Vol. 7, No. 4, December 2025

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

IoT-Based Smart Fertigation System for Citrus Plants using Fuzzy Logic Control

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Received: Nov 1, 2025

Revised: Nov 19, 2025

Accepted: Dec 2, 2025

Published: Dec 10, 2025

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DOI:

10.63158/journalisi.v7i4.1318

Abstract. This study develops and evaluates an IoT-based smart fertigation system for citrus plants using a fuzzy logic control (FLC) algorithm integrated with an ESP32 microcontroller and wireless sensors. The research aims to address the limitations of conventional fertigation practices that rely on fixed schedules without considering real-time soil and climate conditions, which often result in water inefficiency and nutrient imbalance. The developed system integrates sensors for soil moisture, temperature, and air humidity to automatically regulate irrigation duration through triangular membership functions and a fuzzy inference model consisting of 64 fuzzy rule combinations. Over a 30-day observation period, twelve citrus seedlings aged 3-4 months after grafting were organized into four experimental groups: manual fertigation (MF), manual irrigation (MI), smart fertigation (SF), and smart irrigation (SI). Experimental findings indicated that the smart fertigation system-maintained soil moisture within a more stable range of 40-55%, and plants in the SF group experienced approximately 7 cm greater height and a twofold increase in leaf count compared to manually irrigated ones. The smart fertigation treatment also produced more uniform, greener, and healthier foliage, signifying balanced nutrient uptake. Overall, the IoT–FLC integration provides a more adaptive and eco-efficient irrigation model that promotes sustainable management of water and nutrients in tropical citrus cultivation.

Keywords: Smart Fertigation, internet of things, citrus plants, fuzzy logic control, water efficiency

1. INTRODUCTION

Citrus is one of Indonesia's leading horticultural commodities, widely consumed as a nutritional source due to its high vitamin C content [1][2]. Citrus plants are also relatively easy to cultivate, as they can grow well under various conditions, both in greenhouses and in open fields [3]. In citrus cultivation, several key factors influence production success, including planting, fertilization, land preparation, irrigation, and pruning [4]. Soil plays a crucial role as the main growing medium because it affects moisture and temperature, which directly impact plant health. The ideal soil conditions for citrus growth generally maintain a moisture level of 60–80% and a temperature range of 20–30°C [5].

Citrus farming in Indonesia generally still relies on conventional fertigation systems that lack precision in monitoring soil conditions and nutrient availability [6]. These systems typically operate on fixed schedules without considering real-time field conditions, which can lead to under or over-watering, as well as inefficient fertilizer usage [7]. Therefore, the development of a reliable smart fertigation system is necessary to improve accuracy in irrigation and nutrient control. Plant growth is highly influenced by soil conditions as the primary nutrient source particularly parameters such as soil moisture and pH as well as environmental factors like air humidity and temperature. To address these challenges, this study proposes the development of an Internet of Things (IoT)-based smart fertigation system integrated with an artificial intelligence algorithm, namely Fuzzy Logic Control (FLC) [8][9], to automate nutrient solution irrigation using a drip system with liquid organic fertilizer (LOF) [10].

Smart fertigation systems have been widely applied in previous studies, such as in watermelon cultivation [11], drip fertigation for chili plants [12], grape cultivation [13], and IoT-based systems to enhance the productivity and profitability of banana cultivation [7]. However, most existing systems rely on fixed scheduling or threshold-based control, with limited adaptability to dynamic soil and climate variations in tropical environments. Additionally, there is a notable lack of research focused on IoT-based fertigation for citrus plants, despite the fact that citrus species possess unique physiological traits and water needs that set them apart from other horticultural crops. The distinction of this research lies in the focus on citrus plants, which require different care conditions, and

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the use of liquid organic fertilizer derived from citrus peel waste as an eco-friendly alternative source of nutrients. The use of citrus peel waste-based LOF is also intended to promote sustainable agriculture through environmentally friendly resource utilization [14][15].

This study aims to fill this research gap by creating a smart fertigation system based on fuzzy logic [16], specifically tailored for citrus plants. This system incorporates IoT sensors and an ESP32 microcontroller to facilitate automated and real-time management of soil moisture, air temperature, and irrigation duration. The significant contributions of this work include: 1) the creation of a fuzzy inference model comprising 64 rule combinations for informed irrigation decision-making, 2) the establishment of an IoT-enabled control and monitoring framework, and 3) a comparative analysis of manual versus smart fertigation methods in relation to the growth performance of citrus plants.

2. METHODS

2.1. Component of Fertigation System

The intelligent fertigation system in this study was developed using a combination of sensors, control modules, and supporting hardware designed to automate irrigation and nutrient delivery for citrus plants. The soil moisture sensor (FC-28) was employed to measure the volumetric water content in the soil, while the DHT22 sensor monitored both ambient temperature and air humidity [17]. The FC-28 and DHT22 sensors were selected due to their widespread use, affordability, and adequate accuracy for continuous environmental monitoring in tropical agricultural settings, although both require regular calibration to maintain measurement stability. The entire system was managed by an ESP32 microcontroller, which handled data acquisition, fuzzy logic computation, and wireless communication [18][19]. A relay module and solenoid valve were connected to control the operation of the water pump, allowing precise regulation of irrigation according to the system's fuzzy logic output. A real-time clock (RTC) module ensured accurate time synchronization for irrigation scheduling, while a 4×20 LCD display provided real-time feedback on sensor readings and system status [20]. Additional electronic components, including electrical wiring and a printed circuit board (PCB), were incorporated to support stable circuit integration and ensure reliable performance under

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field conditions. Together, these components formed a compact and efficient IoT-based fertigation system capable of continuous monitoring and adaptive irrigation control.

2.2. Experimental Crops and Nutrition

The field experiment was conducted on citrus crops (Citrus sp.) located in Batu City, East Java Province, Indonesia, at an altitude of approximately 877 meters above sea level. The area is characterized by a tropical highland climate with average temperatures ranging from 23–26°C, relative humidity around 70%, and annual rainfall ranging from 1.500 to 2.500 mm. These environmental conditions provide an ideal setting for citrus cultivation.

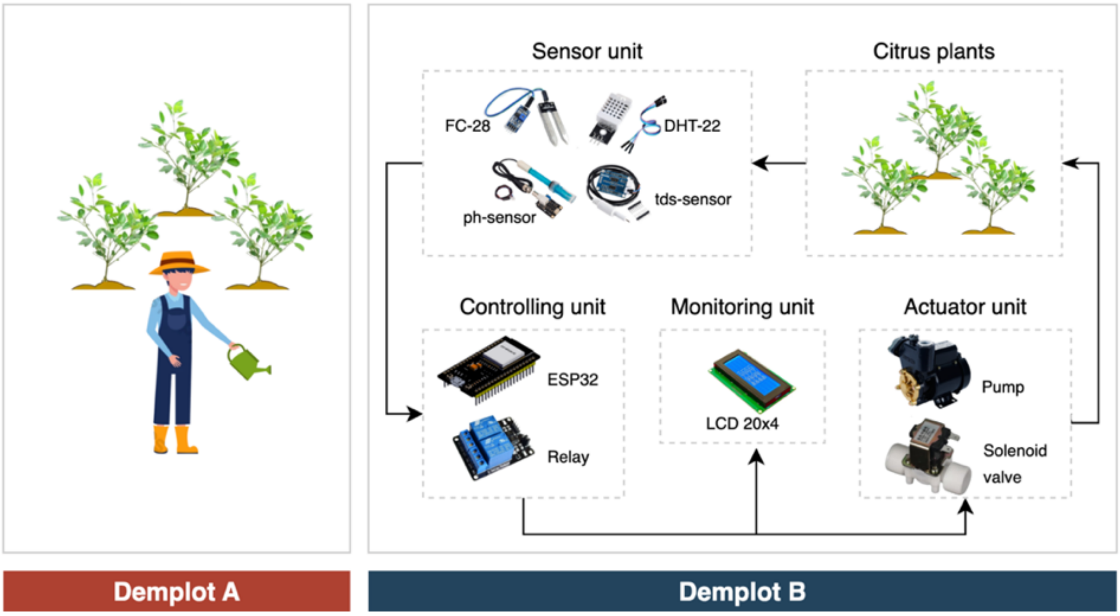

Figure 1. Research design

Two experimental plots were used in this study:

1) Plot A: irrigation performed manually on a fixed schedule.
2) Plot B: irrigation controlled automatically using fuzzy logic based on sensor data.

The citrus plants used in this research were 3-6 months old. Each plant was treated with liquid organic fertilizer (LOF) derived from citrus peel waste, which served as the nutrient solution in both systems. The intelligent fertigation system determined irrigation frequency and duration adaptively, while the conventional plot followed a fixed schedule determined by the operator. Observations were conducted for three months to analyze plant growth parameters, including plant height, number of leaves, and stem diameter, as well as soil condition parameters.

2.3. Sensor Data Acquisition

Data collection was carried out through a continuous acquisition process using multiple sensors integrated into the smart fertigation system. The soil moisture (FC-28), air humidity and temperature (DHT-22) sensors were connected to an ESP32 microcontroller, which acted as the main data acquisition and communication unit. Sensor readings were taken every 30 seconds, ensuring real-time monitoring of environmental changes, while pH and TDS sensors were recorded once daily due to their slower rate of variation. The ESP32 transmitted sensor data via the MQTT protocol to a Flask-based service that implemented the fuzzy logic algorithm for real-time decision making [21][22]. The processed data, including temperature, air humidity, soil moisture, watering time, and watering status, were stored in an SQLite database and visualized through a web interface built using Flask and Bootstrap. All readings were also exported into a structured .csv dataset for further analysis. The recorded dataset covered a seven-day initial calibration phase and a three-month performance evaluation period. The data were analyzed using Python in the Google Colab environment to visualize environmental fluctuations and to evaluate how the fuzzy logic controller responded to changes in temperature, humidity, and soil moisture. This integrated architecture ensured that irrigation decisions corresponded accurately to the real-time environmental conditions while maintaining efficient water management in the citrus plantation.

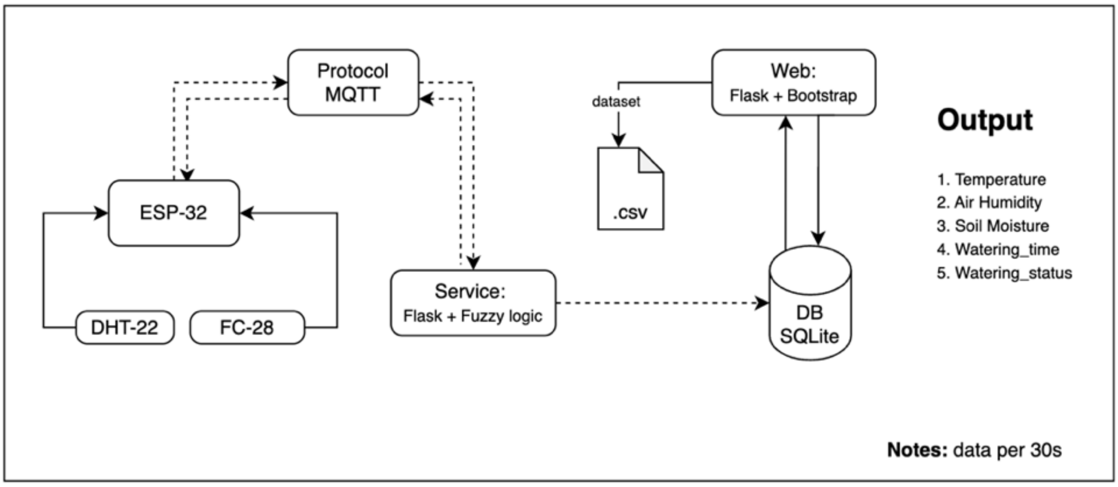

Figure 2. Architecture of data acquisition

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2.4. Fuzzy Logic Control Algorithm

The fuzzy logic control (FLC) algorithm was implemented to determine the irrigation duration adaptively based on three key environmental parameters: temperature, air humidity, and soil moisture [23][24]. The triangular membership function is utilized to represent linguistic concepts that reflect the gradual and imprecise nature of environmental parameters collected from sensors over a 30-day observation period in citrus plants. These parameters include temperature, air humidity, and soil moisture. The fuzzy set variables used in this study are presented in Table 1.

Table 1. Fuzzy set variables

x_1	Range (x_1)	x_2	Range (x_2)	x_3	Range (x_3)
Cool	0 – 20	Very Low	0 – 40	Very Dry	0 – 30
Mild	18 – 27	Low	35 – 70	Dry	20 – 50
Warm	25 – 34	Medium	65 – 90	Moist	40 – 70
Hot	32 – 40	High	85 – 100	Wet	60 – 100

Each input variable: Temperature (x_1), Air Humidity (x_2), and Soil Moisture (x_3) consists of four fuzzy sets that represent distinct environmental states. The combination of these sets generates 64 fuzzy rules that guide the irrigation decision process for citrus crops. The membership distribution for each variable is depicted in Figure 3.

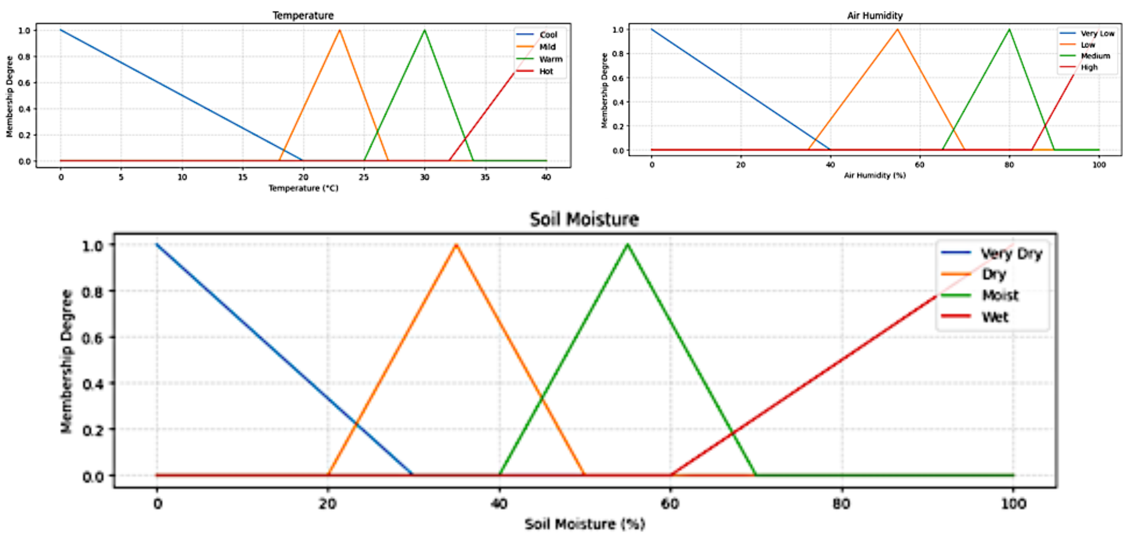

Figure 3. Fuzzy set variable membership

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The output variable, watering duration, ranged from 0 to 120,000 milliseconds and was categorized into five fuzzy sets: no watering, very short, short, medium, and long. The fuzzy rule base was formulated from expert knowledge and empirical observations under tropical field conditions. Some representative rules are as follows:

1) IF soil is wet AND air is very low AND temp is cool THEN no watering
2) IF soil is moist AND air is low AND temp is cool THEN very short watering
3) IF soil is dry AND air is medium AND temp is mild THEN short watering
4) IF soil is dry AND air is low AND temp is warm THEN medium watering
5) IF soil is very dry AND air is high AND temp is hot THEN long watering

The inference process follows the Mamdani approach for rule aggregation, while the centroid method is used for defuzzification to obtain a crisp output representing the exact irrigation duration in milliseconds. This output is transmitted to the ESP32 microcontroller, which controls the solenoid valve and water pump accordingly. Through this mechanism, irrigation decisions are continuously adjusted in real time, ensuring efficient water use and intelligent fertigation management for citrus cultivation.

3. RESULTS AND DISCUSSION

The developed system integrates several electronic components and sensors to support data acquisition and control processes within the intelligent fertigation system for citrus plants. The fuzzy rule-based algorithm was implemented to determine the irrigation duration of nutrient solutions using a triangular membership function for each input variable. The system relies on real-time environmental data obtained from temperature, air humidity, and soil moisture sensors, which are processed through the ESP32 microcontroller to generate the appropriate control actions for irrigation. During the 30-day observation period, the wireless sensor network successfully collected environmental data at scheduled intervals every morning when irrigation typically occurred. The acquired data were stored in a structured format and used as input for the fuzzy logic controller. These data serve as the basis for system calibration and analysis to evaluate how environmental fluctuations influenced the system's decision-making process regarding watering duration. The summarized sensor acquisition data used in this study are presented in Table 2, showing daily variations in temperature, air humidity, and soil moisture over the experimental period.

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Table 2. Sensor acquisition data

Day	Timestamp	Temperature	Air Humidity	Soil Moisture
1	2025-09-12	22.6	88.7	58
2	2025-09-13	22.1	83.9	52
3	2025-09-14	19.9	89.7	47
4	2025-09-15	23.3	80.1	48
5	2025-09-16	22.4	92.8	43
6	2025-09-17	22.6	89.6	42
7	2025-09-18	24.6	77.8	36
8	2025-09-19	25.3	77.9	43
9	2025-09-20	24.7	76.8	42
10	2025-09-21	25.9	68.4	47
11	2025-09-22	25.1	55.4	39
12	2025-09-23	25.3	50.8	43
13	2025-09-24	24.5	77.7	37
14	2025-09-25	25.4	77.8	44
15	2025-09-26	25.8	68.2	39
16	2025-09-27	25	70	43
17	2025-09-28	25.3	65.1	52
18	2025-09-29	24.1	75.5	42
19	2025-09-30	22.6	87.8	43
20	2025-10-01	30.4	60.4	58
21	2025-10-02	29.5	50.4	52
22	2025-10-03	24.9	72.5	27
23	2025-10-04	28.7	34.3	52
24	2025-10-05	26.1	64.7	53
25	2025-10-06	28.1	58.8	26
26	2025-10-07	27.8	51.3	33
27	2025-10-08	27	65.6	50
28	2025-10-09	23.9	73.5	25
29	2025-10-10	23.1	76.7	32
30	2025-10-11	26.6	58.6	45

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3.1. Fuzzification

Fuzzification is the initial process in which crisp (numerical) sensor values are converted into fuzzy linguistic terms based on predefined membership functions. In this study, the input parameters include temperature (x_1), air humidity (x_2), and soil moisture (x_3). The raw sensor data such as x_1 = 26.6°C, x_2 = 58.6%, and x_3 = 45% are processed through triangular membership functions to determine their respective degrees of membership in each fuzzy set. These fuzzy sets correspond to environmental conditions defined for citrus cultivation in tropical regions.

1) **Temperature** (26.6 °C)

μ_{cool} [0,0,20] = 0 (as it is outside the cool value range)

because $x = 26.6 \geq c = 20 \rightarrow \mu = 0$

μ_{mild} [18,23,27] $= \frac{c-x}{c-b} = \frac{27-26.6}{27-23}$ = 0.1

μ_{warm} [25,30,34] $= \frac{x-a}{b-a} = \frac{26.6-25}{30-25}$ = 0.32

μ_{hot} [32,40,40] = 0 (as it is outside the hot value range)

because $x = 26.6 < a = 32 \rightarrow \mu = 0$

2) **Air Humidity** (58.6 %)

$\mu_{very\ low}$ [0,0,40] = 0 (as it is outside the very low value range)

because $x = 58.6 > c = 40 \rightarrow \mu = 0$

μ_{low} [35,55,70] $= \frac{c-x}{c-b} = \frac{70-58.6}{70-55}$ = 0.76

μ_{medium} [65,80,90] = 0 (as it is outside the medium value range)

because $x = 58.6 < a = 65 \rightarrow \mu = 0$

μ_{high} [85,100,100] = 0 (as it is outside the high value range)

because $x = 58.6 < a = 85 \rightarrow \mu = 0$

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3) Soil Moisture (45 %)

$\mu_{very\ dry}$ [0,0,30] = 0 (as it is outside the very dry value range)

because $x = 45 > c = 30 \rightarrow \mu = 0$

μ_{dry} [20,35,50] $= \frac{c-x}{c-b} = \frac{50-45}{50-35}$ = 0.333

μ_{moist} [40,55,70] $= \frac{x-a}{b-a} = \frac{45-40}{55-40}$ = 0.333

μ_{wet} [60,100,100] = 0 (as it is outside the wet value range)

because $x = 45 < a = 60 \rightarrow \mu = 0$

The fuzzification results for Day 30 show that the temperature belongs mainly to the warm category with a membership value of μ = 0.32, and slightly to the mild category (μ = 0.10), indicating a moderately warm environment. The air humidity is classified as low with a strong membership value of μ = 0.76, suggesting that the surrounding air is moderately dry. Meanwhile, the soil moisture exhibits equal memberships in both the dry and moist sets (μ = 0.33 each), implying that the soil condition lies at the transition between slightly dry and moist. In practical terms, the combination of warm temperature, low air humidity, and borderline dry soil represents a field condition in which citrus plants require a moderate level of irrigation.

3.2. Rule application and implication

Rule application is the process of applying the predefined fuzzy rule base derived from expert knowledge and environmental observations to determine the appropriate irrigation duration [25]. The fuzzy input data consist of environmental parameters acquired from sensors, including temperature, air humidity, and soil moisture, which are then mapped into linguistic variables according to the defined membership functions. These inputs are processed using the Mamdani inference model to evaluate the rules that describe the relationship between environmental conditions and the required irrigation time.

A total of 64 fuzzy rules were generated from the combination of four linguistic variables for each input parameter: soil moisture (very dry, dry, moist, wet), air humidity (very low,

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low, medium, high), and temperature (cool, mild, warm, hot). Each rule represents a specific environmental condition and its corresponding irrigation decision. However, only a few representative rules are presented in this section to illustrate the logic of the system. These selected rules closely approximate the fuzzy variable dataset and are grouped into five irrigation categories: no watering, very short, short, medium, and long watering durations

3.3. Implication

The implication stage establishes the relationship between the antecedent (IF part) and the consequent (THEN part) of each fuzzy rule. This process determines how strongly each rule is activated based on the degree of membership (μ) of the environmental parameters obtained from the sensors. In this study, the implication mechanism adopts the Mamdani inference model, where the minimum (MIN) operator is used to define the firing strength (α) of each active rule. The output fuzzy set for each rule is then truncated according to its firing strength before being aggregated with other rules. The firing strength (α) of this rule is determined using the minimum operator: $\alpha = \min(\mu_{dry}, \mu_{low}, \mu_{warm}) = \min(0.333, 0.76, 0.32) = 0.32$. This firing strength ($\alpha = 0.32$) contributes to the aggregated fuzzy output, which is subsequently passed to the defuzzification stage to generate a single crisp watering duration.

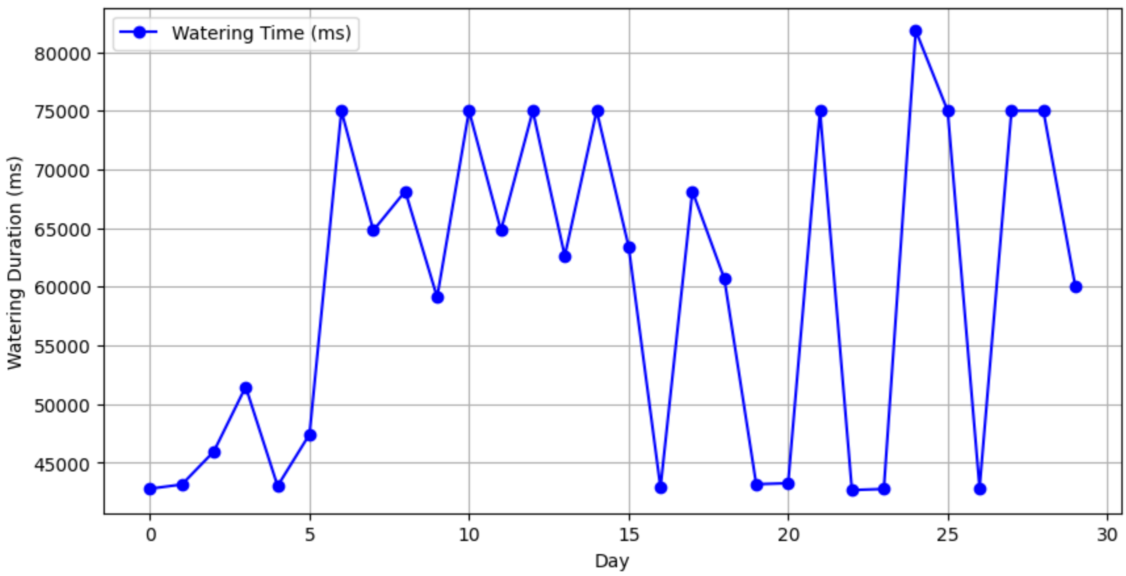

Figure 4. Fuzzy logic control output for watering

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3.4. Defuzzification

Defuzzification is the final step in the fuzzy inference process, where the combined fuzzy outputs are transformed into a single crisp value that determines the actual irrigation duration in milliseconds. In this system, the centroid (center of gravity) method is used because it provides a balanced representation of the aggregated fuzzy areas by considering both the magnitude and distribution of each active fuzzy output. The value ranges for each nutrient solution irrigation duration category are as follows: No Water [0, 0, 0], Very Short [0, 15, 30], Short [25, 45, 60], Medium [55, 75, 95], and Long [90, 120, 120]. The defuzzification result using the centroid method is obtained by converting fuzzy values into crisp values to determine the nutrient solution irrigation duration as illustrated in Figure 4. As a result, the final crisp value from the defuzzification process for nutrient solution irrigation duration in plants yields a duration of 60 seconds for the medium irrigation category. The application result of the fuzzy logic algorithm for irrigating the nutrient solution in citrus plants via a web-based platform can be seen in Figure 5.

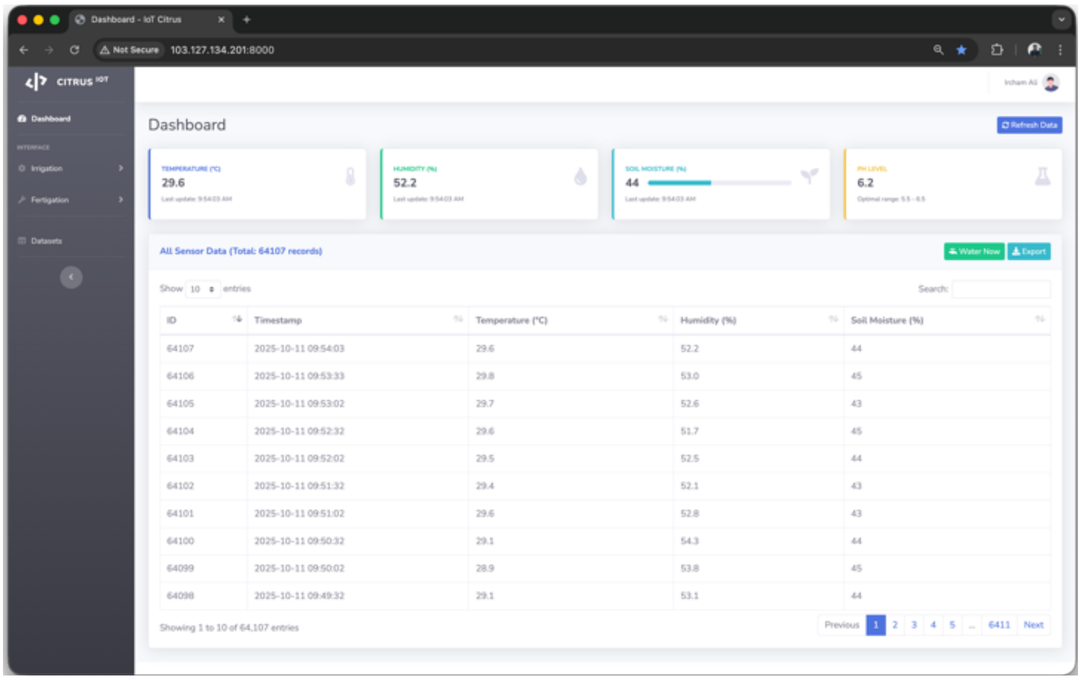

Figure 5. Web-based fertigation system for citrus plants

The results of intelligent fertigation on citrus plants, including the duration and volume of the nutrient solution, based on the variables Temperature (x_1), Air Humidity (x_2), and Soil Moisture (x_3) can be seen in Table 3.

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Table 3. Result of watering application

x_1	x_2	x_3	Time (ms)	Volume (ml)	Status
22.6	88.7	58	42794	400	Medium
22.1	83.9	52	43151	400	Medium
19.9	89.7	47	45959	450	Medium
23.3	80.1	48	51479	500	Medium
22.4	92.8	43	43024	400	Medium
22.6	89.6	42	47426	500	Medium
24.6	77.8	36	75000	750	Long
25.3	77.9	43	64807	600	Medium
24.7	76.8	42	68145	700	Medium
25.9	68.4	47	59111	600	Medium
25.1	55.4	39	75000	750	Long
25.3	50.8	43	64807	600	Medium
24.5	77.7	37	75000	750	Long
25.4	77.8	44	62623	600	Medium
25.8	68.2	39	75000	750	Long
25	70	43	63447	600	Medium
25.3	65.1	52	42882	400	Medium
24.1	75.5	42	68145	700	Medium
22.6	87.8	43	60697	600	Medium
30.4	60.4	58	43175	400	Medium
29.5	50.4	52	43262	400	Medium
24.9	72.5	27	75000	750	Long
28.7	34.3	52	42674	400	Medium
26.1	64.7	53	42769	400	Medium
28.1	58.8	26	81831	800	Long
27.8	51.3	33	75000	750	Long
27	65.6	50	42846	400	Medium
23.9	73.5	25	75000	750	Long
23.1	76.7	32	75000	750	Long
26.6	58.6	45	60051	600	Medium

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3.5. Implementation and growth observation

The experiment was conducted using 12 citrus seedlings aged approximately 3–4 months after budding (post-budding). These seedlings were grouped into four treatment clusters, each containing three plants. Each cluster represented a different irrigation or fertigation treatment method, namely MF (Manual Fertigation) is manual watering combined with nutrient solution, MI (Manual Irrigation) is manual watering without nutrients, SF (Smart Fertigation) is automated watering and nutrient delivery controlled by fuzzy logic, and SI (Smart Irrigation) is automated watering system without nutrients.

Table 4. Growth observation (30 days)

code	y_1	y_2	y_3	y_4	y_5
MF	2	6	8	9	7
MI	1	5	4	5	16
SF	2	14	11	37	35
SI	1	14	13	14	12

The fertigation process in all clusters was performed once daily at 07.00 AM, based on the fuzzy logic control schedule. The plants were grown in polybag media and placed on a semi-shaded rooftop area that received direct sunlight but maintained adequate warmth essential for citrus growth. The optimal soil moisture for citrus plants was maintained between 40-55%, as overly humid conditions promote fungal infections, whereas overly dry conditions can lead to water stress and increased pest attacks. Table 4 presents the average growth observation results of citrus plants during the experimental period. Each growth parameter is coded as follows: y_1 = stem diameter, y_2 = plant height, y_3 = new shoot length, y_4 = number of leaves on new shoots, and y_5 = number of leaves on grafted shoots.

Throughout the four-week observation period, all plants exhibited healthy vegetative development. However, noticeable differences in growth patterns were observed among the four treatment groups, as can be seen in Figure 6. The Smart Fertigation (SF) system consistently produced the best performance in all growth indicators: stem diameter, plant height, shoot elongation, and leaf formation with an average growth score of 19.8, approximately three times higher than manual irrigation (MI). The Smart Irrigation (SI)

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system followed with an average score of 10.8, demonstrating the advantage of automated water control even without nutrient enrichment.

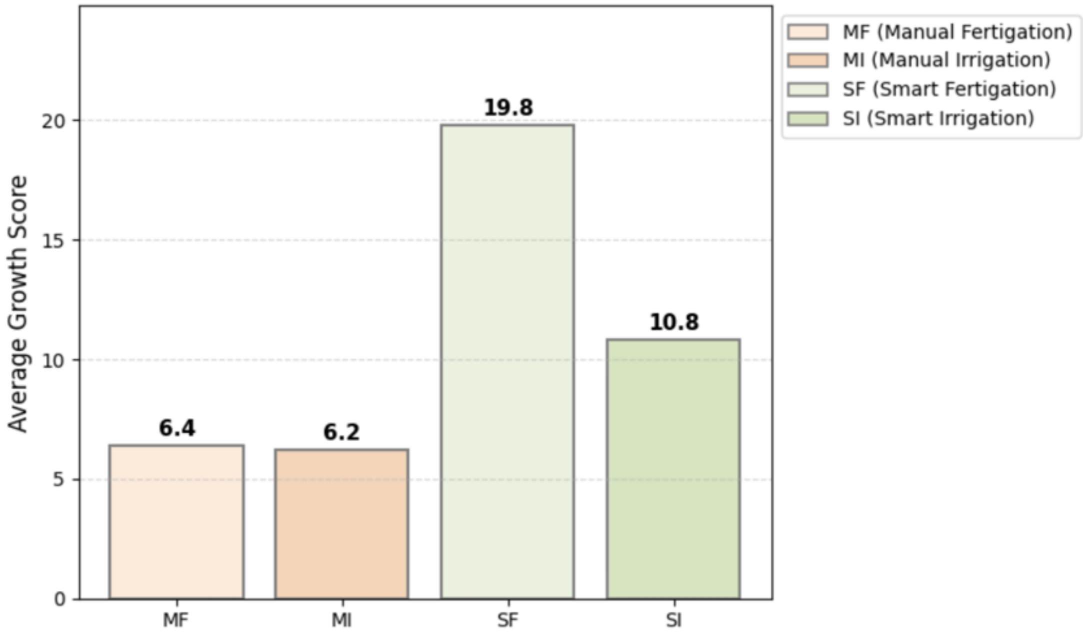

Figure 6. Growth comparison of citrus plants

Plants under Smart Fertigation (SF) showed uniform and stable growth with denser and greener leaves. Their average plant height increased by about 7 cm more compared to those under manual irrigation, and leaves-maintained turgidity throughout hot days. In contrast, plants under Manual Irrigation (MI) occasionally showed temporary wilting before recovery after watering, indicating less stable soil moisture regulation. The heatmap (Figure 7) demonstrates a strong contrast between manual and smart fertigation strategies. SF not only produced the highest scores in all growth categories but also showed a uniform pattern of improvement, while MF and MI treatments remained clustered at lower values, indicating limited growth stimulation.

The fuzzy-based irrigation controller maintained optimal moisture conditions and balanced nutrient delivery according to real-time environmental sensor data. This adaptive decision-making process minimized water loss and improved root nutrient absorption efficiency. The integration of the ESP32 microcontroller with soil, temperature, and humidity sensors enabled continuous feedback and automation, significantly reducing human intervention. During the experiment, several external

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factors affected the acquisition process, including episodic rain events and wind-induced temperature fluctuations, which contributed to microclimate instability around the sensor units. These external factors occasionally influenced data acquisition accuracy, yet the fuzzy controller consistently recalibrated irrigation decisions in response. Overall, the experiment confirms that the fuzzy logic–based smart fertigation system provides superior efficiency, stability, and accuracy in managing water and nutrients compared to manual systems. This approach enhances growth consistency and resource optimization for citrus cultivation, particularly under tropical field conditions.

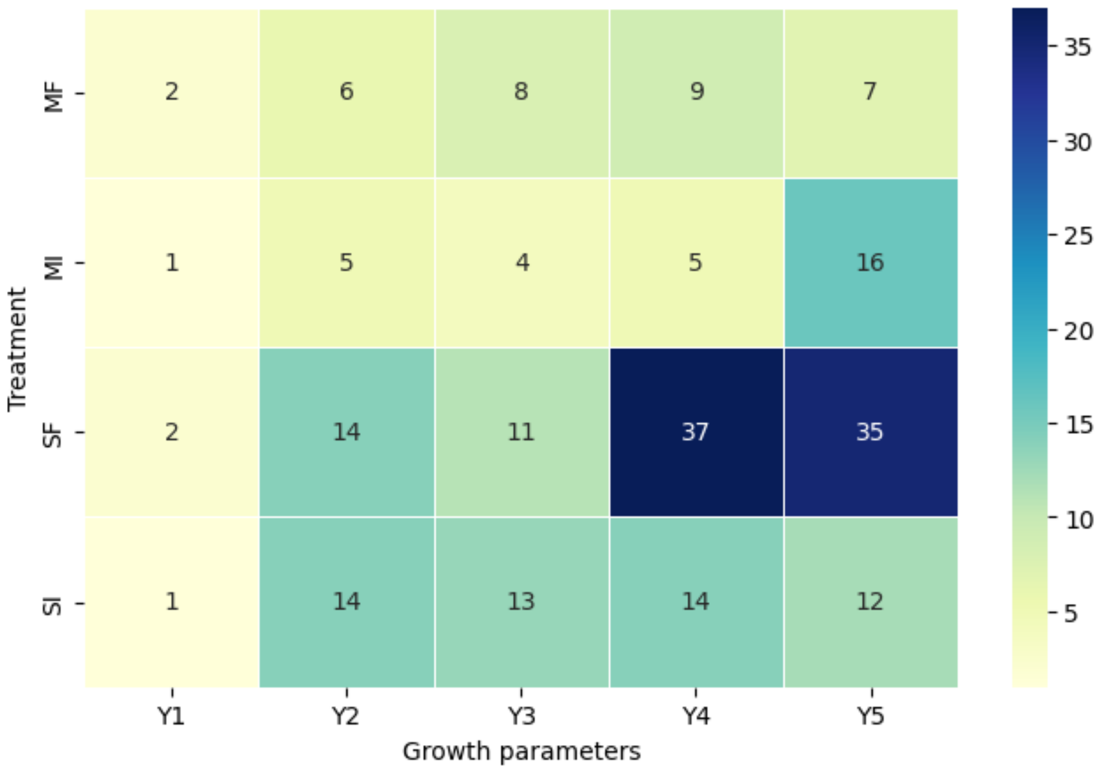

Figure 7. Heatmap comparing plant growth based on parameters and treatments

3.6. Discussion

The results of this study demonstrate the significant advantages of implementing a smart fertigation system based on fuzzy logic control (FLC) for citrus cultivation. The system, designed to automate irrigation and nutrient delivery based on real-time environmental parameters, effectively optimized resource usage and improved plant growth compared to conventional methods. The study focused on integrating key environmental factors such as soil moisture, air humidity, and temperature to determine irrigation duration, making the system adaptable to fluctuating conditions in tropical environments. This adaptability is a significant improvement over traditional fertigation systems, which often rely on fixed schedules or thresholds that do not account for real-time variations in environmental conditions. The positive impact of the smart fertigation system is evident in the comparative analysis of plant growth metrics, which showed that the Smart Fertigation (SF) treatment resulted in significantly higher growth rates in terms of stem diameter, plant height, shoot length, and leaf formation.

The comparison between manual and smart fertigation systems highlights the inherent advantages of automated, sensor-based irrigation. Plants under the Smart Fertigation (SF) treatment showed consistent and stable growth, with a substantial increase in average plant height (7 cm more than the manual irrigation group) and a more vibrant leaf color, suggesting better nutrient uptake and water regulation. In contrast, the Manual Irrigation (MI) group exhibited fluctuations in growth, with plants occasionally showing temporary wilting before recovery, which indicates less efficient soil moisture management. This reinforces the notion that smart fertigation, driven by real-time environmental data, offers significant improvements in water and nutrient management, ensuring optimal plant growth, especially under challenging tropical conditions.

The Fuzzy Logic Control (FLC) algorithm demonstrated its ability to adapt irrigation decisions based on the real-time environmental data collected by the IoT sensors. The fuzzy rule-based system applied various environmental conditions (e.g., temperature, humidity, soil moisture) to make precise irrigation decisions, ensuring that the citrus plants received adequate water and nutrients without wastage. The fuzzy logic's ability to continuously recalibrate irrigation schedules based on fluctuating environmental factors—such as sudden rain or temperature changes—allowed for more efficient water use, minimizing over-watering and nutrient loss. The consistency of the system's decision-making process, even under fluctuating conditions, supports the effectiveness of using fuzzy logic to manage complex agricultural systems that require constant adjustment to maintain ideal growing conditions.

The significant difference in growth performance between the Smart Fertigation (SF) system and other treatments is primarily attributed to the precision and flexibility of the automated system. By utilizing a liquid organic fertilizer (LOF) derived from citrus peel waste, the smart fertigation system also demonstrated an eco-friendly approach to

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nutrient management. This sustainable use of waste material not only provides the plants with essential nutrients but also contributes to reducing environmental waste, promoting a circular economy in agriculture. The system's ability to optimize irrigation based on real-time data, while also using organic fertilizers, underscores its potential to enhance sustainable practices in citrus farming, an area that traditionally struggles with inefficient water and fertilizer usage.

Despite the clear advantages of the smart fertigation system, the study acknowledges some limitations related to external factors such as weather conditions and sensor calibration. Rainfall and wind-induced temperature fluctuations introduced occasional inconsistencies in data acquisition, which might have impacted the precision of the sensor readings. However, the system's ability to adjust to these environmental fluctuations through continuous recalibration demonstrates its resilience and effectiveness in managing unpredictable outdoor conditions. Moreover, while the ESP32 microcontroller successfully facilitated the automation and real-time data processing, the reliance on regular sensor calibration for accurate measurements emphasizes the need for ongoing maintenance to ensure long-term system performance.

In conclusion, this study presents strong evidence supporting the use of IoT-based smart fertigation systems integrated with fuzzy logic control for improving citrus cultivation efficiency. The ability to manage irrigation and nutrient delivery based on real-time environmental data leads to enhanced plant growth, optimized resource use, and sustainability in agricultural practices. The Smart Fertigation (SF) system outperformed manual irrigation methods in terms of plant growth metrics, demonstrating the importance of adaptive, data-driven irrigation systems for modern agriculture. These findings suggest that implementing smart fertigation systems, particularly those powered by fuzzy logic and IoT technologies, could revolutionize the way citrus farms—and potentially other agricultural sectors—manage water, nutrients, and overall farm productivity in tropical climates. Future research could explore further system refinements, sensor innovations, and the integration of additional environmental factors to enhance the system's precision and adaptability.

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4. CONCLUSION

This study has demonstrated the successful design and implementation of a smart fertigation system for citrus plants by combining a fuzzy logic control model with an ESP32 microcontroller and internet of things (IoT). By continuously interpreting soil moisture, air humidity, and temperature data, the system was able to adjust irrigation duration in real time, ensuring that water and nutrients were supplied in accordance with actual environmental conditions. The smart fertigation system setup-maintained moisture levels between roughly 40-55%, avoiding the significant fluctuations typically associated with manual irrigation. Plants receiving automated fertigation displayed stronger vegetative performance, growing approximately 7 cm taller on average and producing denser foliage.

More importantly, the system proved to be practical in the field. It reduced dependence on manual monitoring, prevented excessive water use, and helped maintain a favorable growth environment. Because the fuzzy logic sets and rules can be modified, the same system can be adapted for other crops. However, its deployment in new regions may require adjustments to account for local soil characteristics and temperature-humidity patterns. To expand its applicability, future investigations should consider multi-season trials, predictive modeling for irrigation scheduling, solar-powered operation, and scalability assessments for broader agricultural use. These efforts will contribute to more robust and sustainable fertigation solutions.

ACKNOWLEDGMENT

This research is part of the basic research program of BIMA funded in 2025. Therefore, the authors would like to express their sincere gratitude to the Ministry of Higher Education, Science, and Technology of Indonesia for the financial support provided. The authors also extend their heartfelt thanks to Universitas Nahdlatul Ulama Indonesia (UNUSIA) for its continuous support and assistance throughout the implementation of this study.

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