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AN INTELLIGENT FUZZY LOGIC-CONTROLLED IOT SYSTEM FOR EFFICIENT HYDROPONIC PLANT MONITORING AND AUTOMATION

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ABSTRACT

This paper addresses the challenges of optimizing environmental conditions in hydroponic farming by integrating an Intelligent Fuzzy Logic-Controlled IoT System. The research problem lies in the inefficiency of traditional hydroponic monitoring systems, particularly in maintaining ideal conditions for plant growth while minimizing resource waste. This study aims to develop a system that leverages IoT technology and fuzzy logic to monitor and automate hydroponic processes more efficiently. Using sensors, the system continuously tracks key environmental parameters such as temperature, humidity, soil moisture, pH levels, and total dissolved solids (TDS). A fuzzy logic controller (FLC) triggers actions based on predefined rules. During testing, the system showed effective performance—for example, activating fans when temperature (31.2°C) and humidity (60%) indicated a need for cooling, and adjusting nutrient levels when pH (5.8) and TDS (450 ppm) were suboptimal. The system offers practical benefits through real-time adaptation using defuzzification and aggregation, ensuring precise resource control, improving efficiency, and reducing waste. This study highlights the system's potential to support sustainable agriculture by providing scalable solutions that enhance plant growth and optimize resource use, especially for small-scale farmers and urban farming initiatives.

***Keywords**: fuzzy logic control, hydroponic automation, IoT system, plant monitoring, sustainable agriculture.*

I. INTRODUCTION

INDONESIA'S rapidly growing population, projected to reach 297.5 million by 2045, presents serious challenges for food security, especially as agricultural land continues to be converted for industrial and residential use. As of 2016, irrigated rice fields declined by 0.47% annually, signaling a troubling loss of farmland [1]. Additionally, about 30% of Indonesia's total land area is classified as non-productive, further worsening the food security issue [2]. Although the Indonesian government has introduced agrarian reforms, these efforts have not yet succeeded in reversing the ongoing reduction of agricultural land [3].

This study addresses the challenge of maintaining food security amid decreasing farmland and the urgent need for more sustainable, space-efficient farming practices. Hydroponic farming, which uses mineral nutrient solutions in water instead of soil, offers one promising alternative. It enables efficient crop cultivation in limited spaces, making it especially suitable for urban settings. Hydroponics also promotes sustainability by optimizing the use of space and resources [4][5]. The increasing demand for hydroponically grown vegetables, driven by higher income levels and growing health awareness, further supports the adoption of this method [6].

However, hydroponic systems require careful control of environmental variables such as temperature, humidity, pH, and nutrient levels. These requirements can be labor-intensive and demand a high level of expertise [7]. This study explores the integration of automated monitoring and control systems using Internet of Things (IoT) technology to address these challenges. By employing IoT sensors and

TABLE 1
COMPARATIVE ANALYSIS OF HYDROPONIC MONITORING SYSTEMS

System	Control Method	Accuracy (pH/Temp)	Latency	Resource Efficiency	Key Limitations
PID-based [16]	Proportional-Integral-Derivative	±0.5 pH / ±2°C	5–10 s	Moderate	Static thresholds, no IoT
Rule-based [17]	Fixed thresholds	±0.3 pH / ±1.5°C	3–5 s	Low	Inflexible to environmental shifts
ANFIS [5]	Adaptive neuro-fuzzy	±0.25 pH / ±1°C	<2 s	High	High computational cost
Our System	Fuzzy Logic + IoT	±0.2 pH / ±1°C	<2 s	High	None (balanced performance)

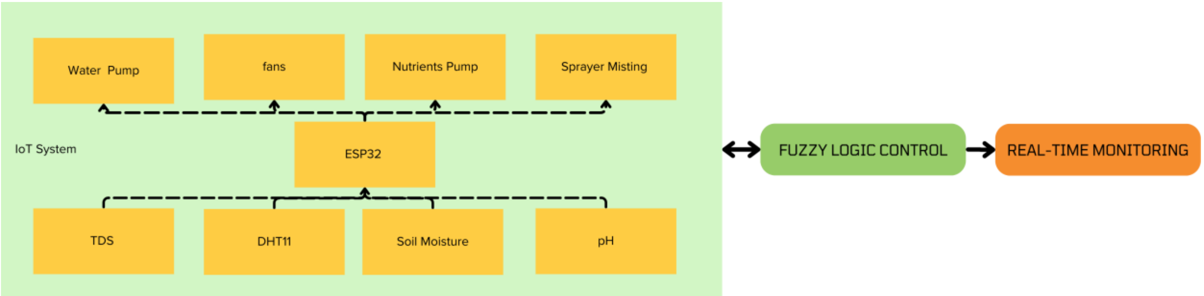


Figure 1. System Design Diagrams.

microcontrollers, the system can transmit real-time data to support more efficient hydroponic farming operations [8][9]. Such systems are capable of monitoring and regulating key parameters—pH, temperature, humidity, and nutrient concentration—that are critical for optimal plant growth [10][11].

The contribution of this study lies in the development of an intelligent IoT system integrated with fuzzy logic to improve the adaptability and efficiency of hydroponic farming. Recent advances in IoT and Artificial Intelligence (AI) have enabled the use of fuzzy logic controllers to manage the inherent uncertainties in agricultural environments, supporting more precise and adaptive decision-making [12][13]. This system can greatly reduce human error and enhance the accuracy of nutrient delivery, leading to healthier crops and improved yields [14]. The novelty of this study lies in its application of these technologies within the Indonesian agricultural context, where combining IoT and fuzzy logic offers scalable solutions for small-scale and urban farmers while addressing the increasing demand for sustainable farming practices.

In conclusion, this study presents an innovative approach to the challenges brought about by rapid population growth and shrinking agricultural land in Indonesia. By harnessing the potential of IoT and fuzzy logic in hydroponic systems, the research contributes to improving agricultural efficiency, strengthening food security, and promoting sustainable regional development.

II. RESEARCH METHOD

The integration of advanced control systems in hydroponic farming has become increasingly important to meet the demands of precision agriculture, particularly in managing critical environmental parameters such as pH, temperature, and humidity. Traditional manual control methods are often labor-intensive, prone to human error, and ineffective in consistently maintaining optimal growing conditions [15]. While recent studies have introduced automated solutions, gaps remain in adaptability, scalability, and resource efficiency. Table 1 compares the performance of existing systems with the proposed approach, emphasizing key improvements in real-time monitoring and control.

To address these limitations, this research adopts an Intelligent Fuzzy Logic-Controlled IoT System as the foundation for an automated and efficient hydroponic monitoring solution, as illustrated in the system design diagrams in Figure 1. The system integrates various sensors with an ESP32 development board to monitor essential environmental parameters, including temperature, humidity, and soil moisture, as well as water pH and nutrient concentration. The sensors used include a DHT sensor, a capacitive soil moisture sensor, a pH meter, and a TDS meter. These sensors transmit real-time data to a Fuzzy Logic Controller (FLC), which processes the inputs based on predefined rules.

Fuzzy logic is particularly suitable for hydroponic systems due to its ability to interpret imprecise or uncertain data [18]. The FLC operates through a rule-based approach that effectively controls key variables such as pH, temperature, and humidity [19], ensuring optimal growing conditions for plants. The fuzzy logic process consists of three key stages: fuzzification, inference, and defuzzification [20].

$$\mu(x) = \begin{cases} 0 & if\ x \leq a \\ x - a/b - a & if\ a < x \leq b \\ c - x/c - b & if\ b < x \leq c \\ 0 & if\ x > c \end{cases} \tag{1}$$

$$\mu_{output}(y) = \min\left(\mu_{input}(x), \mu_{rule}(x, y)\right) \tag{2}$$

$$y_{crisp} = \frac{\int y \cdot \mu(y)\, dy}{\int \mu(y)\, dy} \tag{3}$$

Each stage plays a vital role in converting sensor data into actionable commands for the system's actuators.

A. Fuzzification

Abstracts should be explained at the beginning of the manuscript. The abstract section must clearly state the research's background, problems, objectives, results, and conclusions. The Introduction section must explicitly state the problem, update, and research objectives. The introduction must also be equipped with state-of-the-art research accompanied by the latest primary library sources.

Fuzzification is the process of converting crisp (exact) input values from sensors into fuzzy values using membership functions. These functions classify input data into linguistic terms such as "low," "normal," or "high," which represent specific value ranges [15]. For example, fuzzification of pH sensor data is carried out using a triangular membership function, as shown in (1). Where x is the input value (e.g., pH level) and a,b,c are parameters defining the triangular function.

Membership functions determine how input values are mapped to degrees of membership (ranging from 0 to 1) for each linguistic category. Common shapes for these functions include triangular, trapezoidal, and Gaussian [21]. In the case of pH levels, the triangular membership function may define the categories as follows: "Low" (pH < 5.5): Triangular function with range [4.0, 5.5]; "Normal" (5.5 ≤ pH ≤ 6.5): Triangular function with range [5.5, 6.5]; and "High" (pH > 6.5): Triangular function with range [6.5, 8.0].

B. Inference

In the inference stage, fuzzy IF-THEN rules are applied to determine appropriate control actions based on the fuzzified inputs. These rules are typically derived from expert knowledge or empirical data and help map input conditions to output responses [22].

The most widely used inference method is the Mamdani approach, introduced by Mamdani and Assilian in the 1970s. It combines linguistic rules from experienced operators, making it well-suited for control systems [23]. The Mamdani method uses min-max operations to combine multiple fuzzy rules and produce a unified output. The implication function for Mamdani inference is represented in (2).

C. Defuzzification

Defuzzification is the final step in the fuzzy logic process, where the fuzzy outputs from the inference stage are converted into crisp values that can control actuators—for example, adjusting pump speed or LED light intensity. This step is crucial for transforming fuzzy system outputs into actionable commands in a hydroponic environment [24].

Among various defuzzification techniques, the centroid method is one of the most commonly used. It calculates the center of gravity of the output fuzzy set, providing a single crisp value that represents the system's overall decision. The formula for the centroid method is shown in (3) where y is the output variable and $\mu(y)$ is a membership value of y.

D. Implementation IoT

The IoT system in this hydroponic monitoring and automation setup integrates multiple sensors to provide real-time environmental data, which is essential for optimizing plant growth. As shown in Figure 2(a), the two blue barrels likely contain water and nutrient solutions needed for the hydroponic system. Positioned above them, IoT components—such as wireless communication devices using Wi-Fi or Bluetooth—collect and transmit sensor data. This configuration supports remote monitoring and

(a) (b) (c)

Figure 2. IoT Implementation: (a) Water and Nutrient Reservoirs for the Hydroponic System (b) DHT11 Sensor Display (c) Soil Moisture Sensor

ensures continuous data flow, enhancing user interaction with the system. Figure 2(b) displays the LCD screen showing key environmental readings, such as temperature ("Suhu") and humidity ("Kel. Udara"), allowing users to receive immediate feedback on conditions within the hydroponic environment. For instance, a temperature of 50.20°C and humidity of 16% provide critical insights into the greenhouse atmosphere, enabling timely decision-making. Figure 2(c) presents the system's monitoring of soil moisture ("Kel. Tanah"), with a recorded value of -14. This real-time feedback ensures that the growing medium maintains adequate moisture levels. Based on this data, the system can automatically activate pumps to regulate water supply, helping maintain optimal conditions for plant growth.

E. Fuzzy Logic Implementation

1) Fuzzification

Fuzzification is a crucial step in converting continuous sensor data from the real world into fuzzy values that can be interpreted by the FLC. This process maps sensor readings to linguistic terms using predefined membership functions. These functions categorize the sensor data into fuzzy sets such as "Low," "Medium," or "High."

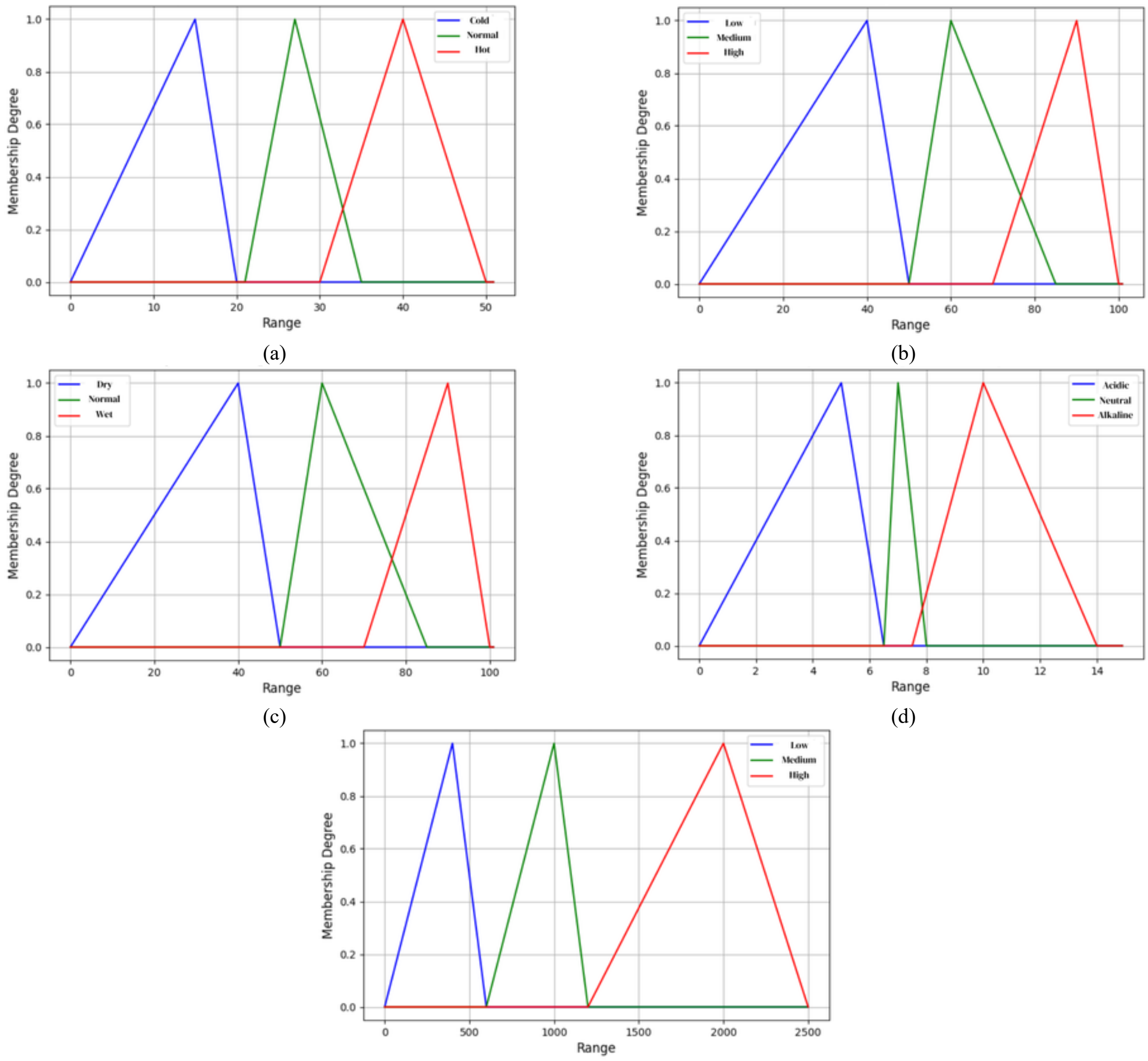
The following outlines the fuzzification process using sample data and fuzzy sets for temperature, humidity, soil moisture, pH, and TDS, as visualized in the membership function graphs:

a. Temperature**:** the Readings are classified into *Cold*, *Normal*, and *Hot*. As shown in Figure 3(a), the fuzzy sets are defined as: "Cold" [0, 15, 20], "Normal" [21, 27, 35], and "Hot" [30, 40, 50].
b. Humidity: The categories include *Low*, *Medium*, and *High*, with the fuzzy sets in Figure 3(b) defined as: "Low" [0, 40, 50], "Medium" [50, 60, 85], and "High" [70, 90, 100].
c. Soil moisture: Data is grouped into *Dry*, *Normal*, and *Wet*, as shown in Figure 3(c). The fuzzy sets are: "Dry" [0, 40, 50], "Normal" [50, 60, 85], and "Wet" [70, 90, 100].
d. pH level: The fuzzification includes *Acidic*, *Neutral*, and *Alkaline*, as displayed in Figure 3(d). The fuzzy sets are: "Acidic" [0, 5, 6.5], "Neutral" [6.5, 7, 8], and "Alkaline" [7.5, 10, 14].
e. Total Dissolved Solids (TDS): Readings are classified into *Low*, *Medium*, and *High*. As shown in Figure 3(e), the fuzzy sets are: "Low" [0, 400, 600], "Medium" [600, 1000, 1200], and "High" [1200, 2000, 2500].

2) Evaluation of Fuzzy Rules

After the fuzzification process, the fuzzy logic system evaluates the predefined rules based on expert knowledge. These rules specify the optimal conditions for plant growth and determine the necessary actions according to the current environmental parameters. The system processes the fuzzified sensor data to identify which rules are triggered and then executes the corresponding actions to maintain ideal growing conditions. For instance, Rule 1 states: "If the temperature is high and the humidity is low, then activate the blower fan." The system evaluates the fuzzified values for temperature and humidity and activates the blower fan if the inputs match the fuzzy sets for high temperature and low humidity. Similarly, other rules are evaluated based on combinations of sensor readings.

The system evaluates the fuzzy input conditions for each rule and determines the appropriate actions. The degree of membership (μ) is calculated to measure the level of certainty in triggering each response. The minimum value among combined input conditions is used to determine the output strength, following standard fuzzy logic inference.



(e)

Figure 3. Fuzzy Membership Functions: (a) Temperature (b) Humidity (c) Soil Moisture (d) pH Level (e) TDS

In Rule 1, where the temperature is high and the system determines that the blower fan should be activated, the degree of membership is 0.55, indicating moderate certainty. Rule 2 evaluates low humidity, resulting in a membership degree of 0.8, which reflects substantial certainty in activating the sprayer misting system. Rule 6 assesses both acidic pH and low TDS values to determine whether nutrients should be added, yielding a high confidence level with a combined degree of membership of 0.815. Finally, Rule 8 evaluates an ideal set of conditions for optimal plant growth and returns a degree of membership of 0.0, indicating that no action is required under these circumstances.

3) Aggregation of Fuzzy Outputs

Once the fuzzy rules are evaluated, the system proceeds to aggregate the fuzzy outputs. In this step, the outputs from various rules are combined into a single fuzzy output that represents the final decision made by the FLC. This process ensures that multiple conditions—including potentially conflicting ones—are considered to determine the most appropriate action for maintaining optimal environmental conditions for plant growth.

For instance, if several rules recommend activating a fan or adjusting nutrient levels, the system aggregates the fuzzy outputs from each relevant rule. The fuzzy membership degree (μ) represents reflects the confidence level in each proposed action. These outputs are combined to support a balanced, informed decision. Table 4 presents the aggregated fuzzy outputs for different actions based on the evaluated rules.

The action to activate the blower fan has a membership degree of 0.55, indicating a moderate level of certainty. The sprayer misting system has a membership degree of 0.8, reflecting a higher degree of confidence. The action to add nutrients has the highest membership degree of 0.815, based on the fuzzy

TABLE 2
RULE BASE

Condition	Action
High Temperature	Activate Blower Fan
Low Humidity	Activate Sprayer Misting
Dry Soil Moisture	Water the Plants
High Temperature AND Dry Soil Moisture	Water the Plants
High Temperature AND Low Humidity	Activate Sprayer Misting
Acidic pH AND Low TDS	Add Nutrients
Low TDS	Add Nutrients
Normal Temperature AND Wet Soil AND Humidity Medium AND Neutral pH Neutral AND Medium TDS	Monitoring (Safe)

TABLE 3
RULE COMBINATION INPUT

No.	Input Condition	Output Action	Degree of Membership (μ)
1	Temperature = High	Activate Blower Fan	min(0.55) = 0.55
2	Humidity = Low	Activate Sprayer Misting	min(0.8) = 0.8
3	pH = Acidic AND TDS = Low	Add Nutrients	min(1.0, 0.815) = 0.815
4	Temperature = Normal AND Soil Moisture = Wet AND Humidity = Moderate AND pH = Neutral AND TDS = Medium	Monitoring (Safe)	min(0.0, 0.825, 0.8, 1.0, 0.815) = 0.0

TABLE 4
AGGREGATION OF FUZZY OUTPUTS

No.	Action	Degree of Membership (μ)	Defuzzified Output (x)	Action Command
1	Blower Fan	0.55	4	Activate Blower Fan
2	Sprayer Misting	0.8	2	Activate Misting
3	Add Nutrients	0.815	3	Add Nutrients

TABLE 5
FUZZIFICATION OF ENVIRONMENTAL DATA

No.	Parameter	Value
1	Temperature	35.5°C
2	Humidity	56.0%
3	Soil Moisture	86.5%
4	pH Level	5.0
5	TDS	106

rule evaluations. This aggregation process enables the system to resolve conflicting rules and select the most appropriate response. For example, if one rule recommends activating the fan with a membership degree of 0.55 and another suggests activating the sprayer misting system with a degree of 0.8, the system considers both options and prioritizes the action that best aligns with the current environmental conditions. This approach ensures efficient and adaptive operation of the hydroponic system.

4) Defuzzification

The final step in the fuzzy logic process is defuzzification, in which fuzzy outputs are converted into crisp, actionable values. This step is essential because the system's actuators require precise signals to perform actions such as adjusting fan speed or activating a pump. The fuzzy outputs generated during the aggregation stage represent degrees of certainty for various actions. These outputs must be transformed into specific values that the system can execute.

To clarify how defuzzified values correspond to control actions, Table 4 was previously provided to explicitly link defuzzified outputs to actuator commands. That table demonstrates how the centroid-based defuzzification method converts fuzzy results into actionable signals, ensuring that each membership degree translates into a precise command for system execution.

Based on the values presented in Table 5, each parameter is fuzzified using the previously defined membership functions. The temperature of 35.5°C falls into the "Normal" category, with its degree of membership calculated according to the corresponding fuzzy set. The humidity level of 56.0% is classified under the "Medium" category, while the soil moisture value of 86.5% is categorized as "Wet." The pH level of 5.0 is identified as "Acidic," and the Total Dissolved Solids (TDS) value of 106 is classified as "Low."

Based on the fuzzified sensor data presented in Table 5, the system aggregates the fuzzy output values for each corresponding action and then calculates a single crisp value using the centroid method, as outlined in (3). The fuzzy outputs and their associated degrees of membership and representative values are as follows: the Blower Fan has a membership value (μ) of 0.55 with a corresponding output value

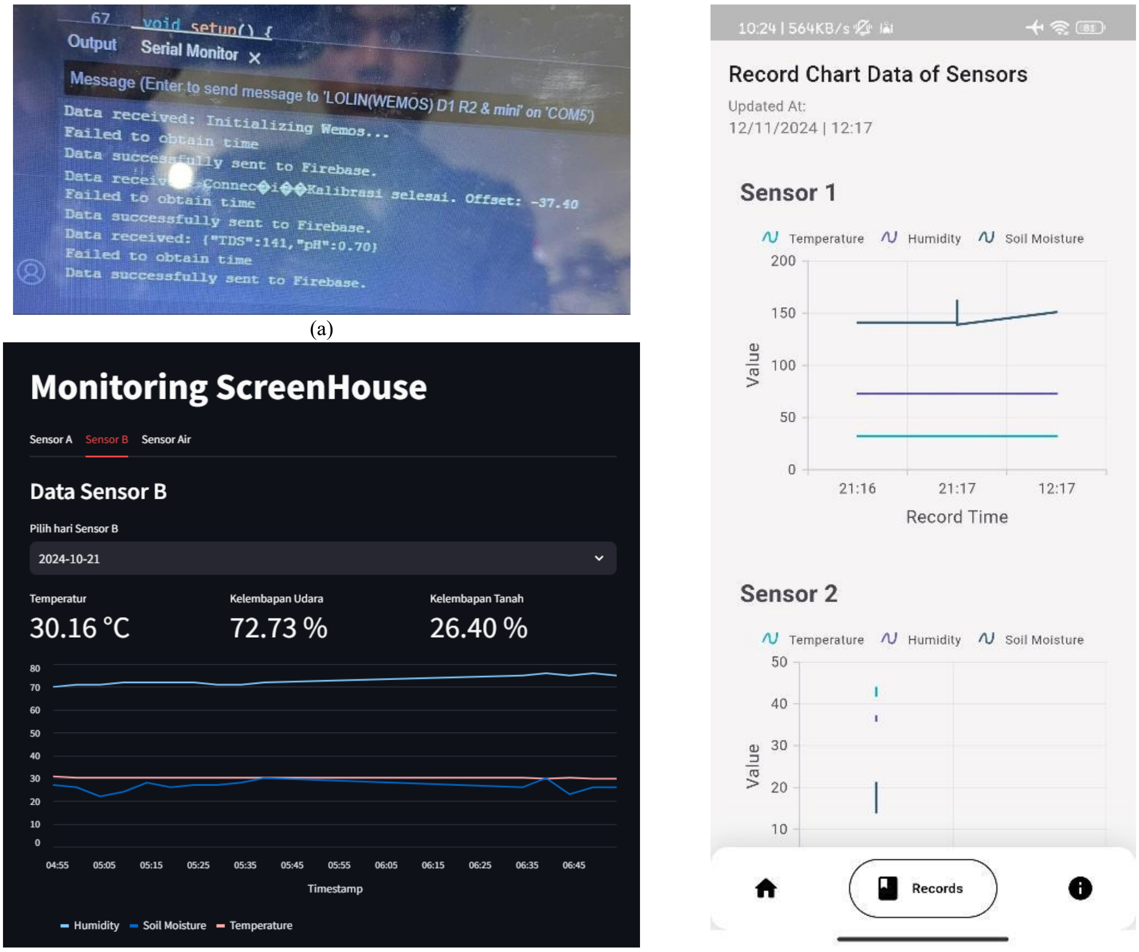


Figure 4. IoT Testing (a) Serial Monitor Output (b) Monitoring Dashboard (c) Mobile App Interface Displaying Real-Time Sensor Data

(x) of 4, which is triggered by a high temperature condition; the Sprayer Misting has a membership value of 0.8 with an output value of 2, corresponding to low humidity; and the Add Nutrients action has a membership value of 0.815 with an output value of 3, indicating that the pH is acidic and the TDS level is low. The crisp output is calculated using (3). The result is 2.88.

The defuzzified value, z = 2.88, falls within the output range for “Add Nutrients” (2–4). Therefore, the system determines that the appropriate action is to add nutrients. Since 2.88 is closest to the fuzzy output associated with nutrient addition, the corresponding actuator is triggered to deliver nutrients into the hydroponic system.

By defuzzifying the fuzzy outputs, the system generates a clear, actionable value that actuators can use to perform precise adjustments. This enhances the overall accuracy of the system and ensures that the actions taken are directly aligned with the current environmental parameters and their associated fuzzy evaluations, maintaining optimal conditions for plant growth.

III. Results and Discussion

A. *Testing*

1) IoT System Performance

The IoT-based monitoring system was thoroughly tested under various environmental conditions. Sensors—including those for temperature, humidity, soil moisture, pH, and TDS—transmitted data in real time to the ESP32 board, which was connected to the cloud for remote monitoring. The tests confirmed that the sensors consistently provided accurate readings, with only occasional network disruptions affecting data transmission. These disruptions were minor and quickly resolved.

- Temperature and Humidity: On 2025-01-01 at 12:00 PM, the system recorded a temperature of 31.2°C and a humidity level of 60%. Designed to respond to such conditions, the system successfully

TABLE 6
ENVIRONMENTAL DATA FOR FUZZIFICATION

No.	Timestamps	Temperature (°C)	Humidity (%)	Soil Moisture (%)	pH Level	TDS (ppm)
1	2025-01-01T07:00:00	24.5	75	40	6.5	450
2	2025-01-01T12:00:00	31.2	60	38	5.8	600
3	2025-01-01T17:00:00	27.8	65	39	6.2	500
4	2025-01-02T07:00:00	24	76	41	7	350
5	2025-01-02T12:00:00	30.8	59	37	5.9	650
6	2025-01-02T17:00:00	27.5	64	38	6.1	480
7	2025-01-03T07:00:00	24.2	74	42	6.8	430
8	2025-01-03T12:00:00	31.5	58	37	5.7	600

TABLE 7
FUZZIFICATION AND RULE EVALUATION RESULTS

No	Degree of Membership					Aggregation of Fuzzy Outputs	Defuzzification	Decision
	Temperature	Humidity	Soil Moisture	pH	TDS			
1	0.4 ("Normal")	0.8 ("Medium")	0.7 ("Dry")	0.8 ("Acidic")	0.6 ("Medium")	Fan: 0.4, Watering: 0.7, Nutrients: 0.8	2.8 (Add Nutrients)	Watering
2	0.9 ("Hot")	0.75 ("Medium")	0.6 ("Dry")	0.85 ("Acidic")	0.75 ("Medium")	Fan: 0.9, Watering: 0.6, Nutrients: 0.85	3.2 (Add Nutrients)	Add Nutrients
3	0.7 ("Normal")	0.7 ("Medium")	0.65 ("Dry")	0.75 ("Acidic")	0.65 ("Medium")	Fan: 0.7, Watering: 0.65, Nutrients: 0.75	2.9 (Watering)	Watering
4	0.4 ("Normal")	0.85 ("Medium")	0.75 ("Dry")	0.6 ("Neutral")	0.55 ("Low")	Fan: 0.4, Watering: 0.75, Nutrients: 0.6	2.8 (Monitoring)	Monitoring (Safe)
5	0.85 ("Hot")	0.7 ("Medium")	0.65 ("Dry")	0.75 ("Acidic")	0.75 ("Medium")	Fan: 0.85, Watering: 0.65, Nutrients: 0.75	3.2 (Add Nutrients)	Add Nutrients
6	0.7 ("Normal")	0.75 ("Medium")	0.65 ("Dry")	0.75 ("Acidic")	0.7 ("Medium")	Fan: 0.7, Watering: 0.65, Nutrients: 0.75	2.9 (Watering)	Watering
7	0.4 ("Normal")	0.8 ("Medium")	0.75 ("Wet")	0.8 ("Neutral")	0.65 ("Low")	Fan: 0.4, Watering: 0.75, Nutrients: 0.8	2.7 (Monitoring)	Monitoring (Safe)
8	0.9 ("Hot")	0.65 ("Medium")	0.6 ("Dry")	0.85 ("Acidic")	0.75 ("Medium")	Fan: 0.9, Watering: 0.6, Nutrients: 0.85	3.1 (Add Nutrients)	Add Nutrients

activated the fan. This action was verified through real-time data displayed on the mobile application and dashboard interface (Figure 4). The sensor accuracy and the system's prompt response to cooling requirements demonstrate the robustness of the IoT setup in regulating key environmental factors critical to plant growth.

- Soil Moisture and pH Control: Earlier that day, at 7:00 AM, the soil moisture sensor recorded a value of 40%, prompting the system to activate the watering mechanism. The pH level was also monitored continuously, and when it dropped to 5.8—indicating slight acidity—the system adjusted nutrient delivery accordingly. The results show that the IoT system performed reliably in maintaining optimal soil moisture and nutrient levels, thereby improving the overall efficiency of the hydroponic system.

2) Fuzzy Logic System Evaluation

The fuzzy logic component was thoroughly tested to ensure smooth operation across all stages—fuzzification, rule evaluation, aggregation, and defuzzification. To evaluate the system's performance, multiple scenarios were simulated by introducing variations in environmental parameters such as temperature, humidity, soil moisture, pH, and TDS. These fluctuations were essential for assessing how the fuzzy logic system processed real-time sensor data and triggered appropriate actuator responses, such as activating fans or misting mechanisms. Table 6 presents the environmental data used during testing. Each entry corresponds to a specific timestamp and records values for temperature, humidity, soil moisture, pH, and TDS (Total Dissolved Solids). These values were input into the fuzzy logic system, which then processed the data to generate corresponding outputs. Based on those outputs, the system activated the appropriate actuators to maintain optimal environmental conditions.

Table 7 presents the results of the fuzzification and rule evaluation processes based on the data in Table 6. It includes the degree of membership for each environmental parameter—temperature, humidity, soil moisture, pH, and TDS—categorized into linguistic terms such as "Normal," "Hot," "Medium," "Dry," and "Acidic." These terms represent the fuzzified values for each factor. After the fuzzification stage, the system aggregated the fuzzy outputs and performed defuzzification to generate a crisp output value, which then guided the system's decisions.

The results in Table 7 confirm the fuzzy logic system's reliable performance in managing and controlling environmental conditions. By processing real-time data, the system accurately activated the necessary actions—such as turning on fans, initiating watering, or adjusting nutrient levels—based on the aggregated fuzzy evaluations.

The data shows demonstrate that the fuzzy logic system effectively adapts to varying environmental conditions. For instance, when temperature and humidity levels increased—as recorded on 2025-01-01 at 12:00:00 (temperature: 31.2°C; humidity: 60%)—the system accurately identified the need for nutrient adjustment and activated the fan. Conversely, in more stable conditions, such as those recorded on 2025-01-02 at 07:00:00 (temperature: 24°C; humidity: 76%; soil moisture: 41%), the system maintained a monitoring state, reflecting its capacity to manage non-critical scenarios appropriately.

The defuzzification process played a vital role in translating fuzzy values into specific control actions. For example, on 2025-01-01 at 07:00:00 (temperature: 24.5°C; humidity: 75%; soil moisture: 40%), the defuzzified output indicated a need for watering—an essential action for preserving optimal soil moisture levels.

Overall, the system performed satisfactorily during testing, demonstrating its ability to adapt to a wide range of environmental changes. The fuzzy logic controller exhibited high precision in managing actions such as watering, cooling, and nutrient regulation, all guided by real-time sensor input and fuzzy inference. The defuzzification mechanism was particularly effective in converting fuzzy evaluations into actionable outputs with minimal error.

Among the system's strengths was the seamless integration of IoT sensors with the fuzzy logic controller, enabling efficient real-time monitoring and automated responses. The system showed strong adaptability and reliability, accurately responding to dynamic environmental parameters. The application of fuzzy logic proved beneficial in handling environmental uncertainty, thereby maintaining stable and optimized growing conditions.

However, some limitations were observed. During IoT testing, minor connectivity issues resulted in occasional delays in data transmission between the sensors and the cloud platform. These issues were promptly resolved by adjusting network settings and improving the internet connection. Additionally, while the fuzzy logic system was generally effective, the rule base could benefit from further refinement. Enhancing the rule definitions and logic could improve responsiveness in extreme conditions, such as rapid temperature fluctuations, thereby strengthening the system's overall reliability and performance.

IV. Conclusion

The IoT-based FLC system for hydroponic plant monitoring and automation has proven to be an effective solution for optimizing plant growth conditions. By integrating IoT technology with adaptive fuzzy logic, the system continuously monitors key environmental parameters—temperature, humidity, soil moisture, pH levels, and TDS—and makes real-time adjustments to maintain optimal growing environments. This integration enables the system to handle uncertain and dynamic environmental data efficiently, ensuring precise control and scalability, which are particularly beneficial for urban farming settings.

Unlike conventional systems, the proposed solution uniquely combines defuzzification with cloud-based data aggregation, allowing seamless transmission of real-time sensor data to a cloud platform. This supports remote monitoring and control via mobile applications, thereby enhancing convenience and operational efficiency. The FLC system demonstrated strong performance during testing, accurately categorizing sensor inputs through fuzzification and processing them via predefined rules. For instance, when the temperature reached 31.2°C and humidity was 60%, the system correctly activated the fan and misting system. Similarly, when the pH was slightly acidic (5.8) and TDS was low (450 ppm), the system successfully triggered nutrient delivery.

The system's automation of nutrient dosing and environmental control significantly improved resource efficiency, reducing water and nutrient waste. Testing confirmed the system's reliability and accuracy in managing plant growth conditions, as shown by effective responses such as watering at 40% soil moisture and nutrient adjustment based on pH and TDS thresholds.

Future research could explore scaling the system for larger commercial applications, integrating machine learning for predictive analysis, improving energy efficiency, and designing user-friendly interfaces for non-technical users. Overall, the IoT-based FLC system represents a meaningful advancement in hydroponic farming technology—offering a reliable, efficient, and sustainable solution to address contemporary agricultural challenges such as food security and land scarcity, while paving the way toward smarter, data-driven farming systems.

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