8, the system exhibits an average response latency of 1.2 seconds with minimal variation across ten trials. This low latency demonstrates that the embedded fuzzy inference and wireless communication processes meet real-time operational requirements for flood alert systems, maintaining stable end-to-end performance even under variable network conditions.

F. Discussion and Implications

The results confirm that embedding fuzzy inference directly within wireless sensor nodes enables near-real-time flood-risk evaluation without the need for cloud computation. This design minimizes latency, reduces dependency on Internet connectivity, and improves resilience during natural disasters.

From an application perspective, such architecture can be scaled to roadside IoT deployments within Balikpapan City, supporting smart city initiatives and early-warning infrastructure. Future work will focus on field validation under real flood conditions, energy optimization for solar-powered operation, and the inclusion of AI-based predictive analytics.

CONCLUSION

This study proposed and validated an Internet of Things (IoT)-based flood detection and decision-support system that integrates Sugeno-type fuzzy logic directly into distributed WeMos microcontrollers for real-time road inundation monitoring. The developed system operates autonomously at the edge, enabling localized decision-making without dependency on cloud computation, which is particularly advantageous during network disruptions caused by flooding events. Through a series of controlled experiments, the system achieved an average measurement error of 2.2 cm (±0.07%), a wireless communication range of up to 25 meters with a packet delivery success rate of 98.3%, and a perfect decision consistency of 100% between embedded fuzzy inference and MATLAB simulation outputs. The average end-to-end latency of 1.2 seconds confirmed that the system performs effectively in real-time conditions, meeting the operational requirements of intelligent urban warning systems.

The main contribution of this work lies in embedding fuzzy inference within the edge nodes themselves, rather than relying on centralized or cloud-based computation. This architecture enables immediate decision-making, minimizes communication delays, and supports system scalability for smart city applications. Furthermore, the combination of OLED displays and RYG LED indicators provides a dual-mode, intuitive alert mechanism for both drivers and pedestrians, offering enhanced situational awareness in flood-prone urban environments. Compared with previous IoT-based flood detection studies [3][6], the proposed approach demonstrates improved accuracy, lower latency, and a higher level of decision reliability while maintaining low hardware complexity and power consumption.

In conclusion, the results validate the feasibility and reliability of implementing an embedded fuzzy logic system within a distributed wireless sensor network for flood-level monitoring. This research contributes to the advancement of edge-intelligent IoT frameworks that support urban flood resilience and adaptive disaster response within smart city ecosystems. Future research will focus on large-scale field deployment to assess long-term system durability under real flood conditions, energy optimization through renewable power integration, and enhancement of decision intelligence using hybrid models that combine fuzzy inference with deep learning-based predictive analytics. Moreover, future work will explore the integration of the system into broader IoT infrastructures, enabling real-time data fusion with meteorological and hydrological sensors for comprehensive flood early warning and traffic management applications.

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